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Challenges for Medical Students in Applying Ethical Principles to Allocate Life-Saving Medical Devices During the COVID-19 Pandemic: Content Analysis

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Abstract

Background: The emergence of the COVID-19 pandemic has posed a significant ethical dilemma in the allocation of scarce, life-saving medical equipment to critically ill patients. It remains uncertain whether medical students are equipped to navigate this complex ethical process.

Objective: This study aimed to assess the ability and confidence of medical students to apply principles of medical ethics in allocating critical medical devices through the scenario of virtual patients.

Methods: The study recruited third- and fourth-year medical students during clinical rotation. We facilitated interactions between medical students and virtual patients experiencing respiratory failure due to COVID-19 infection. We assessed the students’ ability to ethically allocate life-saving resources. Subsequently, we analyzed their written reports using thematic analysis to identify the ethical principles guiding their decision-making.

Results: We enrolled a cohort of 67 out of 71 medical students with a mean age of 34 (SD 4.7) years, 60% (n=40) of whom were female students. The principle of justice was cited by 73% (n=49) of students while analyzing this scenario. A majority of them expressed hesitancy in determining which patient should receive life-saving resources, with 46% (n=31) citing the principle of nonmaleficence, 31% (n=21) advocating for a first-come-first-served approach, and 25% (n=17) emphasizing respect for patient autonomy as key influencers in their decisions. Notably, medical students exhibited a lack of confidence in making ethical decisions concerning the distribution of medical resources. A minority, comprising 12% (n=8), proposed the exploration of legal alternatives, while 4% (n=3) suggested medical guidelines and collective decision-making as potential substitutes for individual ethical choices to alleviate the stress associated with personal decision-making.

Conclusions: This study highlights the importance of improving ethical reasoning under time constraints using virtual platforms. More than 70% of medical students identified justice as the predominant principle in allocating limited medical resources to critically ill patients. However, they exhibited a lack of confidence in making ethical determinations and leaned toward principles such as nonmaleficence, patient autonomy, adherence to legal and medical standards, and collective decision-making to mitigate the pressure associated with such decisions.
Introduction
The COVID-19 pandemic has caused millions of deaths and countless hospitalizations worldwide owing to critical conditions caused by the virus [1]. This has raised the ethical dilemma of allocating scarce life-saving devices to critically ill patients [2-5]. Physicians often make clinical decisions based on scientific evidence to avoid moral distress [3,6,7]. However, clinical decisions may have to be made under time constraints. Preparing physicians to apply appropriate ethical principles, have self-confidence in making choices, and prevent moral trauma has become essential during the pandemic [8].

The principles of autonomy, justice, beneficence, and nonmaleficence commonly serve as guiding references for allocating scarce medical resources [9]. However, these principles have multiple interpretations when facing limited resources and can be based on utilitarianism, egalitarianism, or deontology [10]. Utilitarianism believes that the primary obligation is not to treat people equally, but to maximize the greatest amount of happiness for the greatest number of people; the best actions would be based on what brings the best benefit. By contrast, egalitarianism upholds the rights and interests of individuals, which should be equally protected [10]. Deontology judges the morality of choices by its conformity with a moral norm [11], regardless of its consequences. Persad et al [12] present a comprehensive framework for the allocation of scarce medical resources grounded in the core principles of autonomy, justice, beneficence, and nonmaleficence. Their framework encompasses 4 distinct ethical value categories, including equal treatment, prioritization of the most vulnerable, maximizing overall benefits, and recognition of social usefulness. Within each category, 2 competing ethical principles emerge, yielding a total of 8 subprinciples that provide detailed guidance aligned with the overarching ethical values [12]. The core values or principles that medical students prefer or overlook when facing ethical dilemmas are unclear and require further study.

The School of Medicine for International Students at I-Shou University has a 4-year Doctor of Medicine program that collaborates with the Ministry of Foreign Affairs and enrolls college graduates from countries with official diplomatic ties to Taiwan. Due to the limited medical resources in such students’ home countries, they may face the challenge of a shortage of life-saving medical facilities in clinical practice. Therefore, equipping them with the knowledge and skills to allocate life-saving medical devices to critically ill patients, based on reasonable principles of medical ethics, is crucial. The use of virtual patients for teaching medical humanities may strengthen the effectiveness of medical ethics education [13,14]. Considering the challenges imposed by the COVID-19 pandemic, this solution aims to offer a secure and personalized training environment, transcending the boundaries of time and space. By doing so, students can become fully engrossed in virtual scenarios, enriching their learning experiences.

The objective of this study was to assess the ability and confidence of medical students to apply principles of medical ethics in allocating critical medical devices through the scenario of virtual patients.

Methods
Study Design
We designed a virtual scenario and asked medical students to allocate lifesaving medical devices to only 1 patient. In this scenario, a 62-year-old COVID-19-infected patient with respiratory failure was admitted to the intensive care unit. Medical students were instructed to interview a virtual patient and review the patient’s laboratory and imaging findings. They then were asked to make clinical diagnoses and adopt appropriate ethical principles to determine whether to remove the extracorporeal membrane oxygenation (ECMO) device from an 80-year-old patient currently using it and reallocate it to the new younger patient. After making their decision, the students were requested to write a short essay addressing the ethical conflicts they encountered in making the choice.

Ethical Considerations
We explained the rationale for this qualitative study and recruited third- and fourth-year medical students from the School of Medicine for International Students Program when they undertook clinical rotation at the hospital. All participants completed the virtual clinical scenarios within 4 hours in May 2021, during the COVID-19 pandemic in Taiwan, after signing an informed consent form. This study was approved by the E-Da Hospital Institutional Review Board (no. EMRP05109N and EMRP041111N), and the data were not identifiable. The teaching and evaluation of students were not affected by whether they participated in the research.

Case Scenario
Leona is a 62-year-old retired woman. She had been well without any underlying disease until recently being diagnosed with COVID-19 pneumonitis. Her lung condition continuously deteriorated, and ECMO was the last resort to support her tissue oxygenation. However, the only available ECMO machine was currently being used by an 80-year-old patient with multiple chronic illnesses who remained unstable after receiving ECMO treatment, with minimal chances of recovery.

The students were given the above scenario to assess and answer relevant questions. One of the questions was “Will you continue to let the 80-year-old patient use the ECMO, or let Leona use...
the ECMO instead? Please explain your decision and your reasons to support it.”

The medical students could use the 4 principles of medical ethics or base their responses on their individual analytical perspectives and reasoning for the allocation of limited medical resources.

Data Analysis
Age (>25 vs ≤ 25 years) and sex (male vs female) served as basic demographic variables, with the age of 25 years as a threshold of maturity. Grade (third vs fourth year) represented differences in clinical exposure experiences [15]. Textual content analysis was performed by 2 of the authors to search for keywords and summarize the students’ responses independently. The keywords were encoded and categorized for both quantitative and qualitative analyses. We used the principles of summative content analysis, which combines the quantitative counting of specific content or words or terms with latent content analysis to identify and categorize their meanings. In brief, we created a new coding category for any newly introduced terms in the assignment, and then assessed conceptual similarities to determine whether to further organize these codes into additional categories with appropriate names.

The qualitative analysis consisted of the following steps:

1. The coding items included the final decision of the students (for whom to use), which core medical ethical principles were applied with various degrees in their choices, and whether viewpoints other than ethics, such as medical guidelines or legislation, were mentioned.

2. The reasons for the students’ final decisions were classified according to the patient they selected, either the 62-year-old younger patient or the 80-year-old patient with multiple comorbidities. Our analysis focused on encoding the ethical justifications provided by the medical students to support their final decisions. We omitted considerations related to their alternative choices during the decision-making process.

3. The classification of reasoning for those who made a decision was primarily based on the students’ understanding and interpretations in their essays, which Persad et al [12] mentioned were equality, vulnerability, maximizing the quality of life, and contribution to society. The original resource allocation principles were designed for the distribution of medical supplies among a group of individuals. However, the present case pertains to the treatment decision for an individual patient, further complicated by the fact that one patient had already been put on a ventilator. By contextualizing the principles within the framework of the present case, we eliminated the applicability of 4 subprinciples: lottery, saving the most lives, reciprocity, and giving priority to the worst off (ie, sickest first).

4. If students displayed reluctance in making a choice, we also coded their explanations for the perception that ethical decision-making might not be suitable, categorizing these explanations as “undetermined” or “both unqualified.”

5. The main reasons for the students’ final decisions were classified into medical, legal, and ethical perspectives.

6. The coding process was independently judged by 2 researchers with expertise in qualitative research. Any inconsistencies in coding were resolved by reviewing the classification descriptions to refine the precision of category definitions and revisiting the context to ensure accurate coding.

Results
Student Demographics
From 2021 to 2022, a total of 71 international third- and fourth-year clinical medical students who were facing the COVID-19 pandemic most significantly were enrolled. Of these, 67 students (33 third-year and 34 fourth-year students) from 12 countries participated in the study. Because 4 fourth-year medical students did not participate, the response rate was 94%. Overall, 40 (60%) participants were female and 61 (91%) were older than 25 years. Most medical students were from the Kingdom of Eswatini, accounting for 48% (n=32) of the total group (Table 1 and Multimedia Appendix 1).
Table 1. Basic information of the students.

<table>
<thead>
<tr>
<th>Demographic</th>
<th>Medical students (n=67), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>27 (40)</td>
</tr>
<tr>
<td>Female</td>
<td>40 (60)</td>
</tr>
<tr>
<td>Age (years)</td>
<td></td>
</tr>
<tr>
<td>&gt;25</td>
<td>61 (91)</td>
</tr>
<tr>
<td>≤25</td>
<td>6 (9)</td>
</tr>
<tr>
<td>Seniority year</td>
<td></td>
</tr>
<tr>
<td>Third</td>
<td>33 (49)</td>
</tr>
<tr>
<td>Fourth</td>
<td>34 (51)</td>
</tr>
<tr>
<td>Country of origin</td>
<td></td>
</tr>
<tr>
<td>The Kingdom of Eswatini</td>
<td>32 (48)</td>
</tr>
<tr>
<td>Saint Lucia</td>
<td>7 (10)</td>
</tr>
<tr>
<td>Belize</td>
<td>7 (10)</td>
</tr>
<tr>
<td>Kiribati</td>
<td>5 (7)</td>
</tr>
<tr>
<td>Honduras</td>
<td>3 (4)</td>
</tr>
<tr>
<td>The Marshall Islands</td>
<td>3 (4)</td>
</tr>
<tr>
<td>Saint Kitts and Nevis</td>
<td>3 (4)</td>
</tr>
<tr>
<td>Paraguay</td>
<td>2 (3)</td>
</tr>
<tr>
<td>Saint Vincent &amp; The Grenadines</td>
<td>2 (3)</td>
</tr>
<tr>
<td>Palau</td>
<td>1 (1)</td>
</tr>
<tr>
<td>Haiti</td>
<td>1 (1)</td>
</tr>
<tr>
<td>Solomon Islands</td>
<td>1 (1)</td>
</tr>
</tbody>
</table>

Choosing the Best Candidate for ECMO Allocation

Of the 67 participating students, age group (<25 vs ≥25 years old), sex (male vs female), and seniority year (third vs fourth year) did not affect patient selection preferences, and a larger proportion of students from Eswatini (21/32, 66%) selected the 80-year-old patient for ECMO compared to the rest of the students (39/67, 58%). The majority of students decided to continue treating the 80-year-old patient with ECMO (Table 2).

Additionally, 5 (8%) students argued that the medical information provided was not sufficient to make decisions that were highly dependent on factors such as the patient’s condition, the course of the disease, and legal requirements. One student (1%) suggested that, in accordance with medical guidelines, neither patient met the conditions to be a candidate for ECMO. A possible reason for them to abstain from decision-making could be the pressure they experienced while facing an ethical dilemma. As one student (no. 16) stated:

*Doctors should not take the treatment away of one person and give it to another, regardless of the odds of survival rate of these two patients, because it means that we are taking the role of God, deciding who lives and who dies.*

Another student (no. 20) stated:

*I don’t believe I have the right to decide who is more deserving or who needs this equipment more.*

Table 2. Choosing the most suitable patient for extracorporeal membrane oxygenation treatment.

<table>
<thead>
<tr>
<th>Patient selected</th>
<th>Students (n=67), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>80-year-old</td>
<td>39 (58)</td>
</tr>
<tr>
<td>62-year-old</td>
<td>22 (33)</td>
</tr>
<tr>
<td>Undetermined</td>
<td>5 (8)</td>
</tr>
<tr>
<td>Both unqualified</td>
<td>1 (1)</td>
</tr>
</tbody>
</table>
Students’ Perspective of Allocating Limited Resources

Building upon the framework proposed by Persad et al [12], this study identified 4 coding categories after excluding subprinciples that were deemed inapplicable to the current case. In accordance with the students’ final decisions regarding the most suitable recipient for ECMO, we categorized the reasons endorsed by the students (Table 3). The primary justifications for selecting an 80-year-old patient included nonmaleficence (n=31, 46%), first-come-first-served (n=21, 31%), and patient autonomy (n=17, 25%). Students grounded their decisions in 3 of the 4 ethical principles, arguing that in this particular scenario, those advocating for the principle of nonmaleficence contended that physicians lacked the authority to withdraw a life-saving device in active use. “First-come-first-served” represents 1 of the 4 interpretive angles of the justice principle from Persad’s framework. Students believed that the life of each patient held equal value, and those who received treatment first should be allowed to continue treatment. Students who mentioned patient autonomy were particularly concerned about the absence of informed consent and its potential legal implications for health care providers.

The reasons for selecting the 62-year-old patient primarily revolved around the principle of justice. The utilitarian principle of maximum benefit was the most popular: 31% (n=21) of students mentioned that medical resources should be reserved for patients who can survive the longest and have the best quality of life. When comparing who had better survival probabilities, some students suggested that medical guidelines should serve as the basis for the final decision. Overall, 10% (n=7) of students made decisions depending on who had contributed more to society as a whole, and 4% (n=3) prioritized the disadvantaged, where the disadvantaged can be interpreted as the younger patient.

Students who expressed an “undetermined” stance believed that decision-making authority should be entrusted to guidelines, which could be either principles collectively established by physicians within the hospital (n=4, 6%), hospital policies (n=4, 6%), local laws (n=4, 6%), or decisions made by the hospital’s ethics committee (n=3, 4%). Alternatively, some advocated for decisions to be made collectively by physicians within the hospital (n=1, 1%), by the patients’ families (n=1, 1%), or based on other information relevant to the patient’s condition (n=1, 1%). One student expressed a “both unqualified” position and approached the issue from a medical rather than an ethical perspective. The student asserted that, based on the guidelines, neither of the 2 patients met the criteria for usage.

### Table 3. Multiple-choice analysis of the reasoning for case selection among students.

<table>
<thead>
<tr>
<th>Reasoning for selected patient</th>
<th>Students (n=67), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>80-year-old</strong></td>
<td></td>
</tr>
<tr>
<td>Nonmaleficence (physician has no right to withdraw)</td>
<td>31 (46)</td>
</tr>
<tr>
<td>Treat patients equally (first come, first served)</td>
<td>21 (31)</td>
</tr>
<tr>
<td>Patient’s autonomy (law issue)</td>
<td>17 (25)</td>
</tr>
<tr>
<td>Withdraw can’t prove 62-year-old patient’s survival</td>
<td>2 (3)</td>
</tr>
<tr>
<td><strong>62-year-old</strong></td>
<td></td>
</tr>
<tr>
<td>Higher survival rate, save the maximum quality of life (medical issue)</td>
<td>21 (31)</td>
</tr>
<tr>
<td>Rewarding social usefulness</td>
<td>7 (10)</td>
</tr>
<tr>
<td>Giving priority to the worst off; youngest first</td>
<td>3 (4)</td>
</tr>
<tr>
<td><strong>Undetermined</strong></td>
<td></td>
</tr>
<tr>
<td>Decided by medical guidelines, collective decision</td>
<td>4 (6)</td>
</tr>
<tr>
<td>Decided by hospital</td>
<td>4 (6)</td>
</tr>
<tr>
<td>Depend on law</td>
<td>4 (6)</td>
</tr>
<tr>
<td>Decided by the ethics committee</td>
<td>3 (4)</td>
</tr>
<tr>
<td>Decided by 80-years-old patient’s family member</td>
<td>1 (1)</td>
</tr>
<tr>
<td>Depend on other medical information</td>
<td>1 (1)</td>
</tr>
<tr>
<td><strong>Both unqualified</strong></td>
<td></td>
</tr>
<tr>
<td>Both are unqualified for ECMO&lt;sup&gt;a&lt;/sup&gt; per guidelines</td>
<td>1 (1)</td>
</tr>
</tbody>
</table>

<sup>a</sup>ECMO: extracorporeal membrane oxygenation.

### Adequacy of Using Medical Ethical Principles

In total, 73% (n=49) of students cited the principle of justice while analyzing this case. When ethical principles were in conflict, the principle of justice was most commonly cited. The frequencies of ethical principles considered by medical students in making final decisions (coding as simple choice) were as follows: 48% (n=32) used the principle of justice, 25% (n=18) used the principle of nonmaleficence, 12% (n=8) used the principle of patient autonomy, and 9% (n=6) were unable to provide a definitive response.
Confidence in Ethical Decision-Making

Overall, 75% (n=50) of the participants analyzed the case from other perspectives, such as medicine and law, and 25% (n=18) made their final decision based on the principles mentioned in the clinical guidelines. These students were more inclined toward the scientific mode of thinking, believing that evidence-based medicine is objective and may provide clear standards that can give them a sense of security. Students no. 23 and 31, respectively, indicated the following:

I can respond to this situation based on scientific evidence.

A comprehensive assessment of the pathology of the patient’s current condition and the state of illness is a major consideration in decision-making.

For 12% (n=8) of the medical students, their final decisions were made from a legal perspective; that is, they stated that the decision should be made in accordance with the law of the state. They emphasized that physicians should protect themselves from being sued and provide decision-making authority to the patient or family. The patients or their family members should sign the emergency consent form, allowing the patient or family to participate in decision-making. As stated by student no. 40:

Medical care providers must consider medical laws, including those for removing the machine from the patient and withholding services from patients.

Additionally, 6% (n=4) of the medical students believed that medical institutions should provide clear guidelines or set up ethics committees to make collective decisions, thus preventing individual doctors from facing the pressure of decision-making. Student no. 18 stated:

I will follow the organization’s code of ethics. The handling rules approved by a specific organization that will guide you in such situations so that you do not face a violation of the law.

Discussion

Principal Findings

ECMO is recommended for severe COVID-19-related acute respiratory distress syndrome to reduce mortality [16]. Currently, there is no evidence-based ethical guidance for prioritizing ECMO when resources are limited during the COVID-19 pandemic [17]. Justice is the preferred principle in virtual settings, although students have diverse interpretations. Nearly half of the students used additional principles, such as nonmaleficence and respect for patient autonomy, to prevent further harm while making ethical decisions. Multiple perspectives were adopted by three-fourths of the students.

The context of clinical situations is important for making clinical decisions based on ethical dilemmas [18]. The use of virtual patients for medical education may strengthen the effectiveness of medical ethics education [13,14]. Using virtual patients for clinical decision-making training among international medical students offers several advantages [19-21]. It provides a safe training environment amidst the COVID-19 pandemic and allows for diverse case presentations from multiple countries and cultures [22]. The application of virtual care has flourished internationally during the post-COVID era. The Cleveland Medical Center in the United States has also explored the integration of remote and virtual health care. Medical institutions in the southern United States have proved that virtual diagnosis and treatment can alleviate caregiver burden and promote patient care [23]. Our study has provided evidence that combining virtual training with ethical reasoning in solving ethical dilemmas may present a safe environment for learning clinical decision-making and offer opportunities for improvement.

Students were asked to think about and answer questions according to the situation of the virtual patient. More than half of the students chose the oldest or the sickest patient to be the best candidate. The clinical scenario that was tested involved ex-post triage, which entails discontinuing ongoing treatment in favor of a newly arrived patient. Particularly in the context of a pandemic with limited resources (eg, ventilators), the primary objective is to maximize overall benefits for all individuals. While challenging, medical physicians may need to make the difficult decision of reallocating life-saving facilities from the most critically ill patients to those who have a higher probability of survival [5]. During a pandemic, rationing may require the withdrawal of care in order to provide ventilators to patients who are given higher priority, a reason foreign to many front-line clinicians [24]. Sharing and leveraging the diverse responses of medical students themselves can serve as a valuable reference for fostering innovative approaches in medical ethics education and facilitating ethical deliberation on challenging medical issues.

Medical students must define problems, identify potential solutions, and also inform patients about the current treatment options. The students’ understanding of patient autonomy and informed consent was superficial and formalistic; they were more concerned about obtaining consent or documents to avoid legal proceedings. Recent discussions on the principles of patient autonomy have concluded that superficial autonomy cannot guarantee patient autonomy [25-27]. Moreover, physicians should make more efforts to meet the best interests of patients [28,29]. Considering students’ diverse backgrounds, it is important to take into account their various learning styles to enhance and personalize educational materials [30].

The inability to establish a definitive ethical guideline capable of resolving issues stemming from the scarcity of medical resources underscores the complexity of the situation. Furthermore, factors such as patients possessing varying medical needs, financial capabilities to cover medical expenses, and the policies of health care institutions can all impact the ethical judgments of students [31,32]. Therefore, teachers can take the opportunity to emphasize to students that the premise of patient autonomy and informed consent is to uphold the patient’s right to live, and promoting the well-being of the patient is the core value of the principle of patient autonomy. To ensure the patient’s autonomy is respected, physicians should make decisions that benefit the patient’s overall health and care.

Students were unfamiliar with philosophical and ethical reasoning and were under pressure to make ethical decisions about allocating life-saving medical modalities. They tended to
analyze ethical issues from both medical and legal perspectives [33,34]. Most medical students relied on objective medical guidelines, legal documents, or hospital management systems to help them make decisions while lacking life-saving medical modalities. Experts might erroneously assume that by dutifully adhering to the code’s regulations they fulfill all pertinent ethical obligations. Similarly, many people hold the belief that by fulfilling all applicable legal prerequisites, they have fulfilled their moral duties. It is important to note that what may be deemed ethically correct does not always find support within the confines of the law. Legal education places emphasis on the introduction of statutes and their applicability, while ethical education delves into the reasoning process underlying diverse ethical decisions. Within medical ethics education, an exploration of students’ abilities to discern the implications of various ethical decisions and make informed value judgments is paramount [35]. Some students believe that developing medical guidelines can serve as a substitute for individual ethical decision-making. Use of the specification method to solve ethical dilemma questions has limitations. If a specification eliminates contingent conflict, it may be arbitrary, lack impartiality, or fail for other reasons. We cannot avoid judgements that balance different principles or rules in the very act of specifying them. It also seems pointless or unduly complicated to engage in specification in many circumstances [35].

To foster the development of medical students’ ethical thinking, it becomes crucial to provide them with opportunities to analyze cases using established ethical frameworks with proper guidance [5]. Furthermore, facilitating the sharing of diverse perspectives on case analysis can also prove valuable in nurturing community-specific morality, which draws its foundations from culture, religion, and institutional systems [35]. Based on our study, we proposed that the necessity of strengthening medical ethics education stems from the following: acknowledging physicians’ needs for independent ethical decisions during a pandemic, recognizing the irreplaceability of clinical ethical judgment over legal rules and medical guidelines, elevating students’ ethical reasoning abilities, and elucidating the core value and application scope of patient autonomy.

This study explored the current status of critical ethical decision-making from the diverse perspectives of international medical students and provided information using a virtual patient scenario. Heist et al [36], using case summaries, found that 5 sessions of virtual patient case scenarios significantly improved students’ clinical reasoning abilities. In light of the rapid advancement of virtual medical education platforms amidst the COVID-19 pandemic, it is suggested that medical schools proactively integrate a series of diverse virtual patient ethics decision-making exercises. This strategic inclusion aims to foster robust and well-rounded ethical education training for medical students, equipping them with the necessary skills to navigate complex ethical dilemmas in their future medical practice.

Through incorporating the survey in the formal class activity, we received a robust 94% response rate from a diverse group of medical students [37]. However, this study has some limitations. First, the interface and language processing technique of the virtual system could be more user-friendly in mimicking the true clinical interaction with patients. The responses of virtual patients were based on a predetermined script derived from a limited database design, making it difficult to respond to students’ more in-depth or spontaneous questions. Second, owing to the limited number of participants (n=67) and the fixed setting of a single virtual patient, students’ responses may not have been extrapolated. If the current medical resources and institutional policy differ, students might make various decisions.

Conclusion
This study addressed the need for practical clinical ethics training in medical education by using virtual patients to offer students simulated scenarios for cultivating decision-making experiences. It compiled diverse perspectives from students of various cultural backgrounds, enhancing their capacity for comprehensive ethical considerations. The research suggests a more effective curriculum development approach by combining individual case studies with a collective analysis of answers. As future physicians, these students will benefit from this training when making time-sensitive ethical decisions based on all stakeholders’ viewpoints. This study also identifies a lack of student confidence in making ethical decisions related to patients’ lives. It highlights the need to foster the independent ethical decision-making competency of medical students.

Acknowledgments
We thank the School for International Medical Students, College of Medicine of I-Shou University for offering the teaching material and facilities; the library of the E-Da Hospital for research resources and space; and the National Science and Technology Council for their support. This project was funded by the National Science and Technology Council, Taiwan (grants MOST-109-2511-H-650-002-MY2 and MOST 111-2410-H-650-002).

Authors’ Contributions
H-YH contributed to the conception of this work, data analysis and interpretation, and writing of manuscript. RYH contributed to the conception of work, data acquisition, writing of the manuscript. G-CL contributed to data analysis and interpretation. J-YL and CA contributed to the substantial revision of the manuscript with English editing. C-HL contributed to the conception of this work, oversaw the quality, and contributed to substantial revisions. The authors have read and approved the final manuscript.
References


Abbreviations

**ECMO**: extracorporeal membrane oxygenation
A Generative Pretrained Transformer (GPT)–Powered Chatbot as a Simulated Patient to Practice History Taking: Prospective, Mixed Methods Study

Friederike Holderried

Abstract

Background: Communication is a core competency of medical professionals and of utmost importance for patient safety. Although medical curricula emphasize communication training, traditional formats, such as real or simulated patient interactions, can present psychological stress and are limited in repetition. The recent emergence of large language models (LLMs), such as generative pretrained transformer (GPT), offers an opportunity to overcome these restrictions.

Objective: The aim of this study was to explore the feasibility of a GPT-driven chatbot to practice history taking, one of the core competencies of communication.

Methods: We developed an interactive chatbot interface using GPT-3.5 and a specific prompt including a chatbot-optimized illness script and a behavioral component. Following a mixed methods approach, we invited medical students to voluntarily practice history taking. To determine whether GPT provides suitable answers as a simulated patient, the conversations were recorded and analyzed using quantitative and qualitative approaches. We analyzed the extent to which the questions and answers aligned with the provided script, as well as the medical plausibility of the answers. Finally, the students filled out the Chatbot Usability Questionnaire (CUQ).

Results: A total of 28 students practiced with our chatbot (mean age 23.4, SD 2.9 years). We recorded a total of 826 question-answer pairs (QAPs), with a median of 27.5 QAPs per conversation and 94.7% (n=782) pertaining to history taking. When questions were explicitly covered by the script (n=502, 60.3%), the GPT-provided answers were mostly based on explicit script information (n=471, 94.4%). For questions not covered by the script (n=195, 23.4%), the GPT answers used 56.4% (n=110) fictitious information. Regarding plausibility, 842 (97.9%) of 860 QAPs were rated as plausible. Of the 14 (2.1%) implausible answers, GPT provided answers rated as socially desirable, leaving role identity, ignoring script information, illogical reasoning, and calculation error. Despite these results, the CUQ revealed an overall positive user experience (77/100 points).

Conclusions: Our data showed that LLMs, such as GPT, can provide a simulated patient experience and yield a good user experience and a majority of plausible answers. Our analysis revealed that GPT-provided answers use either explicit script information or are based on available information, which can be understood as abductive reasoning. Although rare, the GPT-based chatbot provides implausible information in some instances, with the major tendency being socially desirable instead of medically plausible information.
simulated patient; GPT; generative pretrained transformer; ChatGPT; history taking; medical education; documentation; history; simulated; simulation; simulations; NLP; natural language processing; artificial intelligence; interactive; chatbot; chatbots; conversational agent; conversational agents; answer; answers; response; responses; human computer; human machine; usability; satisfaction

**Introduction**

Communication is one of the core competencies of health care professionals [1,2]. In the medical context, communication serves multiple functions, including relationship building, information gathering, and decision-making [3]. The ability to communicate with patients is crucial for their health outcomes [4,5]. Furthermore, inadequate communication can result in missed diagnostic opportunities and thus poses a hazard to patient safety [6,7]. Consequently, medical curricula worldwide incorporate either dedicated communication courses or a communication curriculum, depending on the level of curricular integration [8-10]. Formats that allow for the acquisition of communication competencies include theoretical lessons, peer-assisted learning, learning with simulation patients, and learning with real patients [11,12].

In this study, we assessed the potential of large language models (LLMs), such as generative pretrained transformer (GPT), in enhancing communication training. One key skill in medical communication is history taking, which is required in almost all medical fields to make a correct diagnosis and initiate treatment [13]. This learning objective typically starts with taking a systematic history (ie, assessing the history regarding all relevant body functions and organ systems). To practice history taking, the learner is required to have an interactive encounter [14], and courses frequently rely on simulated or real patients [15]. These formats are associated with high costs and a high organizational effort, however, which shortens the time available to acquire these skills. These restrictions often do not allow all students to interactively practice a skill or practice for more than 1 repetition [16]. Furthermore, learning in these settings often occurs supervised by the patient and peer group, thereby impacting performance and possibly inhibiting rather shy students from using the learning opportunity [17,18].

Chatbots offer a significant potential to overcome these restrictions, thereby enhancing the utility thereof in health care and medical education settings. Chatbots have thus become valuable tools in health care; their nonjudgmental and easily accessible nature makes them particularly well suited for responding to patient inquiries and concerns [19,20]. The use of chatbots in medical education offers equally promising opportunities. In particular, chatbots are of interest tool-wise in the area of virtual patients [21,22].

The advance of chatbots is significantly supported by the developments of LLMs, such as GPT, which progressed considerably in 2022 [23]. This progress in artificial intelligence (AI) technology opens up new horizons for innovative, cost-effective, and accessible learning methods [24,25]. GPT has performed surprisingly well regarding medical knowledge, including board exams [26-28]. The combination of excellent language skills and medical knowledge predispose GPT to perform as a chatbot. Moreover, LLMs allow for unsupervised and repeated learning, thereby enabling all students to learn for as long as it is needed. However, LLMs, such as GPT, are language models using a next-word prediction paradigm [29] and are thus prone to “hallucinations” (ie, producing nonsensical content) [30]. Moreover, LLMs are also known to occasionally escape prompts.

Chatbots have been used in medical education before the broader application of LLMs [31]. However, these virtual simulated patients did not reach human performance in terms of language expression and dynamics [31]. Although chatbots to practice history taking have been developed based on pre-LLM technology [32], it is unknown whether and how LLMs, such as GPT, can be used as a simulated patient to acquire communication skills. To investigate the previously uncharted potential of GPT as a simulated patient, we conducted a mixed methods study. Here, we present our analysis of GPT capabilities, as a chatbot as well as an improved version of an AI-optimized illness script.

**Methods**

**Study Outline**

First, we developed an illness script [33] that contained relevant medical information from a fictitious patient and a prompt to make GPT-3.5 (OpenAI) act as a simulated patient. We introduced the chatbot to medical students through a web interface, allowing them to voluntarily practice their history-taking skills. The conversations were recorded and systematically analyzed to explore the conversations with the GPT-powered chatbot. We focused on feasibility and usability and performed a quality assessment of GPT’s text output.

**Setting and Participants**

During a large-scale skill-refreshing event with participants from all our faculty, students were invited to voluntarily participate in our investigation. After they provided informed consent, students were provided with a laptop on which the interface was ready to use. After entering demographic information, students could chat for as long as they felt necessary.

Since our participants were native German speakers, we conducted all interactions with GPT in German and later translated the data and screenshots into English for this paper.

**Chat Platform**

To enable the interaction between students and GPT, we created a chat interface through which the students could post written
questions to a virtual patient and receive written answers (Figure 1). This interface enabled us to guide user input and send system messages to GPT. The system was developed as a local HTML file. It used JavaScript code for processing and tailwindcss for layout. We called the OpenAI application programming interface (API) using the JavaScript Fetch API and making calls to OpenAI’s chat/completions endpoint using gpt-3.5-turbo. Model parameters were left at default settings. The complete chat history for each user input up to that point was sent to the model. At the conclusion of the conversation, the full chat history was saved to a text file for further processing.

Figure 1. Screenshot of self-developed web interface.

Prompt Development
Next, we developed prompts that were needed to make GPT act as a simulated patient. The prompts were designed to guide GPT’s behavior and ensure it provided medically accurate and relevant responses. Presented in detail next, our prompt included a chatbot-optimized illness script as well as a behavioral instruction prompt.

Chatbot-Optimized Illness Script With a Medical Case
We developed a fictitious medical case in a format that could be posted to GPT. As our learning objective was to take a systematic history, we intended to provide all required details. A short version with some information about the case is presented in Table 1, and the full case is provided as Multimedia Appendix 1.
In addition to the required medical information, it was necessary to instruct GPT to behave as a simulated patient, which is why we developed a behavioral prompt. To achieve this, we used our custom interface to test the answers provided by GPT by conducting the interviews ourselves. Where we noticed a failure to stick to the provided medical information, we tried to improve the manner in which the information was presented. For improvements to the prompt, we relied on our experience as well as the advice and model explanation provided by OpenAI [34].

During the iterative process of prompt development, 2 areas of improvement were evident: the role-play aspect (ie, that GPT sticks to the role as a patient) and the medical aspect (ie, that GPT provides answers as close as possible to the given information, while sounding human).

Regarding role-play, the model often struggled to maintain its assigned role, especially during discussions of potentially serious medical issues. We had little success with providing details of the role or simply reinforcing that the goal was to impersonate a patient. Instead, we found the most helpful tweak was adding “patient name:” at the end of any user input, where “patient name” would be replaced by the name specific to each case. This resulted in GPT generating a continuation of “patient name:,” making it more probable that the LLM would actually produce the intended answer. Other tweaks were to begin the initial system message with the patient’s name and continue to use this name to “address” GPT in this manner. We also instructed the model to not assist the user in this setting but to impersonate the patient, although we found this to have a much smaller effect than the other changes. Notably, the model was instructed to provide short answers to reduce reading times.

We provided GPT with the case description, preceded by instructions to use this information for answering medical questions. We also provided a list of all categories the student should ask about in the interview. The list contained possible answers and information for each category; for this list, we also included a statement about its format (ie, we explicitly stated that “[the list] will have the form ‘category’: ‘information or possible answer if asked’”). In general, surrounding factual information with an explicit description of its content and format increased the reliability of using that information.

It is important to note that formatting was also important, as the model sometimes picked up patterns in formatting in its own answers. Since the medical information was first produced with common text editing software, a simple copy and paste into our system also copied large amounts of formatting, such as indents, bullet points, or whitespace. Cleaning this formatting from the prompt helped the model avoid repeating these patterns in the output.

In a similar way, we tried to give more structure to the prompt by using special delimiter statements, such as “===DIALOGUESTART.” These were intended to help the model switch from reading in medical information to

### Table 1. Illness script “Nausea, weight loss, and chronic fatigue” (shortened version).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Details</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Patient details</strong></td>
<td>• Ferdinand Wunderlich, 48 years of age</td>
</tr>
<tr>
<td></td>
<td>• Occupation: administrative employee in the finance department of a municipal hospital</td>
</tr>
<tr>
<td></td>
<td>• Personal life: overweight, previously tried diets unsuccessfully; enjoys family time, has two sons aged 8 and 6 years; not physically active</td>
</tr>
<tr>
<td></td>
<td>• Initial consultation with a new general practitioner</td>
</tr>
<tr>
<td><strong>Medical concerns</strong></td>
<td>• Presenting with nausea (especially after large meals), significant weight loss (10 kg in 6 weeks), and chronic fatigue</td>
</tr>
<tr>
<td></td>
<td>• Muscle cramps mainly in the legs and frequent at night</td>
</tr>
<tr>
<td></td>
<td>• Mental fatigue, with forgetfulness at work</td>
</tr>
<tr>
<td></td>
<td>• Has felt run down and tired for about 5-6 months, with symptoms intensifying in the past 4-8 weeks</td>
</tr>
<tr>
<td></td>
<td>• Feels severely limited by his current condition</td>
</tr>
<tr>
<td><strong>Accompanying symptoms</strong></td>
<td>• Multiple minor infections recently</td>
</tr>
<tr>
<td></td>
<td>• Episodes of dizziness (ie, light-headedness) occurring 1-2 times daily</td>
</tr>
<tr>
<td></td>
<td>• Dry skin</td>
</tr>
<tr>
<td></td>
<td>• Increased thirst (drinks about 4-5 L of water daily) and frequent urination day and night</td>
</tr>
<tr>
<td><strong>Medical history</strong></td>
<td>• Known hypertension, currently on blood pressure medication (Hygroton 50 mg and ramipril 5 mg)</td>
</tr>
<tr>
<td></td>
<td>• Shortness of breath during exertion</td>
</tr>
<tr>
<td></td>
<td>• Fatty liver diagnosed 3 years ago</td>
</tr>
<tr>
<td></td>
<td>• Right inguinal hernia treated surgically 3 years ago</td>
</tr>
<tr>
<td></td>
<td>• Mild constipation</td>
</tr>
<tr>
<td></td>
<td>• Allergic to penicillin since childhood</td>
</tr>
<tr>
<td></td>
<td>• Previously smoked for 4 years in his twenties</td>
</tr>
<tr>
<td></td>
<td>• Consumes beer occasionally (1-2 times a week)</td>
</tr>
<tr>
<td><strong>Family history</strong></td>
<td>• Father died of a heart attack</td>
</tr>
<tr>
<td></td>
<td>• Mother died at 79 years of age and had diabetes later in life</td>
</tr>
<tr>
<td></td>
<td>• Brother diagnosed with colon cancer</td>
</tr>
</tbody>
</table>

**Behavioral Prompt**

In addition to the required medical information, it was necessary to instruct GPT to behave as a simulated patient, which is why we developed a behavioral prompt. To achieve this, we used our custom interface to test the answers provided by GPT by conducting the interviews ourselves. Where we noticed a failure to stick to the provided medical information, we tried to improve the manner in which the information was presented. For improvements to the prompt, we relied on our experience as well as the advice and model explanation provided by OpenAI [34].

During the iterative process of prompt development, 2 areas of improvement were evident: the role-play aspect (ie, that GPT sticks to the role as a patient) and the medical aspect (ie, that GPT provides answers as close as possible to the given information, while sounding human).

Regarding role-play, the model often struggled to maintain its assigned role, especially during discussions of potentially serious medical issues. We had little success with providing details of the role or simply reinforcing that the goal was to impersonate a patient. Instead, we found the most helpful tweak was adding “patient name:” at the end of any user input, where “patient name” would be replaced by the name specific to each case. This resulted in GPT generating a continuation of “patient name:,” making it more probable that the LLM would actually produce a sensible utterance by the patient. Other tweaks were to begin the initial system message with the patient’s name and continue to use this name to “address” GPT in this manner. We also instructed the model to not assist the user in this setting but to impersonate the patient, although we found this to have a much smaller effect than the other changes. Notably, the model was instructed to provide short answers to reduce reading times.

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It is important to note that formatting was also important, as the model sometimes picked up patterns in formatting in its own answers. Since the medical information was first produced with common text editing software, a simple copy and paste into our system also copied large amounts of formatting, such as indents, bullet points, or whitespace. Cleaning this formatting from the prompt helped the model avoid repeating these patterns in the output.

In a similar way, we tried to give more structure to the prompt by using special delimiter statements, such as “===DIALOGUESTART.” These were intended to help the model switch from reading in medical information to
impersonating a patient. However, our approach was not successful, as the model started to repeat such patterns in its output, sometimes even initiating further switches, for example, by inserting “===DIALOGUEEND” itself. We had more success in achieving the desired behavior using structuring with explicit descriptions in natural language, as described before.

**Full Prompt**
The full prompt including both aforementioned parts is presented in **Textbox 1**.

**Textbox 1.** Prompt sent to the generative pretrained transformer (GPT) application programming interface (API) in JavaScript Object Notation (JSON) format. The prompt consists of a behavioral instruction prompt and the first user message. Further dialogue was appended during the interview.

```json
{
  "role": "system",
  "content": "Hello Mr. Wunderlich, in the following you will assume the role of an acting patient. You will not assist the user, but answer questions based on the following information: Your name is Ferdinand Wunderlich,
  
  […] Further Case Information …]

  Here is some more information on your complaints, Mr. Wunderlich. These are in the form of ‘Category’: ‘Information or possible answer on request’
  
  Chief complaint, if applicable, with: Nausea and weight loss (most recently 10 kg in 6 weeks) Chronic fatigue, exhaustion and lack of drive
  
  Localization and spread: The muscle cramps occur mainly in the legs.
  
  […] Further details (see illness script) …]

  In the following, you will take the role of Ferdinand Wunderlich, […], that is, you will answer as Ferdinand Wunderlich. Try to keep your answers rather short.
  
  }

  {
  "role": "user",
  "content": "[USER INPUT]
  "Ferdinand Wunderlich:"
  
  }
```

**Qualitative Analysis**
To gain a more profound understanding of the conversation between chatbot and participant, we conducted a qualitative analysis (ie, the Braun-Clarke inductive approach [35]) of the question-answer pairs (QAPs). All QAPs were thus aggregated and stored in a Microsoft Excel (version 16.0.10394.20022) sheet. For each question and answer, the word count was automatically analyzed using an Excel formula. Each QAP was assessed by 1 rater (author FH) for the aspects listed in Table 2. In equivocal cases, the items were discussed with another rater (author MM) until consensus was reached.
<table>
<thead>
<tr>
<th>Aspect and categories</th>
<th>Example(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Conversation part</strong></td>
<td></td>
</tr>
</tbody>
</table>
| Greeting/introduction | Student: “Good day, my name is Mrs Müller, and I am your attending physician. What brings you to me today?”  
GPT: “Good day, Mrs Müller. I have been experiencing nausea, weight loss, chronic fatigue, and lethargy for some time and would like to find out what could be causing it.” |
| Medical history | Student: “How much are you limited in your daily life?”  
GPT: “I am now severely restricted. After a long day at work, I am incapable of doing anything in the evening, and I also notice that I keep forgetting things at work. This way, I cannot manage either my work or the tasks at home in the family.”  
Student: “I will ask you briefly about a few other points that could be relevant. Do you have headaches?”  
GPT: “No, I do not have headaches.” |
| Goodbye/outlook | Student: “Okay. We will now conduct some examinations. Thank you for your responses.”  
GPT: “Thank you for the questions and your attention. I hope we can find the cause of my complaints and a suitable treatment option.” |
| Interactive exchange | Student: “I will discuss this with my boss and let you know tomorrow.”  
GPT: “Okay, that sounds good. Thank you for your help. I look forward to your feedback tomorrow.” |
| **Student’s question covered by the illness script** |
| Question not covered by the script | Student: “Have you been on vacation recently?”  
Student: “I imagine you sit a lot at your work. Do you have any back pain?” |
| Question indirectly/partially covered by the script | Student: “Are your lymph nodes enlarged?”  
Student: “Do you have a history of thyroid disease?” |
| Question explicitly covered by the script | Student: “What medications are you taking and at what dosage?” |
| Statement (no question) | Student: “Thank you for the conversation! I would now like to conduct a physical examination and initiate further diagnostics.” |
| **GPT’s answer uses the illness script** |
| Answer based on explicit script information | GPT: “For several months, I have been increasingly struggling with chronic fatigue and a lack of drive. The weight loss of 10 kg in the past 6 weeks has additionally worried me.” |
| Answer based on implicit script information | GPT: “No, no laboratory diagnostics have been carried out so far.” |
| Answer based on fictitious information | GPT: “No, due to the current situation around the COVID-19 pandemic, I have not traveled recently.” |
| **Answer medically plausible (regarding case and illness script)** |
| +2: Answer plausible, highly specific for case | Student: “Okay, how much do you drink in a day?”  
GPT: “I currently drink about 4-5 L a day, I have a noticeably increased thirst.”  
Student: “All right, you also mentioned weight loss. How many kilograms are we talking about?”  
GPT: “I have lost about 10 kg in the past 6 weeks.” |
| +1: Answer plausible, relevant for case | Student: “Do you have any accompanying pain?”  
GPT: “So far, I have not noticed any particular pains, except maybe occasional muscle cramps in my legs.” |
| 0: Answer plausible, not case specific | Student: “Have you ever had surgery?”  
GPT: “Yes, I had laparoscopic surgery for a right inguinal hernia 3 years ago.” |
Chatbot Usability Questionnaire

To assess how our participants perceived the simulated patient, we used the Chatbot Usability Questionnaire (CUQ) [36]. This 16-item questionnaire measures the personality, user experience, error management, and onboarding of a chatbot and has recently been validated [37]. After ending the chatbot sessions, our participants were asked to fill out a written version of the CUQ, and the CUQ score was calculated using the tool provided by the authors [38].

Quantitative Analysis

Statistical analysis and figure generation were performed with R statistical software (version 4.3.1; R Foundation for Statistical Computing) [39]. For the CUQ, we provided relative numbers of Likert categories. For counts, we reported the total (n) as well as percentages. Numerical data were inspected for normal distribution and provided as the mean and SD. If a Gaussian distribution could not be assumed, median and 25%-75% quartiles (Q25-Q75) were provided. We used the Spearman correlation coefficient to check for correlations, considering \( P<.05 \) as statistically significant.

Ethical Considerations

The study was approved by the Ethics Committee of the Faculty of Medicine at University Hospital Tübingen (385/2023A). Data were kept anonymous and were not associated with students. Although the participant got an opportunity to use the chatbot without providing consent that the data could be used for our study, all students consented that their data could be used.

Results

Demographic Data of Participants

A total of 28 students participated in the experiment, 24 (85.7%) of whom identified as female and 4 (14.3%) as male; no participants identified as nonbinary. Their ages ranged from 19 to 31 years (mean 23.4, SD 2.9 years). Of the 28 participants, 26 (92.9%) studied human medicine and 2 (7.1%) studied midwifery. The semesters varied from the second to the tenth semester, and 1 (3.6%) participant was in their final year. No participant was excluded from the analysis.

Conversation Length and Part of Conversation

A total of 28 conversations yielded 826 QAPs. Each conversation consisted of a median of 27.5 QAPs (Q25-Q75: 19.8-36.5 QAPs). The questions asked by participants yielded a median of 6 words (Q25-Q75: 6-9 words). The answers provided by GPT had a median of 16 words (Q25-Q75: 11-23 words). The Spearman correlation coefficient between the word count of the question and the word count of the answer was significant (\( P<.01 \), with \( \rho=0.29 \), indicating a positive but mild correlation. A scatter plot is displayed in Figure 2.

Of the 826 QAPs, most were related to history taking (n=782, 94.7%). A minority reflected interactive exchange (n=17, 2.1%), greeting/introduction (n=15, 1.8%), and goodbye/outlook (n=12, 1.6%).
Content Analysis of Conversations

*How Do Questions and Answers Relate in the Context of the Script?*

In the subsequent assessment, we examined whether the questions posed by the students were covered by the script. We then analyzed how the GPT responses were based on the information provided in the script (Figure 3).
Figure 3. Sankey plot for “Student’s question covered by the illness script” and “GPT’s answer uses the illness script” categories in relationship to one another. Numbers indicate the total QAPs per group or connection, and connections without numbers are 0. GPT: generative pretrained transformer; QAP: question-answer pair.

For questions explicitly covered by the script (n=502, 60.3%), 471 (94.4%) of GPT’s answers were based on explicit script information, 22 (4.4%) on implicit script information, and 6 (1.2%) on fictitious information. When the questions were indirectly or partially covered by the script (n=112, 13.4%), 54 (48.2%) of GPT’s responses were based on explicit information, 47 (42%) on implicit information, and 11 (9.8%) on fictitious information. For questions not covered by the script (n=195, 23.4%), 36 (18.5%) of GPT’s answers used explicit script information, 49 (25.1%) used implicit script information, and 110 (56.4%) used fictitious information. In instances where students provided statements without posing questions (n=24, 2.9%), 5 (23.8%) of GPT’s responses were based on the explicit script, 8 (38.1%) on the implicit script, and 8 (38.1%) on fictitious information. A total of 33 (3.8%) QAPs were excluded, because they could not be assessed in 1 of the 2 evaluated categories.

Are the GPT Answers Plausible?

When analyzing the answers in detail, 33 (4%) of the 826 QAPs concerned multiple aspects (ie, related to different questions or multiple parts of the illness script). We consequently further divided 32 (97%) QAPs into 2 QAPs and 1 (3%) QAP into 3 QAPs. In total, this resulted in 860 QAPs that were used for the subsequent qualitative plausibility analysis.

We further analyzed whether the GPT-provided responses were medically plausible. Of the 860 QAPs, 842 (97.9%) were rated as plausible. Specifically, 264 (30.7%) were rated as “answer plausible, highly specific for case,” 252 (29.3%) as “answer plausible, relevant for case,” and 326 (37.9%) as “answer
plausible, not case specific.” A smaller proportion (n=14, 1.6%) were rated as rather implausible, while 2 (0.2%) were found to be very implausible. This rating could not be applied to 2 (0.2%) QAPs.

**Correlation Between Reliance on the Illness Script and Plausibility**

We further analyzed whether the answers used explicit or implicit information from the illness script or fictitious information (Figure 4).

Figure 4. Sankey plot for “GPT’s answer uses the illness script” and answer plausibility categories in relationship to one another. Numbers indicate the total QAPs per group or connection, and connections without numbers are 0. GPT: generative pretrained transformer; QAP: question-answer pair.

Among answers that used explicit script information (n=578, 67.7%), 218 (37.7%) were “plausible, highly specific for the case,” 161 (27.9%) were “plausible, relevant for the case,” and 197 (34.1%) were “plausible, not case specific,” with a mere 2 (0.3%) answers being rather implausible and none very implausible.

Among answers stemming from implicit script information (n=136, 15.9%), 21 (15.4%) were “plausible, highly specific for the case,” 44 (32.4%) were “plausible, relevant for the case,” and the majority (n=70, 51.5%) were “plausible, not case specific.” Only 1 (0.7%) answer was deemed rather implausible, and none were rated as very implausible.

In the context of fictitious information (n=140, 16.4%), the answers were varied: 25 (17.9%) were “plausible, highly specific for the case,” 46 (32.9%) were “plausible, relevant for the case,” and 58 (41.4%) were “plausible, not case specific.” Additionally, 9 (6.4%) answers rated as were rather implausible, and 2 (1.4%) were viewed as very implausible.
Furthermore, 6 (0.7%) answers could not be categorized.

Analysis of Implausible Answers

Finally, we analyzed all answers rated as rather or very implausible. Of the 14 (2.1%) answers that were rated as rather implausible, 7 (50%) were rated as socially desirable. A recurrent example for this category could be observed when the GPT-powered chatbot was asked for its eating habits; in these cases, the answers contained popular eating recommendations, instead of eating habits that were plausible for our case. For another 2 (14.3%) answers, the model did not stick to its rule as a simulated patient but tried to assist the user (ie, when greeted, the simulated patient asked the doctor, “How can I help you?”). For 1 (7.1%) other QAP, the model referred to the doctor by the name of the patient, which thus rated this QAP as “GPT leaving its role identity.” In another case, information clearly evident from the script (ie, vertigo) was not used and the simulated patient stated that he did not suffer from vertigo. One more rather implausible QAP was illogical in itself (ie, “But due to my weight loss, I have had a reduced appetite lately.”).

Among the 2 (0.2%) QAPs rated as very implausible, GPT escaped its role in 1 (50%) case. Herein, the participant asked about what can be seen in the physical exam, and the GPT-provided answer was, “Sorry, I am a language AI and do not have access to visual information. I can only provide information that is given to me through text input. Please consult a doctor for a complete clinical examination.” The second QAP was rated as very implausible due to a calculation error by GPT: When our chatbot was asked how much he drinks during 1 week, the answer was 10-12 L. Our script indicated 4-5 L per day, however, which would be an average of 28-35 L per week.

Chatbot Usability Questionnaire

The results of the CUQ are displayed in Figure 5 (also see Multimedia Appendix 2 for numeric results).
Within the personality category, the majority of respondents \((n=16, \text{57\%})\) felt the chatbot’s personality was realistic and engaging and 9 (32\%) strongly agreed. When considering whether the chatbot seemed too robotic, a large proportion \((n=13, \text{46\%})\) disagreed and 2 (7\%) strongly disagreed. The chatbot was perceived as welcoming during the initial setup by 12 (43\%) of respondents, and 8 (29\%) respondents strongly agreed. A significant portion \((n=15, \text{54\%})\) strongly disagreed, and 12 (43\%) disagreed with the notion that the chatbot seemed unfriendly. In terms of understanding, 12 (43\%) respondents agreed and 16 (57\%) strongly agreed that the chatbot understood them well.

For the user experience category, the chatbot was seen as easy to navigate by 10 (36\%) respondents, with a notable 18 (64\%) strongly agreeing. In contrast, when asked whether it would be easy to get confused when using the chatbot, 17 (61\%) disagreed.
and 8 (29%) strongly disagreed. The chatbot’s ease of use was highlighted by 11 (39%) respondents agreeing and 16 (57%) strongly agreeing. Most respondents disagreed with the perception that the chatbot was complex: 12 (43%) disagreed and 13 (46%) strongly disagreed.

In the error handling category, a majority (n=16, 57%) of the respondents remained neutral about the chatbot coping well with errors. Of the remainder, most respondents were positive about the error handling, with 6 (21%) agreeing and 4 (14%) strongly agreeing. Conversely, 6 (21%) respondents strongly disagreed and 10 (36%) disagreed that the chatbot seemed unable to handle errors, with only a minority (n=3, 11%) agreeing.

For the onboarding category, 12 (43%) respondents agreed and another 12 (43%) strongly agreed that the chatbot explained its scope and purpose well. Accordingly, 8 (29%) respondents agreed, 7 (25%) disagreed, and 5 (18%) strongly disagreed with the statement that the chatbot gave no indication as to its purpose.

For questions not related to a factor, 18 (64%) respondents agreed and 8 (29%) strongly agreed that chatbot responses were useful, appropriate, and informative. Accordingly, 14 (50%) respondents strongly disagreed and 12 (43%) disagreed that chatbot responses were irrelevant. Additionally, 18 (64%) respondents strongly disagreed and 7 (25%) disagreed with the statement that the chatbot failed to recognize many inputs.

Overall, the CUQ score was 77 (Q25-Q75: 71-83) out of a maximum score of 100, which indicated a positive user experience with the chatbot.

**Improved AI-Capable Illness Script**

Finally, we analyzed the QAPs for aspects on how to improve the illness script. Of 302 QAPs where the student’s question was either not covered or only indirectly/partially covered by the script, we were able to further classify 301 (99.7%) QAPs as to whether the script needs to be updated. The 1 (0.3%) unclassified QAP consisted of an uncontextual exchange and was thus discarded.

**QAPs Implicating an Update of the Illness Script**

For the majority of the QAPs (n=141, 46.8%), no update was required, as the information was not relevant for the case, although it was medically relevant. A further 14 (4.7%) QAPs were neither medically relevant nor relevant for the case, also not implicating an update. For 86 (28.6%) QAPs, however, we determined that an already existing criterion in our illness script needed further details. Moreover, for 60 (19.9%) of the analyzed QAPs, we judged that our illness script needed additional criteria.

**Detailed Additions to Existing Criteria**

More detailed specifications were recommended for some of the already existing criteria. These encompassed the specification of vomiting, nausea, stress, daily symptom progression, timing of individual symptoms throughout the day, attempts at relief, prior investigations, urine output, bedding/nightclothes, and stool.

**Specific New Criteria Required**

A closer examination of the content revealed several specific criteria that were absent but found to be relevant. These included dietary habits, activity/sports, pain, travel abroad, urine, and potential autoimmune diseases.

**Improved Script Version**

Based on the aforementioned information, we generated an updated version of our illness script (Multimedia Appendix 3).

**Discussion**

**Principal Findings**

In this study, we investigated the capabilities of GPT used as a chatbot to practice history taking, a core competency of medical professionals [1,2]. Using a mixed methods approach, we provided a comprehensive overview of the performance of GPT, as well as the perception of our participants about the chatbot. Our main findings can be divided into 2 areas: the performance of GPT as a simulated patient and how medical students perceive this chatbot as a conversational agent.

**Performance of GPT as a Simulated Patient**

When developing our chatbot, our focus was the feasibility of using an LLM model as a simulated patient. Before incorporation of our chatbot, we developed a prompt consisting of behavioral instructions and a chatbot-optimized illness script. Our analysis revealed that GPT was capable of providing most of the answers that were medically plausible and in line with the illness script. When questions were covered by the script, GPT was capable of referring to them, even when the information was only present in an implicit form (Figure 3). Even if questions were not covered by the script, GPT used the information from our medical case to generate answers that were mostly medically plausible. However, our analysis revealed that the degree of plausibility decreased when less information was present in the script (Figure 4).

The ability of GPT to act as a simulated patient requires reasoning capabilities (ie, thinking about something in a logical and systematic way) [40-45]. There are different types of scientifically recognized reasoning, such as deductive reasoning that applies a general rule to a specific case, inductive reasoning that uses specific observations to draw a general rule, and abductive reasoning that finds the best conclusion for some observations [40]. Although LLMs, such as GPT, have been successful in various reasoning areas [46], our investigation revealed some caveats.

As most of the GPT answers were based on explicit script information, providing the user with these details did not necessitate the generation of new ideas and was thus a mere task of reformulating the given information for the context of a conversation. As a LLM [29], it was not surprising that GPT mastered this task. Regarding information that is not or only indirectly evident from the script, however, we postulated that both abductive and commonsense reasoning capabilities would be required; for these answers, we observed more implausible answers when compared to answers that were based on explicit script information.
Indeed, GPT-3.5 is known to perform reasonably well in both abductive and commonsense reasoning tasks [46,47]; our data confirmed these observations. There were a few instances when GPT provided implausible responses, however, and our content analysis revealed a tendency toward socially desirable answers. These errors could be interpreted as “escaping” abductive reasoning and applying deductive reasoning instead, thereby using general principles (eg, about a healthy diet) for a specific case. A similar observation was made by Espejel et al [46], when GPT “ignored” provided information and instead “relies on its general knowledge and understanding of the world.”

Regarding our illness script, these examples highlight that the illness script must include details about the patient role, especially when the patient displays traits that do not match popular or socially accepted norms. Although our script was capable of providing most information required for history taking either explicitly or implicitly, some criteria missed important details, while other criteria were completely missing. With the intention of keeping the illness script as short as possible and thereby reduce the work for teachers, we used the data from our study to amend our illness script.

Of note, we found a positive correlation between the word count of the question and the word count of the answer of GPT. Although the correlation was rather mild, possible interpretations for this behavior include GPT mimicking the language style (and length) of the interview, as well as inputs containing multiple questions, thus provoking longer answers. Although our analysis does not provide insight into this question, our data imply that future prompts should focus more on specifying the conversation style of GPT to achieve a standardized patient experience.

Perception of Medical Students

After exploring the performance of GPT as a simulated patient, we interviewed our participants about their perceptions of our chatbot using the CUQ. Confirming the qualitative analysis we performed, the students rated our chatbot as realistic and engaging. Again, in line with our qualitative data, the chatbot was rated as useful, appropriate, and relevant, with only a negligible number of students stating that the chatbot did not recognize their inputs; notably, some issues were detected with our chatbot being robotic. These data largely confirm the linguistic capabilities of GPT-3.5, with its output even showing personality traits [48-51]. Given the importance of the chatbot’s authenticity to provide students with a plausible conversation partner to practice their skills, the results of the CUQ are reassuring that GPT is capable of providing this experience.

Comparison With Prior Work

Owing to the costs and potential disturbances associated with the use of real or simulated patients in communication training [52,53], there has been great interest in the use of virtual simulated patients as chatbots for communication training [21,31]. In the past years, studies were published using chatbots to cover a wide range of conditions and domains [52,53]. In addition to physician-patient communication skills, chatbots have been used for interprofessional communication [54] and for skill assessments [55]. However, in contrast to our study, most of these studies were performed before the broad accessibility of LLMs, such as GPT. These chatbots have thus been restricted in their authentic skills, capability of adoption (ie, in terms of personality, cases, etc), and ability to be transferred to different health care domains [31]. Although we also focused on 1 patient case, the ability of LLMs makes them theoretically capable of adapting to a given situation. Furthermore, our assessment using the CUQ revealed that our chatbot was perceived as realistic. This indicates that LLMs, such as GPT, when investigated rigorously, might be able to overcome the aforementioned restrictions.

As is the case with the technology used to process and generate language, previous studies have used various interfaces [52,53]. Similar to our study, many rely on web-based chat-like interfaces, and good usability seems to be of importance for acceptance by the learners [56]. Indeed, the CUQ used in our study also revealed that our user interface yields a good user experience. However, even with good acceptance, chat-like interfaces are limited to written language, thus restricting communication to the verbal domain. Therefore, newer approaches integrate chatbots in virtual reality environments [54], paving the way for a more integrated learning experience.

Limitations

Our study has some noteworthy limitations. As this was the first study using GPT as a simulated patient, we focused on 1 language model (ie, GPT-3.5, which we chose for its free availability and fast response time) and 1 patient case. Although we perceived our case as representative for history taking, our data did not allow for generalization to more specialized medical fields, and further studies are required to verify scalability to other medical specialties. Moreover, we focused on history taking, and although our chatbot performed well in general communication skills, it remains unclear how it will perform in other areas. Additionally, history taking is usually performed with spoken language, in contrast to the written language we used in our investigation. As this was a feasibility study, we only interviewed our participants about their perceptions but did not perform any objective skill measurements. We therefore cannot conclude that our participants improved in history taking, which should be addressed in future studies. Furthermore, the majority of our participants were female, which may have reduced the generalizability of our results. Due to the fact that we designed our study as an exploratory feasibility study, we did not perform a sample size calculation and therefore used descriptive statistics almost exclusively. Moreover, our participants were volunteers and thus probably motivated toward AI technology [22], possibly indicating a selection bias.

Conclusion

This study showed that a GPT-powered simulated patient chatbot works well and is perceived favorably among medical students. Although real patients remain the cornerstone of clinical teaching, technology-based education, as shown in this study, could be particularly beneficial for novice learners during their initial learning phases. It is important to note that we did not investigate skill acquisition, which is an important next step when evaluating GPT-based chatbots. Furthermore, our chatbot could be combined with other new technologies, such as speech
recognition and virtual/augmented reality, and thus could offer an even more integrated learning environment. Despite limitations, our study has implications for the field of medical education. Most importantly, we could show that GPT is capable of providing a simulated patient experience using an illness script, paving the way toward technology-assisted acquisition of communication skills. Moreover, by showing the capabilities of GPT-3.5 in history taking, the technology of LLMs might be capable of assisting learners in other areas as well.

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Data Availability
The data sets used and analyzed during this study are available from the corresponding author upon reasonable request.

Authors' Contributions
AHW, FH, and MM were responsible for designing and conducting the study, as well as the acquisition, analysis, and interpretation of data. CSP developed the web interface and the prompts. MM drafted the first version of the manuscript. TFW and LH were involved in the data analysis and interpretation. AN, JAM, JG, LH, and MH made substantial contributions to the study design and interpretation. All authors critically revised the manuscript, and all authors approved the final version of the manuscript and agreed to be accountable for all aspects of the work.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Full prompt.
[PDF File (Adobe PDF File), 20 KB - mededu_v10i1e53961_app1.pdf]

Multimedia Appendix 2
CUQ results table. CUQ: Chatbot Usability Questionnaire.
[PDF File (Adobe PDF File), 72 KB - mededu_v10i1e53961_app2.pdf]

Multimedia Appendix 3
Illness script.
[PDF File (Adobe PDF File), 174 KB - mededu_v10i1e53961_app3.pdf]

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34. Welcome to the OpenAI developer platform. OpenAI. URL: https://platform.openai.com [accessed 2024-01-03]


**Abbreviations**

AI: artificial intelligence
The Scope of Virtual Reality Simulators in Radiology Education: Systematic Literature Review

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Abstract

Background: In recent years, virtual reality (VR) has gained significant importance in medical education. Radiology education also has seen the induction of VR technology. However, there is no comprehensive review in this specific area. This review aims to fill this knowledge gap.

Objective: This systematic literature review aims to explore the scope of VR use in radiology education.

Methods: A literature search was carried out using PubMed, Scopus, ScienceDirect, and Google Scholar for articles relating to the use of VR in radiology education, published from database inception to September 1, 2023. The identified articles were then subjected to a PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)–defined study selection process.

Results: The database search identified 2503 nonduplicate articles. After PRISMA screening, 17 were included in the review for analysis, of which 3 (18%) were randomized controlled trials, 7 (41%) were randomized experimental trials, and 7 (41%) were cross-sectional studies. Of the 10 randomized trials, 3 (30%) had a low risk of bias, 5 (50%) showed some concerns, and 2 (20%) had a high risk of bias. Among the 7 cross-sectional studies, 2 (29%) scored “good” in the overall quality and the remaining 5 (71%) scored “fair.” VR was found to be significantly more effective than traditional methods of teaching in improving the radiographic and radiologic skills of students. The use of VR systems was found to improve the students’ skills in overall proficiency, patient positioning, equipment knowledge, equipment handling, and radiographic techniques. Student feedback was also reported in the included studies. The students generally provided positive feedback about the utility, ease of use, and satisfaction of VR systems, as well as their perceived positive impact on skill and knowledge acquisition.

Conclusions: The evidence from this review shows that the use of VR had significant benefit for students in various aspects of radiology education. However, the variable nature of the studies included in the review reduces the scope for a comprehensive recommendation of VR use in radiology education.

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KEYWORDS

virtual reality; simulators; radiology education; medical imaging; radiology; education; systematic review; literature review; imaging; meta analysis; student; students; VR; PRISMA; Preferred Reporting Items for Systematic Reviews and Meta-Analyses

Introduction

The use of technology in education helps students achieve improved acquisition of professional knowledge and practical skills [1-3]. Virtual reality (VR) is a modern technology that simulates experience by producing 3D interactive situations and presenting objects in a virtual world with spatial dimensions [4,5]. VR technology can be classified as nonimmersive or immersive [6]. In a nonimmersive VR, the simulated 3D environment is experienced through a computer monitor [6]. On the other hand, an immersive VR provides a sense of presence in a computer-generated environment, created by producing realistic sights, sounds, and other sensations that replicate a user’s physical presence in a virtual environment [6,7]. Using VR technology, a person can look about the artificial world, navigate around in it, and interact with simulated objects or items [5,8]. Due to the broad nature of VR technology,
it has many applications, some of which are in the field of medicine [9,10].

The use of VR in medicine started in the 1990s when medical researchers were trying to create 3D models of patients’ internal organs [11-13]. Since then, VR use in the field of medicine and general health care has increased substantially to cover many areas including medical education. Radiology education has also come to see the use of VR technology in the recent past [14]. The use of VR in radiology education enables students to practice radiography in a virtual environment, which is radiation free [15]. Additionally, the use of VR enables effective and repeatable training. This allows trainees to recognize and correct errors as they occur [16,17]. The aim of this review is to explore the scope of VR in radiology education.

## Methods

This systematic review has been performed using the PRISMA (Preferred Reporting Items for Systematic Review and Meta-Analysis) guidelines [18] [Checklist 1]).

### Information Sources and Study Selection

The bibliographic databases used were PubMed, Scopus, ScienceDirect, and Google Scholar. A systematic literature search was conducted for articles published from database inception to September 1, 2023. Topic keywords were used to generate search strings. The search strings that were used are provided in Table 1. Only the first 10 pages of Google Scholar results were exported. The identified studies were then subjected to a study selection process. The search string for ScienceDirect was shorter because the database only allows a maximum of 8 Boolean operators, hence the sting had to be shortened. The search in PubMed was limited to the title and abstract. The searches in Scopus and ScienceDirect were limited to title, abstract, and keywords.

### Table 1. Search strings used in the systematic review.

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<td>(“virtual reality” OR “immersive reality” OR “simulated reality” OR simulator OR simulate) AND (radiology OR radiography OR imaging OR radiologist) AND (education OR teaching)</td>
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<tr>
<td>ScienceDirect and Google Scholar</td>
<td>(“virtual reality” OR “immersive reality” OR “simulated reality” OR simulator) AND (radiology OR radiography OR imaging) AND (education OR teaching)</td>
</tr>
</tbody>
</table>

### Inclusion and Exclusion Criteria

Original research articles written in the English language were included in the review. Studies conducted on medical, dental, and allied health sciences students (undergraduate and postgraduate) from any part of the world were included in the review. Studies exploring the use of VR learning in radiology education were included.

Narrative reviews, scoping reviews, systematic reviews, meta-analyses, editorials, and commentaries were excluded. Studies that did not align with the required study objective were excluded.

### Method of Quality Assessment

Randomized controlled trials (RCTs) and randomized experimental studies were appraised using the RoB 2 tool from the Cochrane Collaboration [19]. A visualization of the risk-of-bias assessment was done using the web-based robvis tool [20]. Cross-sectional studies were appraised using the appraisal checklist for analytical cross-sectional studies from the Joanna Briggs Institute [21].

### Data Extraction

Each article included in the review was summarized in a table, including basic study characteristics. The extracted attributes were study author(s), publication year, study design, type and number of participants, type of radiology education under study, and the outcome being assessed. The extracted data are provided in Table 2.
# Table. Data extraction table of the studies included in the systematic review.

<table>
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<th>Participants</th>
<th>Aspect of radiology</th>
<th>Study outcome</th>
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<td>31 first-year radiologic technology student</td>
<td>Diagnostic radiology</td>
<td>Assessing radiographic image quality</td>
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<tr>
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<td>Randomized experimental trial</td>
<td>48 medical imaging students</td>
<td>General radiology</td>
<td>Student satisfaction and technical skills (ie, patient positioning, equipment positioning, and mean proficiency)</td>
</tr>
<tr>
<td>Gunn et al [24]</td>
<td>Randomized experimental trial</td>
<td>45 medical imaging student</td>
<td>Diagnostic radiology</td>
<td>Technical radiographic skills</td>
</tr>
<tr>
<td>Gunn et al [25]</td>
<td>Cross-sectional study</td>
<td>28 medical imaging students and 38 radiation therapy students</td>
<td>Interventional radiology</td>
<td>Students’ perceived confidence in performing diagnostic and planning CT scans</td>
</tr>
<tr>
<td>Jensen et al [26]</td>
<td>Cross-sectional study</td>
<td>10 radiography students</td>
<td>General radiology</td>
<td>Self-perceived clinical readiness of radiography students regarding the acquisition of wrist radiographs</td>
</tr>
<tr>
<td>Kato et al [27]</td>
<td>Randomized experimental trial</td>
<td>30 first-year radiologic technology student</td>
<td>General radiology</td>
<td>Radiographic skills proficiency</td>
</tr>
<tr>
<td>Nilsson et al [28]</td>
<td>Randomized experimental trial</td>
<td>57 dental students</td>
<td>Oral radiology</td>
<td>Interpretation of spatial relations in radiographs using parallax</td>
</tr>
<tr>
<td>Nilsson et al [29]</td>
<td>Randomized experimental trial</td>
<td>45 dental students</td>
<td>Oral radiology</td>
<td>Interpretation of spatial relations in radiographs using parallax</td>
</tr>
<tr>
<td>O’Connor and Rainford [30]</td>
<td>Randomized experimental trial</td>
<td>191 radiography students</td>
<td>General radiology</td>
<td>Patient preparation, room preparation, patient care, radiographic technique, and image appraisal</td>
</tr>
<tr>
<td>O’Connor et al [15]</td>
<td>Cross-sectional study</td>
<td>105 first-year radiography students</td>
<td>General radiology</td>
<td>Reporting student experience</td>
</tr>
<tr>
<td>Rainford et al [31]</td>
<td>Cross-sectional study</td>
<td>35 radiography students and 100 medical students</td>
<td>Interventional radiology</td>
<td>Reporting student experience</td>
</tr>
<tr>
<td>Rowe et al [32]</td>
<td>Randomized experimental trial</td>
<td>188 radiography students</td>
<td>General radiology</td>
<td>Technical skills (ie, duration of the exam, frequency of machinery movement, frequency of incorrect machinery movement, frequency of radiographic exposure errors, and frequency of patient positioning errors)</td>
</tr>
<tr>
<td>Sapkaroski et al [33]</td>
<td>Cross-sectional study</td>
<td>92 medical radiation science students</td>
<td>General radiology</td>
<td>Reporting student experience</td>
</tr>
<tr>
<td>Sapkaroski et al [34]</td>
<td>RCT</td>
<td>76 first-year radiography students</td>
<td>Radiation technology</td>
<td>Patient positioning</td>
</tr>
<tr>
<td>Sapkaroski et al [35]</td>
<td>RCT</td>
<td>76 radiography students</td>
<td>General radiology</td>
<td>Students’ perception about developing radiographic hand positioning skills.</td>
</tr>
<tr>
<td>Shanahan [36]</td>
<td>Cross-sectional study</td>
<td>86 first-year radiography students</td>
<td>General radiology</td>
<td>Reporting student perception</td>
</tr>
<tr>
<td>Wu et al [37]</td>
<td>Cross-sectional study</td>
<td>18 medical students</td>
<td>General radiology</td>
<td>Reporting student perception</td>
</tr>
</tbody>
</table>

<sup>a</sup>RCT: randomized controlled trial.
<sup>b</sup>CT: computed tomography.
Results

Search Results
The database search identified a total of 2877 studies; 374 (13%) studies were from PubMed, 2169 (75.4%) were from Scopus, 234 (8.1%) were from ScienceDirect, and 100 (3.5%) were from Google Scholar. Before the screening procedure, 37 duplicates were removed. During title and abstract screening, 2808 articles were excluded since they did not align with the eligibility criteria. The remaining 32 articles were then subjected to a full-text review, and 15 were excluded for reasons provided in Figure 1, which shows the study selection process [38]. At the end of the process, 17 studies were found eligible for inclusion in the review.

Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart showing the study selection process.

Characteristics of Included Studies
Among the 17 studies, 3 (18%) RCTs, 7 (41%) randomized experimental trials, and 7 (41%) cross-sectional studies were included. The studies encompassed various aspects of radiology education, including dental radiology [28,29], diagnostic radiology [22,24], and interventional radiology [25,31].

Results of Quality Assessment
Among the 7 cross-sectional studies, 2 (29%) scored “good” in overall quality and the remaining 5 (71%) scored “fair.” The
results for the quality appraisal of cross-sectional studies are shown in Table 3. Studies were appraised using the checklist for analytical cross-sectional studies from the Joanna Briggs Institute [21]. Among the 10 randomized trials, 3 (30%) had a low risk of bias, 5 (50%) showed some concerns, and 2 (20%) had a high risk of bias. These results are shown in Table 4. RCTs were appraised using the RoB 2 tool from the Cochrane Collaboration [19]. A risk-of-bias graph (Figure 2) and a risk-of-bias summary (Figure 3) are also provided.

Table. Appraisal for cross-sectional studies included in the systematic review.

<table>
<thead>
<tr>
<th>Study</th>
<th>Item 1(^a)</th>
<th>Item 2(^b)</th>
<th>Item 3(^c)</th>
<th>Item 4(^d)</th>
<th>Item 5(^e)</th>
<th>Item 6(^f)</th>
<th>Item 7(^g)</th>
<th>Item 8(^h)</th>
<th>Overall quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gunn et al [25]</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Good</td>
</tr>
<tr>
<td>Jensen et al [26]</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
<td>N/A(^i)</td>
<td>Yes</td>
<td>Yes</td>
<td>Fair</td>
</tr>
<tr>
<td>O’Connor et al [15]</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>N/A</td>
<td>Yes</td>
<td>No</td>
<td>Fair</td>
</tr>
<tr>
<td>Rainford et al [31]</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>N/A</td>
<td>Yes</td>
<td>Yes</td>
<td>Fair</td>
</tr>
<tr>
<td>Sapkaroski et al [33]</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Unclear</td>
<td>No</td>
<td>N/A</td>
<td>Yes</td>
<td>Unclear</td>
<td>Fair</td>
</tr>
<tr>
<td>Shanahan [36]</td>
<td>No</td>
<td>Yes</td>
<td>Unclear</td>
<td>Yes</td>
<td>Yes</td>
<td>Unclear</td>
<td>Yes</td>
<td>Yes</td>
<td>Good</td>
</tr>
<tr>
<td>Wu et al [37]</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>N/A</td>
<td>Yes</td>
<td>Yes</td>
<td>Fair</td>
</tr>
</tbody>
</table>

\(^a\)Item 1: were the criteria for inclusion in the sample clearly defined?
\(^b\)Item 2: were the study subjects and the setting described in detail?
\(^c\)Item 3: was the exposure measured in a valid and reliable way?
\(^d\)Item 4: were objective, standard criteria used for measurement of the condition?
\(^e\)Item 5: were confounding factors identified?
\(^f\)Item 6: were strategies to deal with confounding factors stated?
\(^g\)Item 7: were the outcomes measured in a valid and reliable way?
\(^h\)Item 8: was appropriate statistical analysis used?
\(^i\)N/A: not assessable.
Table. Risk-of-bias assessment for randomized trials included in the systematic review.

<table>
<thead>
<tr>
<th>Study</th>
<th>D1&lt;sup&gt;a&lt;/sup&gt;</th>
<th>D2&lt;sup&gt;b&lt;/sup&gt;</th>
<th>D3&lt;sup&gt;c&lt;/sup&gt;</th>
<th>D4&lt;sup&gt;d&lt;/sup&gt;</th>
<th>D5&lt;sup&gt;e&lt;/sup&gt;</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ahlqvist et al [22]</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>Some concerns</td>
<td>Some concerns</td>
</tr>
<tr>
<td>Bridge et al [23]</td>
<td>Low</td>
<td>Low</td>
<td>Some concerns</td>
<td>Low</td>
<td>Low</td>
<td>Some concerns</td>
</tr>
<tr>
<td>Gunn et al [24]</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>Kato et al [27]</td>
<td>Some concerns</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Some concerns</td>
</tr>
<tr>
<td>Nilsson et al [28]</td>
<td>Some concerns</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
</tr>
<tr>
<td>Nilsson et al [29]</td>
<td>Low</td>
<td>Low</td>
<td>High</td>
<td>Low</td>
<td>Some concerns</td>
<td>High</td>
</tr>
<tr>
<td>O’Connor and Rainford [30]</td>
<td>High</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Some concerns</td>
<td>Some concerns</td>
</tr>
<tr>
<td>Rowe et al [32]</td>
<td>Low</td>
<td>High</td>
<td>Some concerns</td>
<td>Low</td>
<td>Low</td>
<td>Some concerns</td>
</tr>
<tr>
<td>Sapkaroski et al [34]</td>
<td>Low</td>
<td>Some concerns</td>
<td>Some concerns</td>
<td>High</td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td>Sapkaroski et al [35]</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
<td>Low</td>
</tr>
</tbody>
</table>

<sup>a</sup>D1: risk of bias arising from the randomization process.

<sup>b</sup>D2: risk of bias due to deviations from the intended interventions (effect of assignment to intervention).

<sup>c</sup>D3: risk of bias due to missing outcome data.

<sup>d</sup>D4: risk of bias in measurement of the outcome.

<sup>e</sup>D5: risk of bias in selection of the reported result.
Figure 2. Risk-of-bias graph using a traffic light plot for different domains (D1 to D5) [22-24,27-30,32,34,35].
Type of VR Hardware and Software Used in the Studies

The studies used a wide range of VR software and hardware. Some of the studies used 3D simulation software packages displayed on 2D desktop computers [22,24,25,36], whereas others used headsets for an immersive VR environment [15,23,26,35,37]. The most used VR teaching software were the CETSOL VR Clinic software [33,35], Virtual Medical Coaching VR software [15,30,32], Projection VR (Shaderware) software [36], SieVRt VR system (Luxsonic Technologies) [37], medical imaging training immersive environment software [23], VR CT Sim software [25], VitaSim ApS software [26], VR X-Ray (Skilitics and Virtual Medical Coaching) software [27], and radiation dosimetry VR software (Virtual Medical Coaching Ltd) [31].

Effect of VR Teaching on Skill Acquisition

Ahlqvist et al [22] looked at how virtual simulation can be used as an effective tool to teach quality assessment of radiographic images. They also compared how it fared in comparison to traditional teaching. The study reported a statistically significant improvement in proficiency from before training to after training. Additionally, the study reported that the proficiency score improvement for the VR-trained students was higher than that for the students trained using conventional method.

In the study conducted by Sapkaroski et al [34], students in the VR group demonstrated significantly better patient positioning...
skills compared to those in the conventional role-play group. The positioning parameters that were assessed were digit separation and palm flatness (the VR group scored 11% better), central ray positioning onto the third metacarpophalangeal joint (the VR group scored 23% better), and a control position projection of an oblique hand. The results for the control position projection indicated no significant difference in positioning between the 2 groups [34].

Bridge et al [23] also performed a performance comparison between students trained by VR and traditional methods. They assessed skills about patient positioning, equipment positioning, and time taken to complete a performative role-play. Students in the VR group performed better than those in the control group, with 91% of them receiving an overall score of above average (>3). The difference in mean group performance was statistically significant ($P=0.0366$). Similarly, Gunn et al [24] reported improved and higher role-play skill scores for students trained using VR software simulation compared to those trained on traditional laboratory simulation. The mean role-play score for the VR group was 30.67 and that for the control group was 28.8 [24].

Another study reported that students trained using VR performed significantly better (ranked as “very good” or “excellent”) than the control group (conventional learning) in skills such as patient positioning, selecting exposure factors, centering and collimating the x-ray beam, placing the anatomical marker, appraisal of image quality, equipment positioning, and procedure explanation to the patient [30]. Another recently conducted study found that the VR-taught group achieved better test duration and fewer errors in moving equipment and positioning a patient. There was no significant difference in the frequency of errors in the radiographic exposure setting such as source-to-image distance between the VR and the physical simulation groups [32].

Nilsson et al [28] developed a test to evaluate the student’s ability to interpret 3D information in radiographs using parallax. This test was applied to students before and after training. There was a significantly larger ($P<0.01$) pre-post intervention mean score for the VR group (3.11 to 4.18) compared to the control group (3.24 to 3.72). A subgroup analysis was also performed, and students with low visuospatial ability in the VR group had a significantly higher improvement in the proficiency test compared to those in the control group. The same authors conducted another follow-up study to test skill retention [29]. Net skill improvement was calculated as the difference in test scores after 8 months. The results from the proficiency test showed that the ability to interpret spatial relations in radiographs 8 months after the completion of VR training was significantly better than before VR training. The students who trained conventionally showed almost the same positive trend in improvement. The group difference was smaller and not statistically significant. This meant that, 8 months after training, the VR group and the traditionally trained group had the same skill level [29].

Among the included studies, only 1 reported that the VR group had lower performance in proficiency tests and radiographic skill tests, compared to a conventionally trained group. The study, conducted in 2022, showed that the proficiency of the VR group was significantly lower than that of the conventional technique group in performing lateral elbow and posterior-anterior chest radiography [27]. An itemized rubric evaluation used in the study revealed that the VR group also had lower performance in most of the radiographic skills, such as locating and centering of the x-ray beam, side marker placement, positioning the x-ray image detector, patient interaction, and process control and safety [27]. The study concluded that VR simulation can be less effective than real-world training in radiographic techniques, which requires palpation and patient interaction. These results may be different from those of other studies due to different outcome evaluation methods and since they used head-mounted display VR coaching, whereas the other studies, except O’Connor et al [15], used VR on a PC monitor.

All of the studies except Kato et al [27] agreed that VR use was more effective for students in developing radiographic and radiologic skills. Despite this general agreement, there were slight in-study variations in learning outcomes, which made some of the studies look at factors that may influence skill and knowledge acquisition during VR use. In studies such as Bridge et al [23], it was noted that the arrangement of equipment had the greatest influence on the overall score. After performing a multivariable analysis, Gunn et al [24] reported that there was no effect of age, gender, and gaming skills or activity on the outcome of VR learning. In the study by Shanahan [36], a few students (19/84, 23%) had previously used VR simulation software. This had no bearing on the learning outcomes. Another observation in the same study was that student age was found to significantly affect the student’s confidence about skill acquisition after VR training [36].

**Students’ Perception of VR Uses for Learning**

The findings from the study by Gunn et al [25] revealed that 68% of students agreed or strongly agreed that VR simulation was significantly helpful in learning about computed tomography (CT) scanning. In another study by Jensen et al [26], 90% of the students strongly agreed that VR simulators could contribute to learning radiography, with 90% reporting that the x-ray equipment in the VR simulation was realistic. In the study by Wu et al [37], most of the students (55.6%) agreed or somewhat agreed that VR use was useful in radiology education. Similarly, 83% of the students in Shanahan’s [36] study regarded VR learning with an ease of use. In the same study, students also reported that one of the major benefits of VR learning include using the simulation to repeat activities until being satisfied with the results (95% of respondents). Students also stated that VR enabled them to quickly see images and understand if changes needed to be made (94%) [36]. In the study by Gunn et al [25], 75% of medical imaging students agreed on the ease of use and software enjoyment in VR simulated learning. In the same study, 57% of the students reported a positive perceived usefulness of VR. Most respondents (80%) in the study by Rainford et al [31] favored the in-person VR experience over web-based VR. Similarly, 58% of the respondents in the study conducted by O’Connor et al [15] reported enjoying learning using VR simulation. In the study by Wu et al [37], 83% of students agreed or strongly agreed that they enjoyed using VR for learning. Similarly, the
Studies by Rainford et al [31] and O’Connor et al [15] reported student recommendation of 87% and 94%, respectively, for VR as a learning tool.

**Students’ Perceived Skill and Knowledge Acquisition**

In the study by Bridge et al [23], students who trained using VR reported an increase in perceived skill acquisition and high levels of satisfaction. The study authors attributed this feedback to the availability of “gold standards” that showed correct positioning techniques, as well as instant feedback provided by the VR simulators. Gunn et al [25] examined students’ confidence in performing a CT scan in a real clinical environment after using VR simulations as a learning tool. The study reported an increase (from before to after training) in the students’ perceived confidence in performing diagnostic CT scans. Similarly, the study by Jensen et al [26] reported that the use of VR had influenced students’ self-perceived readiness to perform wrist x-ray radiographs. The study, however, found no significant difference in pre- and posttraining (perceived preparedness) scores. The pre- and posttraining scores were 75 (95% CI 54-96) and 77 (95% CI 59-95), respectively. The study by O’Connor et al [15] looked at the effect of VR on perceived skill adoption. Most of the students in the study reported high levels of perceived knowledge acquisition in the areas of beam collimation, anatomical marker placement, centering of the x-ray tube, image evaluation, anatomical knowledge, patient positioning, and exposure parameter selection to their VR practice. However, most students felt that VR did not contribute to their knowledge of patient dose tracking and radiation safety [15]. In the study by Rainford et al [31], 73% of radiography and medical students felt that VR learning increased their confidence across all relevant learning outcomes. The biggest increase in confidence level was regarding their understanding of radiation safety matters [31]. Sapkaroski et al [33] performed a self-perception test to see how students viewed their clinical and technical skills after using VR for learning. In their study, students reported a perceived improvement in their hand and patient positioning skills. Their study also compared 2 software, CETSOL VR Clinic and Shaderware. The cohort who used CETSOL VR Clinic had higher scores on perceived improvement [33]. Sapkaroski et al [35] compared the student’s perception scores on the educational enhancement of their radiographic hand positioning skills, after VR or clinical role-play scenario training. Although the VR group scored higher, there was no significant difference between the scores for the 2 groups [35]. In the study by Shanahan [36], when the perception of skill development was evaluated, most of the students reported that the simulation positively developed their technical (78%), radiographic image evaluation (85%), problem-solving (85%), and self-evaluation (88%) abilities. However, in the study by Kato et al [27], there was no difference in the perceived acquisition of knowledge among students using traditional teaching and VR-based teaching.

**Discussion**

**Principal Findings**

The results presented in this review reveal strong evidence for the effectiveness of VR teaching in radiology education, particularly in the context of skill acquisition and development [22,24,27,30,32,34].

In this review, quality appraisal of the cross-sectional studies revealed that the strategies for deal with confounding factors was one of the factors directly affecting the reliability of the results. Similarly, the appraisal of the randomized trials revealed that the bias arising due to missing outcome data was one of the factors directly affecting the reliability of the results.

All the studies found that VR-based teaching had a positive impact on various areas of radiographic and radiologic skill development. In comparison to the traditional way of teaching, only 1 study by Kato et al [27] reported VR teaching as inferior to traditional teaching. The studies consistently reported better improvements in proficiency, patient positioning outcomes, equipment handling, and radiographic techniques among students trained using VR. According to Nilsson et al [29], O’Connor et al [15], and Wu et al [37], the improvements were due to the immersive and interactive nature of VR simulations, which allowed learners to engage with radiological scenarios in a dynamic and hands-on manner. The studies also revealed that VR learning has the ability to easily and effectively introduce students to new skills. It was also found that existing skills could be improved, mainly through simulation feedback that happens in real time during training [22,24,28,30,36].

The improvement of skills after VR training have been noted in different domains, including patient positioning, equipment positioning, equipment knowledge, assessment of radiographic image quality, and patient interaction. Improvement was also observed in other skills such as central ray positioning, source-to-image distance, image receptor placement, and side marker placement [22,24,30,32,34]. Two studies, Nilsson et al [28] and Nilsson et al [29], looked at how VR affected the students’ ability to interpret 3D information in radiographs using parallax. They both reported a positive effect. Nilsson et al [29] also gave insights into the long-term benefits of VR training in radiology. Eight months after training, the control (traditionally taught) group in Nilsson et al [29] showed a slight increase in skills, but the VR-trained group still maintained a significantly higher skill level. This finding shows the enduring impact of VR-based education on skill acquisition in radiology. Although most studies supported the effectiveness of VR in radiology education, 1 study reported contrasting results [27]. VR-trained students were found to perform worse than traditionally trained students in conducting lateral elbow and posterior-anterior chest radiography in Kato et al [27]. This difference in results was, according to the authors, attributed to the use of a different rubric evaluation method and the use of a head-mounted display–based immersive VR system, which was not used in other studies. These 2 reasons may be the reason for the variation in study findings.

A wide range of VR software with different functions were used in the studies. In addition to acquiring radiographic images, the CETSOL VR Clinic software facilitated students to interact with their learning environment [33,35]. Students using the Virtual Medical Coaching VR software performed imaging exercise on a virtual patient with VR headsets and hand controllers [15,30,32]. The SiEVRt VR system displayed Digital
Imaging and Communications in Medicine format images in a virtual environment, thus facilitating teaching [37]. The medical imaging training immersive environment simulation software provided automated feedback to the learners including a rerun of procedures, thus highlighting procedural errors [23]. The VR CT Sim software allowed the student virtually to perform the complete CT workflow [25]. Students could manipulate patient positioning and get feedback from the VitaSim ApS software [26]. The VR X-Ray software allowed students to manipulate radiographic equipment and patient’s position with a high level of immersive experience [27]. Radiation dosimetry VR software facilitated virtual movement of the staff and equipment to radiation-free areas, thus optimizing radiation protection [31].

The included studies also looked at factors that could influence skill acquisition when VR is used in radiology education. Bridge et al [23], Gunn et al [24], Kato et al [27], and Shanahan [36] investigated factors such as age, gender, prior gaming experience, and familiarity with VR technology. However, these factors were shown to have no significant effect on VR learning outcomes. This shows that VR education can equally accommodate a wide range of learners, regardless of experience or existing attributes.

Across several studies, positive feedback emerged regarding the utility, ease of use, enjoyment, and perceived impact on skill and knowledge acquisition. The included studies consistently reported positive perceptions of VR use among students [25,26,37]. Gunn et al [25] reported that a significant proportion of medical imaging and radiation therapy students found the use of VR simulation to be significantly helpful in learning about CT scanning. Similarly, Jensen et al [26] and Wu et al [37] reported that a majority of students agreed on the usefulness of VR in radiology education. Another aspect that received positive feedback was the ease of use. Students liked the ability to repeat tasks until they were satisfied with the results and the ability to quickly visualize radiographs to determine the need for revisions [36]. Rainford et al [31] and O’Connor and Rainford [30] found that most students would recommend VR as a learning tool to other students.

Several studies investigated student’s perceptions of skill and knowledge acquisition when using VR for radiology education. Bridge et al [15] and O’Connor et al [23] discovered an increase in students’ perceived acquisition of radiographic skills. Gunn et al [25] reported an increase in students’ perceived confidence to perform CT scans after learning using VR simulations. According to Rainford et al [31], a large percentage of radiography and medical students felt that VR learning boosted their confidence across all relevant learning outcomes, with the highest levels of confidence recorded in radiation safety. Sapkaroski et al [33] discovered that after using VR for learning, students experienced an improvement in their hand and patient placement skills. In summary, the positive feedback from the students shows that VR use in radiology education is a useful, engaging, and effective teaching tool. This perceived acquisition of skills is backed by the results from the proficiency tests.

The VR modalities used in some of the studies allowed remote assistance from an external agent (teacher), as the VR training is conducted in front of a screen while being part of a team, with the teacher making constant corrections and indications [22,24,27]. However, researchers are looking into VR systems with artificial intelligence–supported tutoring, which includes the assessment of learners, generation of learning content, and automated feedback [39].

Conclusion

Findings from the included studies show that VR-based teaching offers substantial benefits in various aspects of radiographic and radiologic skill development. The studies consistently reported that students educated using VR systems improved significantly in overall proficiency, patient positioning, equipment knowledge, equipment handling, and radiographic techniques. However, the variable nature of the studies included in the review reduces the scope for a comprehensive recommendation of VR use in radiology education. A key contributing factor to relatively better learning outcomes was the immersive and interactive nature of VR systems, which provided real-time feedback and dynamic learning experiences to students. Factors such as age, gender, gaming experience, and familiarity with VR systems did not significantly influence learning outcomes. This shows that VR can be used for diverse groups of students when teaching radiology. Students generally provided positive feedback about the utility, ease of use, and satisfaction of VR, as well as its perceived impact on skill and knowledge acquisition. These students’ reports show the value of VR as an important, interesting, and effective tool in radiology education.

Conflicts of Interest

None declared.

Checklist 1

PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist.

[PDF File - 465 KB - mededu_v10i1e52953_app1.pdf]

References


Abbreviations

CT: computed tomography  
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses  
RCT: randomized controlled trial  
VR: virtual reality
information, a link to the original publication on https://mededu.jmir.org/, as well as this copyright and license information must be included.
Inverted Classroom Teaching of Physiology in Basic Medical Education: Bibliometric Visual Analysis

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Abstract

Background: Over the last decade, there has been growing interest in inverted classroom teaching (ICT) and its various forms within the education sector. Physiology is a core course that bridges basic and clinical medicine, and ICT in physiology has been sporadically practiced to different extents globally. However, students' and teachers' responses and feedback to ICT in physiology are diverse, and the effectiveness of a modified ICT model integrated into regular teaching practice in physiology courses is difficult to assess objectively and quantitatively.

Objective: This study aimed to explore the current status and development direction of ICT in physiology in basic medical education using bibliometric visual analysis of the related literature.

Methods: A bibliometric analysis of the ICT-related literature in physiology published between 2000 and 2023 was performed using CiteSpace, a bibliometric visualization tool, based on the Web of Science database. Moreover, an in-depth review was performed to summarize the application of ICT in physiology courses worldwide, along with identification of research hot spots and development trends.

Results: A total of 42 studies were included for this bibliometric analysis, with the year 2013 marking the commencement of the field. University staff and doctors working at affiliated hospitals represent the core authors of this field, with several research teams forming cooperative relationships and developing research networks. The development of ICT in physiology could be divided into several stages: the introduction stage (2013 - 2014), extensive practice stage (2015 - 2019), and modification and growth stage (2020 - 2023). Gopalan C is the author with the highest citation count of 5 cited publications and has published 14 relevant papers since 2016, with a significant surge from 2019 to 2022. Author collaboration is generally limited in this field, and most academic work has been conducted in independent teams, with minimal cross-team communication. Authors from the United States published the highest number of papers related to ICT in physiology (18 in total, accounting for over 43% of the total papers), and their intermediary centrality was 0.24, indicating strong connections both within the country and internationally. Chinese authors ranked second, publishing 8 papers in the field, although their intermediary centrality was only 0.02, suggesting limited international influence and lower overall research quality. The topics of ICT in physiology research have been multifaceted, covering active learning, autonomous learning, student performance, teaching effect, blended teaching, and others.

Conclusions: This bibliometric analysis and literature review provides a comprehensive overview of the history, development process, and future direction of the field of ICT in physiology. These findings can help to strengthen academic exchange and cooperation internationally, while promoting the diversification and effectiveness of ICT in physiology through building academic communities to jointly train emerging medical talents.

(keywords: flipped classroom; flipped classroom teaching; physiology; scientific knowledge map; hot topics; frontier progress; evolution trend; classroom-based; bibliometric visual analysis; bibliometric; visual analysis; medical education; teaching method; bibliometric analysis; visualization tool; academic; academic community; inverted classroom)

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Introduction

In recent decades, student-centered active learning strategies have been implemented in numerous educational institutions worldwide as an alternative to traditional passive learning strategies such as didactic lecturing [1]. As a novel teaching mode, inverted classroom teaching (ICT), first proposed by Lage et al [2] in 2020, is now widely used to enhance the engagement of students in the active learning process. ICT, also known as “flipped classroom teaching,” promotes student participation, engagement, and identification of necessary resources and needs to meet learning objectives by repurposing classroom time for student-centered learning activities [3,4]. The teaching materials are made available for self-study outside of the classroom, while ICT also emphasizes active learning by assigning preclass tasks to students with clear learning objectives. ICT represents a significant advancement in modern classroom design, and its potential for promoting student-centered learning is particularly noteworthy.

Medical institutions were among the first to shift away from traditional didactic methods toward student-centered learning, which has been shown to motivate and empower students to be life-long learners, foster self-growth, and encourage receiving and applying up-to-date information and techniques in various medical fields [5,6]. Since it was first proposed as a teaching model [2], ICT has been used in almost all fields of education, especially in basic medicine and clinical medicine, and has become a focus of educational research. A recent bibliometric analysis on ICT revealed its ability to reallocate the teaching content taught in traditional classrooms outside the classroom for students to study on their own before the class. The resulting saved classroom time is then used for various student-centered learning activities such as problem-based and inquiry-based learning [4,7,8]. With the COVID-19 pandemic wreaking havoc around the globe, ICT has been increasingly incorporated into online teaching and is regarded as a promising and flexible approach for securing high-quality teaching via different forms of teaching media [9]. Despite the overwhelming benefits and compelling cases, researchers have also reported negative examples and disadvantages of using active-learning strategies, such as students lacking learning motivation [10,11], increased workload for both faculty and students [12], longer preparation time [12], and reluctance to discuss the teaching content with peers [13]. Moreover, a systematic theoretical and practical system of ICT in medical education has not yet been established.

Physiology is a bridging course between basic and clinical medicine, which is a core course for students in medicine and related subjects. Physiology is typically scheduled in the first semester of the second year of medical school. This course is often considered challenging for students in the early stages of their medical education owing to its highly conceptual nature, the significant cognitive effort required to acquire academic information, and the combined laboratory experiments associated with theoretical knowledge [9,14,13]. To a certain extent, the history and development of inverted teaching in physiology may serve as a window to probe into the general picture of the use of ICT in basic medical education. However, there is still a vast knowledge gap in the development and application of ICT in physiology courses; for example, it remains unclear how ICT in physiology evolved from the information era to the digital and artificial intelligence era. With the development of CiteSpace, a powerful visualization and analysis software, it has now become feasible to depict and visualize science knowledge graphs [16], including the outline and timeline of ICT in physiology, which can help to address these knowledge gaps in a more quantitative manner than possible with traditional qualitative methods such as a scoping review.

Therefore, in this study, we performed a visual analysis of the ICT in physiology literature from the Web of Science (WoS) database with CiteSpace. The aim was to explore the temporal evolution context and spatial distribution networks of ICT in physiology; investigate the cooperation network among authors, institutions, and countries publishing research in this field using co-occurrence analysis; and uncover hot research topics and development trends through cocitation analysis of references, authors, and journals, along with keyword co-occurrence and clustering analyses.

Methods

Search Strategy

We selected the WoS Core Collection as the data source for this study. To capture a broad range of potentially eligible articles, we used the following search terms with Boolean operators: (“flipped classroom” OR “flipped classroom teaching” OR “flipped study” OR “flipped learning” OR “flipped teaching” OR “flipped instruction” OR “inverted teaching” OR “inverted learning” OR “inverted study” OR “inverted classroom” OR “inverted instruction”) in all fields AND (“Physiology”) in all fields. The search was performed in English to obtain the largest number of documents in the WoS data set on the use of ICT in physiology education. The following inclusion criteria were applied: (1) document type=articles, (2) language=English, (3) years of publication=2000-2023 (November). The exclusion criteria were (1) studies in a field not related to medicine or pedagogy; (2) not published in English; (3) categorized as books, chapters, theses, protocols, study outlines, government publications, posters, editorial materials, duplicates, or non-peer-reviewed articles; and (4) published outside of the time frame of 2000-2023.

Upon applying the above search strategy, 632 indices were retrieved in the WoS data set and 295 records were screened after removing 237 studies using automation tools from the database. Before further screening and retrieval of the full texts...
of the references, all 294 indices with detailed citation records and bibliometric information were exported in both record and reference formats, saved as plain-text files, and stored in the .txt format. The stored records were then input into the CiteSpace software for visualization, as indicated by the user manual [19], which generated clustered plots of bibliometric references and differentiated various topics. The relevant articles pertaining to inverted classroom pedagogy were identified by examining the visualized clusters and topics, and irrelevant literature was excluded by adhering to the guidelines in the CiteSpace manual. In brief, in the cluster plots, irrelevant topics are presented in isolated clusters without citation networks; hence, these dots, representing the irrelevant literature, were removed from the eligible references after reviewing the titles and abstracts.

The full text of the included articles was downloaded and reviewed by two authors independently (YW and ZH), and a consensus was reached through discussion between the two reviewers in the case of any disagreements. In total, 253 studies were excluded after title and abstract screening and a total of 42 articles were included for the final analysis. The flowchart of study selection is provided in Multimedia Appendix 1 and the details of the excluded studies with reasons for exclusion are provided in Multimedia Appendix 2.

Data Analysis Process

CiteSpace 6.1.R6 software was used to visually analyze the literature related to ICT in physiology published up to November 2023. CiteSpace is a knowledge visualization software developed by Chaomei Chen at Drexel University and is now a widely used knowledge mapping tool in various fields of education and teaching [20]. CiteSpace can measure and visualize literature collections in broad fields of the natural and social sciences using cocitations of references, authors, and journals; the co-occurrence of authors, keywords, institutes, and countries; and cluster analysis to create a scientific knowledge network map, explore the critical path of the evolution of the discipline, and analyze the hot spot research topics and frontier trends clearly and scientifically.

In this study, we analyzed the overall national and regional distributions and cooperation of the authors of ICT in physiology research papers through the constructed network cooperation map, and then determined the knowledge base and the core authors of ICT in physiology research through analysis of the literature and author cocitation networks. We further identified the “star” journals publishing research in this field through a cocitation analysis of the source journals. Finally, the hot spot keywords were determined through keyword co-occurrence and clustering analysis based on the frequency and centrality of the keywords, which were used to further explore the hot topics of worldwide research on ICT in physiology. Overall, the methodology used in this study involved cooperative network analysis and cocitation analysis.

Cooperative network analysis was used to identify core authors, leading research institutions, and national/regional cooperation in ICT in physiology research. The nodes in the graph are represented by circles, with larger circles indicating a greater number of items represented, such as papers, authors, institutions, references, and countries. In CiteSpace, intermediary or between centrality is used as a critical indicator of node importance, which is characterized by the shortest number of paths passing through a node. Nodes with a centrality value above 0.1 are considered to be important. In this study, the circle size represents the cited frequency of an article, with purple circles indicating high centrality; thus, larger and deeper-purple circles suggest greater importance of the study in ICT in physiology research.

Cocitation analysis was used to identify relationships between cited articles, authors, and journals in the field of ICT in physiology research. For example, if two articles (or authors or journals) A and B are cited simultaneously by a third article, then a cocitation relationship exists between them. Frequent citation of articles (or authors or journals) together suggests that their research topics, including concepts, theories, or methods, are likely related. Cocitation analysis ranks key papers according to their citation frequency and explains the correlation between their contents and directions through the centrality value. This analysis can also infer literature clusters from various papers that are published during the same period, indicating hot spots in the field. The frequency and relevance of citations represent hot spots in scientific research over time, and these core documents form the knowledge base for the hot spots. In turn, the knowledge base clarifies the cutting-edge nature of the research, as frequently cited papers constitute the corresponding knowledge base [21].

Results

Publication Trends in ICT in Physiology

The year 2013 marks the commencement of the field, in which Tune et al [22] were the first to publish a research paper related to ICT in physiology. The research volume then increased yearly, reaching its peak in 2022. According to the number of publications, different stages of ICT in physiology development can be defined. Before 2017, there were only a small number of papers related to ICT in physiology, marking 2013 - 2017 as the gradual upward stage. In 2018, there was a slight decrease in the number of published papers on the topic, which may be due to the conflicts between conventional teaching and incorporating ICT into physiology teaching, indicating the need for more modification and reflection in practice. Hence, 2018 - 2019 can be considered as the adaptation period. The second gradual upward period appeared during the COVID-19 outbreak in 2021 and then peaked in 2022, indicating a boom period for this field of study.

Authors’ Cooperative Network

An author’s contribution to the area of ICT in physiology can be identified by their significant publications and cooperative connections with other authors, which facilitates understanding the progress in ICT in physiology [23]. Author collaboration appears to be generally limited, and most academic work in this field is conducted in independent teams with minimal cross-team communication.

As shown in Figure 1A, the research author cooperation map highlights various research partnership teams, particularly those
surrounding the authors Gopalan C, Gillam-Krakauer M, and multiple researchers with cooperative connections. Gopalan C has the highest citation count with 5 publications, followed by authors Carbajal MM, Falck AJ, Johnston LC, Feng D, Luo Z, French H, Dadiz R, Vasquez MM, and Gray MM who collaborated on three records with a citation count of 3 each, as depicted in Multimedia Appendix 3.

Since 2016, Gopalan C has published 14 relevant papers, with a significant surge from 2019 to 2022, as illustrated in Figure 1A. Gopalan C, Bingen H, Tveit B, Steindal S, and Krumsvik R have jointly published three papers centered on nursing education [24-26], indicating a stable partnership among these authors who conducted a series of studies on ICT in nursing education. Additionally, some other authors, including Feng D and Luo Z from Central South University in China, have coauthored two papers [27,28].

Figure 1. Network analysis map. The collaboration networks for (A) authors and national/regional collaboration (N=145, E=400) and (B) institutions (N=85, E=216) in the field of inverted teaching in physiology. Node size (N) corresponds to the frequency of inverted teaching in physiology publications from each author/institution. The connecting lines (E) represent collaborative connections between authors/institutions, with thicker lines indicating more frequent collaboration.
National/Regional and Institutional Cooperative Networks

Overall, the extent of collaboration between nations and research institutions is relatively weak, with very low centrality, and the research power of countries is uneven. As seen in Figure 1 and Multimedia Appendix 4, US-based authors published the highest number of inverted teaching in physiology–related papers (18 in total, accounting for over 43% of the total papers). Moreover, their intermediary centrality is 0.24, indicating that they have strong connections and are highly engaged in international cooperation. Chinese authors ranked second, publishing 8 papers; however, their intermediary centrality is only 0.02, suggesting that their papers have limited international influence and lower overall quality, providing little influential power in the field of ICT in physiology. Australia ranked third, with a centrality of 0.01 covered by 3 papers on ICT in physiology.

As shown in Figure 1B and Multimedia Appendix 5, universities and affiliated hospitals are the primary institutions that have published ICT in physiology–related papers. Southern Illinois University Edwardsville and Duke University in the United States have published the most papers in this field since 2018 and have significantly contributed to ICT in physiology research. Other institutions, including the University of Washington, University of Texas, Vanderbilt University, Central South University, University of Rochester, University of Pennsylvania, Yale University, University of Washington, and Baylor College of Medicine, contributed 3 research papers each. As seen from the year color bar on the left bottom corner of Figure 1B, most nodes are labeled in orange, indicating that most institutions published these articles in 2021 and 2022. Specifically, most of the studies performed in the United States are labeled in green and yellow, corresponding to earlier years, indicating the pioneering role of universities in the United States for ICT in physiology research; in particular, authors from Southern Illinois University published an ICT in physiology paper in 2017, which is earlier than most institutions contributing to this field.

Cocitation Analysis of References

The highly cited literature on ICT in physiology is summarized in Table 1, which shows the top 15 most influential articles in this field of research ranked by citation frequency and mediation centrality published between 2013 and 2020. The top-ranked item by citation counts is by Chen et al [21], which was published in 2017 with a citation count of 8 and a centrality of 0.26, followed by the paper published by McLaughlin et al [29] in 2014, also with a citation count of 8.

<table>
<thead>
<tr>
<th>Cited reference</th>
<th>Citation count</th>
<th>Centrality</th>
<th>Publication year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chen et al [21]</td>
<td>8</td>
<td>0.26</td>
<td>2017</td>
</tr>
<tr>
<td>McLaughlin et al [29]</td>
<td>8</td>
<td>0</td>
<td>2014</td>
</tr>
<tr>
<td>Tune et al [22]</td>
<td>5</td>
<td>0</td>
<td>2013</td>
</tr>
<tr>
<td>Gilboy et al [30]</td>
<td>4</td>
<td>0.12</td>
<td>2015</td>
</tr>
<tr>
<td>Pierce and Fox [31]</td>
<td>4</td>
<td>0.15</td>
<td>2012</td>
</tr>
<tr>
<td>Betihavas et al [1]</td>
<td>4</td>
<td>0.5</td>
<td>2016</td>
</tr>
<tr>
<td>Xiao et al [32]</td>
<td>4</td>
<td>0.17</td>
<td>2018</td>
</tr>
<tr>
<td>Hew and Lo [33]</td>
<td>4</td>
<td>0.2</td>
<td>2018</td>
</tr>
<tr>
<td>Day [34]</td>
<td>3</td>
<td>0.07</td>
<td>2018</td>
</tr>
<tr>
<td>French et al [35]</td>
<td>3</td>
<td>0.04</td>
<td>2018</td>
</tr>
<tr>
<td>Blair et al [36]</td>
<td>3</td>
<td>0.06</td>
<td>2020</td>
</tr>
<tr>
<td>Freeman et al [37]</td>
<td>3</td>
<td>0.08</td>
<td>2014</td>
</tr>
<tr>
<td>Akçayır and Akçayır [38]</td>
<td>3</td>
<td>0.3</td>
<td>2018</td>
</tr>
<tr>
<td>Foldnes [39]</td>
<td>3</td>
<td>0.03</td>
<td>2016</td>
</tr>
<tr>
<td>Gross et al [40]</td>
<td>3</td>
<td>0.03</td>
<td>2015</td>
</tr>
</tbody>
</table>

Internet and Higher Education have also provided considerable attention to this topic, implying that modern educational technologies such as information science and the internet play a crucial role in facilitating the inverted classroom mode.

Research Hot Spots Suggested by Keyword Co-Occurrence Analysis

Figure 2 presents the coexistence diagram of ICT in physiology keywords, with each node representing a keyword and the font size indicating the node’s size; that is, a larger font indicates that the keyword appears more frequently. The cluster labels

Cocitation Analysis

As shown in Multimedia Appendix 6 and Multimedia Appendix 7, Gopalan C was found to be the most cited author with a count of 5 and a centrality of 0.02.

Multimedia Appendix 8 summarizes the top 10 journals that published ICT in physiology papers. Advances in Physiology Education was the first journal to publish ICT in physiology research papers and has maintained the highest frequency of citations from 2013 to 2022 (also see Multimedia Appendix 6). Additionally, journals such as Computers & Education and The Internet and Higher Education have also provided considerable attention to this topic, implying that modern educational technologies such as information science and the internet play a crucial role in facilitating the inverted classroom mode.
obtained from the keyword cluster analysis can indirectly reflect the leading research topics, while the timeline map of the keyword clusters can demonstrate the leading research topics by time. **Table 2** lists the top keyword clusters in ICT in physiology research according to the number of occurrences and centrality of each keyword, demonstrating that the top keywords are “flipped classroom,” “active learning,” “student performance,” “performance,” and “medical education.” **Figure 2A** shows that from 2013 to 2022, research on ICT in physiology focused on medical education, performance, engagement, active learning, online teaching, and other aspects. According to the intermediary centrality, “flipped classroom” (0.69) is the most influential keyword, followed by “medical education” (0.2) and “education” (0.14).

**Figure 2.** Co-occurrence map and appearance history of keywords in literature related to inverted teaching in physiology. (A) The map of keyword clusters and the timeline map (N=131, E=459). (B) The co-occurrence map of keywords (N=233, E=795). The node size, N, corresponds to the frequency of publications from each journal. The connecting lines, E, represent collaborative connections between journals, with thicker lines indicating more frequent collaboration.
The keyword co-occurrence analysis showed that in addition to the retrieved topic term “flipped classroom,” “medical education” ranked the highest in terms of word frequency and ranked the third highest according to mediator centrality, reflecting that active learning is a hot topic in ICT in physiology research. The keywords “education,” “performance,” and “engagement” followed closely behind, with the centrality being 0.14, 0.14, and 0.26, respectively (Table 2). This indicates that researchers in the field of ICT in physiology have been paying relatively more attention to performance aspects, which could reflect the effectiveness and satisfaction of ICT in physiology. The keywords “engagement” and “perceptions” also had high co-occurrence numbers and mediator centrality.

### Table. Main keywords in research related to inverted teaching in physiology.

<table>
<thead>
<tr>
<th>Keywords</th>
<th>Co-occurrence number</th>
<th>Mediator centrality</th>
<th>First year of appearance</th>
</tr>
</thead>
<tbody>
<tr>
<td>flipped classroom</td>
<td>22</td>
<td>0.69</td>
<td>2013</td>
</tr>
<tr>
<td>medical education</td>
<td>8</td>
<td>0.2</td>
<td>2016</td>
</tr>
<tr>
<td>education</td>
<td>7</td>
<td>0.14</td>
<td>2020</td>
</tr>
<tr>
<td>performance</td>
<td>6</td>
<td>0.14</td>
<td>2014</td>
</tr>
<tr>
<td>engagement</td>
<td>6</td>
<td>0.26</td>
<td>2015</td>
</tr>
<tr>
<td>flipped teaching</td>
<td>5</td>
<td>0.19</td>
<td>2018</td>
</tr>
<tr>
<td>student performance</td>
<td>4</td>
<td>0.04</td>
<td>2013</td>
</tr>
<tr>
<td>medical students</td>
<td>4</td>
<td>0.19</td>
<td>2016</td>
</tr>
<tr>
<td>active learning</td>
<td>4</td>
<td>0.05</td>
<td>2016</td>
</tr>
<tr>
<td>online teaching</td>
<td>3</td>
<td>0.06</td>
<td>2021</td>
</tr>
<tr>
<td>instruction</td>
<td>3</td>
<td>0.11</td>
<td>2015</td>
</tr>
<tr>
<td>classroom</td>
<td>3</td>
<td>0.09</td>
<td>2015</td>
</tr>
<tr>
<td>modified team-based learning</td>
<td>2</td>
<td>0.02</td>
<td>2017</td>
</tr>
<tr>
<td>dental education</td>
<td>2</td>
<td>0</td>
<td>2017</td>
</tr>
<tr>
<td>classroom model</td>
<td>2</td>
<td>0.05</td>
<td>2017</td>
</tr>
<tr>
<td>science</td>
<td>2</td>
<td>0.03</td>
<td>2017</td>
</tr>
<tr>
<td>faculty</td>
<td>2</td>
<td>0</td>
<td>2021</td>
</tr>
<tr>
<td>covid-19 pandemic</td>
<td>2</td>
<td>0</td>
<td>2022</td>
</tr>
<tr>
<td>physiology education</td>
<td>2</td>
<td>0.04</td>
<td>2016</td>
</tr>
<tr>
<td>bioscience</td>
<td>2</td>
<td>0.01</td>
<td>2019</td>
</tr>
<tr>
<td>perceptions</td>
<td>2</td>
<td>0.04</td>
<td>2022</td>
</tr>
<tr>
<td>higher education</td>
<td>2</td>
<td>0.01</td>
<td>2019</td>
</tr>
<tr>
<td>medical student</td>
<td>2</td>
<td>0.01</td>
<td>2018</td>
</tr>
<tr>
<td>students</td>
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<td>0.01</td>
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</tr>
<tr>
<td>efficacy</td>
<td>2</td>
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<td>2020</td>
</tr>
<tr>
<td>physiology</td>
<td>2</td>
<td>0.02</td>
<td>2015</td>
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<tr>
<td>learning preference</td>
<td>2</td>
<td>0.01</td>
<td>2021</td>
</tr>
<tr>
<td>student perceptions</td>
<td>2</td>
<td>0.02</td>
<td>2016</td>
</tr>
<tr>
<td>too</td>
<td>2</td>
<td>0</td>
<td>2022</td>
</tr>
<tr>
<td>blended learning</td>
<td>2</td>
<td>0.03</td>
<td>2020</td>
</tr>
<tr>
<td>online flipped classroom</td>
<td>2</td>
<td>0</td>
<td>2022</td>
</tr>
<tr>
<td>intrinsic motivation</td>
<td>2</td>
<td>0.03</td>
<td>2014</td>
</tr>
<tr>
<td>self-determination theory</td>
<td>2</td>
<td>0</td>
<td>2021</td>
</tr>
<tr>
<td>learning style</td>
<td>2</td>
<td>0.15</td>
<td>2016</td>
</tr>
</tbody>
</table>

The Research Hot Spots and Frontier Topics Suggested by Keyword Cluster Analysis

Based on other keywords in the same cluster and the popular words obtained by the latent semantic analysis/indexing algorithm, it was found that many popular words in each cluster reflected the current hot spots of ICT in physiology and had
Principal Findings

In this study, we used CiteSpace software to visually analyze the literature related to the use of ICT in physiology published between 2000 and 2023 retrieved from the WoS database. The results of this bibliometric analysis showed that the core authors publishing in the field of ICT in physiology include staff from universities and affiliated hospitals. Some research teams have also formed cooperative relationships. Research in ICT in physiology mainly focuses on active learning, autonomous learning, student performance, teaching effectiveness, blended teaching, personalized flipped teaching, and other related topics.

Overall, studies on the ICT model in the context of physiology remain scarce, with limited collaboration among authors and a consequent lack of a cohesive research network. Regional growth in this field is uneven and international disparities are evident. Despite the many established benefits of ICT, it is not widely used in various nations and regions. This may be attributable to the fact that the development of the ICT model is still in its infancy, and a mature theoretical structure is needed and must be tested over a wide range of professional specialties. In this sense, relevant researchers must increase interaction and collaboration, investigate systematic teaching techniques appropriate for various disciplines, and perform practical testing and assessment of the model. In the future, research power can be integrated to form a cohesive unit through cooperation among research institutions to promote further breakthroughs in ICT research in the context of physiology.

Development of ICT in Physiology

The ICT model has undergone three stages of development, including the introduction stage (2013 - 2014), extensive practice stage (2015 - 2019), and modification and growth stage (2020 - 2022).

Several studies have confirmed that an active-learning strategy is associated with improved student performance, a reduced failure rate, and better learning achievements in basic and clinical medical education [37,41]. Shaffer [42] reported that anatomy course objectives were achieved at a much higher rate after incorporating an active teaching style compared to the achievement rate following traditional teaching. Furthermore, in the clinical discipline, Qutub [43] reported the considerable effectiveness of ICT as an active learning style in a hematology course, enabling students to obtain desirable knowledge and improve their academic performance; moreover, students recognized that ICT as an active learning style was more beneficial than the traditional teaching approach. In 2016, Bethavas et al [1] performed a systematic review of 9 studies on the use of ICT in nursing education and reported that nursing students achieved similar or higher academic outcomes with ICT than with a conventional teaching strategy; however, the students indicated a mixed sense of satisfaction.

Other researchers in medical education and health science programs have reported similar results. For example, in an analysis of 274 papers, Barranquero-Herbosa et al [44] found that ICT in nursing education improves performance and is well-received by both students and instructors. O’Connor et al [45] concluded that reversing the flow of classroom teaching improves academic performance, develops self-directed learning skills, and consolidates acquired knowledge through active learning strategies. Sultan [46] found that flipping the classroom gives students more time for active learning, peer collaboration, and applying and analyzing theoretical knowledge. Moreover, McLean et al [47] showed that ICT could improve students’ preparation, attendance, and participation in the course Medical Sciences 4200, an elective nonthesis-based course that covers content related to physiology, biochemistry, and immunology.

With COVID-19 wreaking havoc worldwide in early 2020, the strict and rapid public health measures put forward led to the suspension of face-to-face education and the transfer of the classroom to online meetings, which also corresponds to the application of blended learning as a pedagogical approach based on a combination of online and face-to-face education processes [48]. This necessary shift during the pandemic greatly facilitated the implementation of ICT in various subjects and expanded the use of other types of education tools. For instance, Bawazeer et al [49] reported the use of polls in virtual sessions on physiology, pharmacology, and pathology courses to assess students’ engagement, understanding, performance, and attendance, and found improvements in understanding and performance. Feng et al [28] reported that incorporating the inverted classroom and a team-based learning strategy in the online setting can enhance the learning outcomes for students in a clinical immunology laboratory course. Although the pandemic and the availability of novel technologies have made blended learning a “new normal” in medical education, the successful adaptation of blended learning requires sufficient teacher training as well as the adoption of appropriate technologies by educational institutions [50].

The Role of ICT in Medical Education

In 2018, Chung et al [51] performed a systematic review on the use of ICT in nursing education, which showed that the basic flipped classroom mode has been frequently used in nursing education; nevertheless, the effects of ICT on learning behavior in physiology courses were not clearly investigated and only a few studies included in the review reported the use of after-class activities to engage students in facilitating the applications of the knowledge learned. Moreover, Lin and Hwang [52] reviewed studies on ICT papers published up to 2017 based on the technology-enhanced learning model, and noted that little attention was paid to the assessment of learners’ higher-order thinking skills and their degree of preparation or cognitive load. Similar findings have also been reported in relation to the application of ICT in subjects other than medicine, including mathematics [53].
Nevertheless, there is no doubt that ICT can efficiently engage students in learning sessions, even during the pandemic [54]. Research investigating students’ perceptions and performance revealed that students have high levels of acceptance for a virtual flipped teaching approach, which was already evident prior to the COVID-19 pandemic [9,55-57].

Lack of a Cohesive Research Network in ICT in Physiology Research

Acknowledging the importance of international cooperation and the role of different countries contributing to research on ICT in physiology may facilitate communication and collaboration among countries. With the highest number of published papers, authors from the United States have been the primary contributors to research on the applications of ICT in physiology courses since 2013.

The positive effects of ICT largely depend on an effective classroom design [58]. Designing an effective inverted classroom, guiding students to engage in inverted classroom learning, and personalizing the ICT to enhance teaching effectiveness and student learning outcomes have increasingly become the main topics of ICT research. These are common challenges encountered by teachers and students in ICT. Since a layered teaching approach adapted to the learning, teaching, and classroom conditions can maximize the expected benefits, various ICT approaches have been developed to date, such as partially inverted classrooms [59], Small Private Online Courses–based inverted classrooms [60], and lecture-based inverted classrooms [61].

Current Hot Spots of ICT in Physiology Research

There are currently three main topics generally discussed in the field of ICT: preparation before class, classroom activities, and consolidation after class [23]. The current hot spots of research in ICT for physiology worldwide focus on active learning, inverted classroom design, student perception and engagement, teaching effectiveness, and teaching evaluation, among others, while the scope of the research includes students, teachers, school teaching management, and national educational guidelines and policies. Moreover, our results are consistent with previous bibliometric studies related to the research on ICT in other fields [62]. For instance, a recent review by Cheng et al [62] on the top 100 highly cited ICT papers similarly showed that researchers in this field have largely focused on students’ learning achievements and learning behaviors rather than directly comparing the benefits of inverted and traditional learning. Similarly, Meral et al [63] reported that motivation, perception, and academic achievement/performance were the most common topics in the ICT studies published between 2010 and 2019.

Regarding the research hot spots suggested by the analysis of keywords, we identified the following main areas of focus of research on ICT in physiology at present: (1) ICT theories, including active learning and independent learning; (2) ICT strategies, including inverted design, student characteristics, learning style, learning preference, learning environment, educational technology, and student participation; and (3) ICT evaluations, including academic performance, student performance, and student satisfaction. Specific to disciplines and programs, the field of research on ICT in physiology covers clinical medicine, stomatology, nursing, pharmacy, and veterinary medicine, among others. With respect to the courses, ICT approaches can be applied to general physiology, gastrointestinal and renal physiology, exercise physiology, physiology lab courses, and introductory biology. The applicable levels of education include graduate, undergraduate, professional training, and adult continuing education.

Study Strengths and Limitations

This study has both strengths and limitations. To our knowledge, this is the first study to map the current ICT studies in physiology specifically rather than considering the whole field of ICT. Moreover, the visualization of the quantitative results provides a convenient and comprehensible understanding of the current publication status of studies, research hot spots, and development trends in the field of ICT for physiology.

Although all attempts were made to include relevant nouns and terms in the literature retrieval process, some relevant papers may have nevertheless been missed. Additionally, the search only incorporated “physiology” as the keyword for the teaching subject, which may have led to evidence selection bias in which research that covers all medical courses rather than physiology alone may have been missed and could not be incorporated into the study for analysis. In addition, the search was limited to the WoS database, which may have excluded some important non-English publications. Moreover, each subject has unique characteristics in the application of an inverted teaching model, and the results and conclusions reached based on the analysis of this study may not necessarily be generalized to other subjects; thus, these results should be interpreted with caution.

Conclusion

This study analyzes literature on ICT in physiology, identifying core authors, research topics, and development stages. To date, research in this field has focused on active and autonomous learning, student performance, the teaching effect, blended teaching, and personalized flipping teaching models. The development of ICT is linked to modern information technology, the COVID-19 pandemic, educational teaching concepts, and related teaching reform policies. Based on these findings, further academic exchanges and cooperation in applications of ICT in physiology are encouraged, which can highlight the potential of this teaching model to train the next generation of excellent medical talents.

Acknowledgments

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(2021YXJG005), Annual Experimental Teaching Curriculum Reform Special Project (SYJG202202), and "Four New" Experimental Teaching Curriculum Reform Project at Jinan University (SYJG202301).

Authors’ Contributions
YW and JB conceptualized the study. ZH, BZ, and HF contributed to the methodology. ZH and BZ contributed to data visualization. JB and YW supervised the study. ZH, BT, HF, JB, and YW wrote the initial draft of the manuscript. ZH, BZ, HF, YW, and JB contributed to manuscript review and editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Flowchart of literature selection.
[ PNG File, 65 KB - mededu_v10i1e52224_app1.png ]

Multimedia Appendix 2
Excluded studies with reasons.
[ DOCX File, 89 KB - mededu_v10i1e52224_app2.docx ]

Multimedia Appendix 3
The top 12 authors who published relevant papers on inverted teaching in physiology.
[ DOCX File, 16 KB - mededu_v10i1e52224_app3.docx ]

Multimedia Appendix 4
Distribution of countries publishing papers related to inverted teaching in physiology.
[ DOCX File, 15 KB - mededu_v10i1e52224_app4.docx ]

Multimedia Appendix 5
The top 12 institutions publishing papers related to inverted teaching in physiology.
[ DOCX File, 16 KB - mededu_v10i1e52224_app5.docx ]

Multimedia Appendix 6
(A) The cited reference analysis map of inverted teaching in physiology: N=235, E=684. Node size (N) corresponds to the frequency of publications from each reference. The connecting lines (E) represent collaborative connections between authors, with thicker lines indicating more frequent collaboration. (B) Analysis of cocited journals (N=236, E=996). Node size (N) corresponds to the frequency of publications from each journal. The connecting lines (E) represent citation connections between references, with thicker lines indicating more frequent cocitations.
[ PNG File, 570 KB - mededu_v10i1e52224_app6.png ]

Multimedia Appendix 7
The most influential authors of inverted teaching in physiology research.
[ DOCX File, 15 KB - mededu_v10i1e52224_app7.docx ]

Multimedia Appendix 8
Primary journals that publish research papers in the field of inverted classroom teaching in physiology.
[ DOCX File, 18 KB - mededu_v10i1e52224_app8.docx ]

Multimedia Appendix 9
Information of the main clusters of keywords in research related to inverted teaching in physiology.
[ DOCX File, 17 KB - mededu_v10i1e52224_app9.docx ]

References


Abbreviations

ICT: inverted classroom teaching
WoS: Web of Science

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Evolution of Chatbots in Nursing Education: Narrative Review

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Abstract

Background: The integration of chatbots in nursing education is a rapidly evolving area with potential transformative impacts. This narrative review aims to synthesize and analyze the existing literature on chatbots in nursing education.

Objective: This study aims to comprehensively examine the temporal trends, international distribution, study designs, and implications of chatbots in nursing education.

Methods: A comprehensive search was conducted across 3 databases (PubMed, Web of Science, and Embase) following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram.

Results: A total of 40 articles met the eligibility criteria, with a notable increase of publications in 2023 (n=28, 70%). Temporal analysis revealed a notable surge in publications from 2021 to 2023, emphasizing the growing scholarly interest. Geographically, Taiwan province made substantial contributions (n=8, 20%), followed by the United States (n=6, 15%) and South Korea (n=4, 10%). Study designs varied, with reviews (n=8, 20%) and editorials (n=7, 18%) being predominant, showcasing the richness of research in this domain.

Conclusions: Integrating chatbots into nursing education presents a promising yet relatively unexplored avenue. This review highlights the urgent need for original research, emphasizing the importance of ethical considerations.

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KEYWORDS
nursing education; chatbots; artificial intelligence; narrative review; ChatGPT

Introduction

Nursing education, crucial for positive patient-professional relationships [1,2] and continuous professional development [3], holds a pivotal position in global health care systems [4], driving progress [5] and integrating technological advancements to enhance patient-centered care [6,7]. A study on oncology nursing provided compelling evidence for nurses, addressing challenges and advocating for specialized education and safety measures in the escalating global cancer burden [8]. A recent meta-analysis of 12 studies with 821 participants evaluated the role of virtual reality in nursing education, which revealed substantial enhancements in knowledge but identified no distinguishable disparities in skills, satisfaction, confidence, and performance time, underscoring the imperative for additional investigations in these domains [9]. Another study explored the usability and feasibility of extended reality smart glasses in core nursing skill training for undergraduate students, uncovering positive effects on engagement, learning satisfaction, and competency improvement and highlighting the potential of smart glasses as an impactful educational strategy in nursing training [10]. However, nursing education encounters obstacles such as a worldwide scarcity of nursing expertise [11], uneven distribution of resources [12], potential disparities between theoretical and practical aspects [9], restricted interdisciplinary collaboration [13], insufficient opportunities for professional development [14], and the ramifications of the global COVID-19 pandemic [15].

In the swiftly evolving landscape of artificial intelligence (AI) and smartphone proliferation, the integration of large language models such as ChatGPT into chatbots is emerging as a trend, with chatbots progressively showcasing the potential to revolutionize mental health [16], behavior [17], and knowledge [18] within the dynamic and advancing field of deep learning. Recent studies on education have accentuated the use of chatbots to deliver personalized learning experiences [19,20] by tailoring content delivery to the unique needs of individual students, thereby augmenting comprehension and retention. Concurrently, chatbots provide an easily accessible platform for continuous learning [21], affording students the opportunity to retrieve information at their convenience and cultivating a culture of self-directed learning. Moreover, the interactive attributes of chatbots facilitate real-time feedback, permitting the prompt rectification of misconceptions and fostering a more profound
grasp of intricate health care concepts [22]. The adaptability of chatbots caters to diverse learning styles, ensuring inclusivity in education [23]. Despite these advantages, few studies investigate the integration, development, and feasibility of chatbots within nursing education.

Our aim is to meticulously investigate and amalgamate the existing literature pertaining to the integration of chatbots in nursing education by reviewing selected articles. By scrutinizing studies sourced from 3 prominent databases (PubMed, Embase, and Web of Science), we highlight insightful perspectives on the evolving role of chatbots in nursing education. Approaching this investigation with the perspective of a reviewer, we seek to contribute a nuanced and well-supported analysis of the existing literature on this topic.

**Methods**

**Search Strategy**

We devised pertinent search queries concerning nursing education and chatbots, with the designated search terms detailed in Section 1 in Multimedia Appendix 1. A thorough investigation encompassing 3 databases—PubMed, Embase, and Web of Science—was carried out from their individual inception dates to November 16, 2023.

**Eligibility Criteria for Study Inclusion**

The eligibility criteria were devised in accordance with the PICOS (Population, Intervention, Comparison, Outcome, and Study Design) framework [24]. The study inclusion criteria were meticulously outlined to ensure the accuracy and relevance of the selected research. The specified population comprised nurses or nursing students, including managers and clinical nurses, with a deliberate exclusion of doctors and other professional personnel. The intervention criteria encompassed any chatbot intervention, including chatbot apps, messaging, and web-based interventions, while excluding interventions not specifically focused on chatbots or lacking communication with them. The comparator conditions involved conventional education methods, such as face-to-face or drug interventions, excluding the integration of chatbot interventions. The exclusion criteria also considered comparators that included chatbot interventions at comparable rates but with differing frequencies. The outcomes of interest included results relevant to nursing education, covering levels of medical knowledge, nurses’ engagement with chatbots, and the improvement of practical skills. The study design inclusion criteria accepted any design. Detailed eligibility criteria are shown in Section 2 in Multimedia Appendix 1.

**Selection Process and Outcomes of Interest**

The search findings were imported into Covidence (Veritas Health Innovation) while adhering to established protocols. The screening process involved 2 stages. Initially, titles and abstracts were screened, followed by a thorough review of full-text articles. Duplicated papers were removed using Covidence prior to the screening stages to ensure the integrity of the selection process. Three authors (SZ, XL, and WW) independently and in duplicate executed all screening stages and data extraction, resolving any discrepancies through consultation with the senior author (FZ). To ensure precision and uniformity in data, we formulated a comprehensive data extraction form (SZ and WW) that underwent subsequent refinement (SZ and FZ), in alignment with guidelines from the Cochrane Handbook for Systematic Reviews of Interventions [25]. Before full extraction, the form underwent a pilot test on a subset of included studies. Extracted details from all included studies (SZ, XL, and WW) included elements such as publication details (study ID, title, and year), author particulars (lead author contact information), study specifics (country, study design, and objectives), and conclusions.

**Study Design and Statistical Analysis**

This was a narrative review. After the screening process, we successfully gathered comprehensive data, encompassing publication details (study ID, title, and year), author particulars (contact information for the lead author), study specifics (country, study design, and objectives), and conclusions. Subsequently, we categorized this data based on the respective year, country, and study design. To provide a visual representation of the trends observed, we conducted percentage calculations for each category. These percentages were then used to illustrate the trend over time and to convey the distribution of studies across various categories.

**Results**

In total, 38,412 distinct records were identified. Subsequently, an eligibility assessment was conducted on 77 full-text articles, with 3 articles not retrieved, as depicted in Figure 1. Out of these, 37 were subsequently excluded, resulting in the inclusion of 40 articles that met the eligibility criteria for synthesis [26-65].

Between 2010 and 2020, on average, 1 article was published every 3 - 4 years, culminating in a total of 3 articles, contributing to 8% of the 40 publications. However, a noticeable upswing occurred in 2021, with the publication of 3 (8%) articles. In 2022, the count increased to 6 (15%) articles. The most notable surge transpired in 2023, with the publication of 28 articles, accounting for a substantial 70% of the total publications (Figure 2).
Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram showing the study selection process.
Taiwan province contributed 20% (8/40) of the total articles [31,32,34,35,37,42-44]. Following closely was the United States, contributing 15% (6/40) of the articles [39,40,46,52,55,59]. South Korea secured the third position, representing 10% (4/40) of the articles [41,47,48,63]. Canada [26,28,30], Mainland China [33,50,64], and Singapore [57,58,60] each contributed 8% (3/40) of the articles. Turkey [29,62] contributed 5% (2/40) of the articles. Other countries such as Australia [45], France [38], Germany [49], Hong Kong [36], India [56], Iraq [27], Italy [51], Japan [61], Malta [54], the United Kingdom [53], and Ukraine [65] each contributed 3% (1/40) of the articles.

In our review, the predominant study design was reviews, constituting 20% (8/40) of the total articles [36,46,49,50,56,59,60]. Reviews exemplify a meticulous synthesis of existing literature, providing comprehensive insights and analyses on specific topics. Editorials, comprising 18% (7/40) of the articles [28,39,45,47,52-54], serve as platforms for commentary, opinions, or perspectives on current issues and developments in the field. Commentaries constituted 10% (4/40) of the articles [26,30,35,64], offering critical reflections, analyses, or perspectives on specific subjects. Letters to the editor, making up 8% (3/40) of the articles [27,29,61], provide readers with a platform to express opinions, raise concerns, or offer feedback on published content. Quasi-experimental studies comprised 8% (3/40) of the articles [41,48,58], employing experimental methods without random assignment. Constituting 5% (2/40) of the articles, teaching tips offer valuable insights into effective educational strategies [34,55]. Randomized
controlled trials (RCTs), considered the gold standard in experimental design, constituted 5% (2/40) of the articles [42,62]. Experimental design, symbolizing systematic investigation, was embodied in 3% (1/40) of the articles [31]. Empirical articles, grounded in observations and experiences, constituted 3% (1/40) of the articles [32]. Phenomenological studies, delving into lived experiences and perceptions, comprised 3% (1/40) of the articles [33]. Proof-of-concept studies, showcasing the feasibility of an idea or approach, constituted 3% (1/40) of the articles [38]. Mini reviews, furnishing concise overviews, comprised 3% (1/40) of the articles [65]. Descriptive qualitative studies, concentrating on detailed exploration, accounted for 3% (1/40) of the articles [40]. Experimental studies, engaging in controlled testing, made up 3% (1/40) of the articles [43]. Systematic reviews, characterized by methodical literature synthesis, represented 3% (1/40) of the articles [44]. Articles centering on experimentation methodology represented 3% (1/40) of the articles [51]. Development studies, exploring the creation of new methodologies or tools, constituted 3% (1/40) of the articles [57]. Lastly, articles classified as communications, conveying crucial information or updates, represented 3% (1/40) of the articles (Table 1) [63].
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<td>Uslu and van Giersbergen [62]</td>
<td>The Effects of Manikin-Based and Standardized-Patient Simulation on Clinical Outcomes: A Randomized Prospective Study</td>
<td>Turkey</td>
<td>RCT</td>
<td>2023</td>
</tr>
<tr>
<td>Ye et al [63]</td>
<td>Development of a Chatbot Program for Follow-Up Management of Workers’ General Health Examinations in Korea: A Pilot Study</td>
<td>South Korea</td>
<td>Communication</td>
<td>2021</td>
</tr>
</tbody>
</table>

*RCT: randomized controlled trial.*
Discussion

Principal Findings
In this paper, we comprehensively examined the temporal trends, international distribution, study designs, and implications of chatbots in nursing education to map the challenges and issues to address in the future. Our analysis highlights significant findings, including a marked increase in research publications in 2023, reflecting growing interest in this field. Contributions from Taiwan province, the United States, and South Korea illustrate the global scope of chatbot integration in nursing education. The diverse study designs reviewed, ranging from reviews and editorials to quasi-experimental studies, indicate the extensive research exploring chatbots’ role in enhancing personalized instruction, patient-care simulations, and critical thinking. Despite these advancements, challenges such as the need for rigorous original research, funding, ethical considerations, and resource distribution disparities remain. Furthermore, addressing these issues through international collaboration and targeted research will be crucial for fully realizing the potential of chatbots in nursing education.

AI language models such as chatbots have caused a revolution in nursing education through the provision of personalized and interactive learning activities. Chatbots are implemented in nursing education for personalized instruction, patients-care simulation, and critical thinking enhancement. Chatbots in health care are used for teleconsultation to improve communication skills, support clinical judgment, and enable remote patient monitoring. Chatbots are a key component in addressing the global shortages of knowledge and resources in nursing training. They bridge theoretical and practical aspects, thereby illustrating the potential of this technology to revolutionize learning processes and change the face of health care services and education.

This study aims to shed light on the evolution of chatbots in nursing education through data analysis of temporal trends. The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram facilitates a systematic search procedure, which guarantees a transparent and strict methodology. Indeed, articles published in 2023 accounted for 70% (28/40) of the included articles, which might be due to either increased scholarly interest or intensified effort. This study tries to delve into the technological education aspect of health care, which is a rapidly expanding area. Consequently, it will provide a comprehensive reflection of the dynamic and developing educational sector.

This study provides a new approach about how AI and mobile communication can be applied in and influence nursing education. Chatbots and AI integration can be seen as a technical invention with thrilling effects on mental health, behavior, and knowledge in relation to the field of deep learning. The analysis stresses the sole benefits of chatbots in education, that is, chatbots provide the capacity for individualized learning. The studies focus on problems in nursing education that involve the shortage of global knowledge, condition differences, and lack of relationship between theory and practice and illustrate the ways chatbots can cope with these issues.

A detailed study of the worldwide distribution and categorization of chatbot research on nursing education is carried out with reference to international contexts, highlighting major contributions. The participation of United States and South Korea is notable, and Taiwan province has the largest share, accounting for 20% (8/40) of all articles. This regional perspective highlights the universal nature of adding chatbots to nursing education. As the research methodology analysis reveals, reviews cover 20% (8/40) of the articles, providing exhaustive summaries of the present literature. A diverse range of designs that includes commentaries, quasi-experimental studies, teaching tips, and RCTs explains the extensive and varied research on chatbots in nursing education.

In spite of the huge benefits, there are some barriers that nursing education will face as they try to incorporate chatbots. Original research such as RCTs or cohort studies is the most important part of confirming the efficiency of conversational bots. Funding research about advanced techniques and the application of rigorous process need high levels both of staff and finance. The integrity and the security problems of chatbots that provide wrong advice are highlighted, demonstrating the need for correcting the technical problems in order to ensure ethical and secure operations. Funding should be set aside to close resource distribution disparities, so that students from disadvantaged backgrounds can also have an opportunity to have access to technologically advanced educational resources. Collaboration among those in the academic, technical, and health care disciplines is indispensable as an effort to develop supportive surroundings for the application of chatbots to nursing education globally.

This study demonstrates the substantial changes that chatbots bring into nursing education to make nursing practice more enjoyable. This integration aims at resolving several issues, including the lack of competitiveness from a global perspective and economic disparity, in essence to establish an integrated and dynamic learning environment. Analyzing the small components of chatbots and conducting research on the feasibility, pros, and cons are necessary aims for the future of education. The lack of original research forces us to rely more on the already existing qualitative studies such as commentaries and editorials. Above all, great attention should be given to privacy and ethics when integrating current technologies into the health care education system.

There are some limitations. First, the study only provides a description of the changes over time in articles related to chatbots in nursing education, as well as the distribution of regions and types of articles. Due to the lack of original studies, it does not show the characteristics of papers included in the final analysis. Second, there is uncertainty about whether the specific research topics related to chatbots in nursing education are consistent between countries. Third, there is a lack of in-depth quantitative exploration and discussion regarding the specific application directions of chatbots in nursing education, preventing the formulation of more constructive recommendations.
Conclusion
Integrating chatbots into nursing education presents a promising yet relatively unexplored avenue. This review highlights the urgent need for original research, emphasizing the importance of ethical considerations. This exploration contributes to the evolving landscape of technology in health care education, bridging gaps and fostering a learner-centric approach aligned with contemporary health care demands.

Authors’ Contributions
SZ contributed to conceptualization, methodology, data curation, formal analysis, writing—original draft preparation, and writing—review and editing. XL contributed to methodology, data curation, and writing—original draft preparation. WW contributed to conceptualization, methodology, project administration, and supervision.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Search strategies and eligibility criteria for study inclusion. [DOCX File, 30 KB - mededu_v10i1e54987_app1.docx]

References


Abbreviations
AI: artificial intelligence
**PICOS:** Population, Intervention, Comparison, Outcome, and Study Design  
**PRISMA:** Preferred Reporting Items for Systematic Reviews and Meta-Analyses  
**RCT:** randomized controlled trial

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Measuring the Digital Competence of Health Professionals: Scoping Review

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Abstract

Background: Digital competence is listed as one of the key competences for lifelong learning and is increasing in importance not only in private life but also in professional life. There is consensus within the health care sector that digital competence (or digital literacy) is needed in various professional fields. However, it is still unclear what exactly the digital competence of health professionals should include and how it can be measured.

Objective: This scoping review aims to provide an overview of the common definitions of digital literacy in scientific literature in the field of health care and the existing measurement instruments.

Methods: Peer-reviewed scientific papers from the last 10 years (2013-2023) in English or German that deal with the digital competence of health care workers in both outpatient and inpatient care were included. The databases ScienceDirect, Scopus, PubMed, EBSCOhost, MEDLINE, OpenAIRE, ERIC, OAIster, Cochrane Library, CAMbase, APA PsycNet, and Psyndex were searched for literature. The review follows the JBI methodology for scoping reviews, and the description of the results is based on the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) checklist.

Results: The initial search identified 1682 papers, of which 46 (2.73%) were included in the synthesis. The review results show that there is a strong focus on technical skills and knowledge with regard to both the definitions of digital competence and the measurement tools. A wide range of competences were identified within the analyzed works and integrated into a validated competence model in the areas of technical, methodological, social, and personal competences. The measurement instruments mainly used self-assessment of skills and knowledge as an indicator of competence and differed greatly in their statistical quality.

Conclusions: The identified multitude of subcompetences illustrates the complexity of digital competence in health care, and existing measuring instruments are not yet able to reflect this complexity.

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KEYWORDS
digital competence; digital literacy; digital health; health care; health care professional; health care professionals; scoping review
Introduction

Background
The 2006 European Parliament recommendation on key competences for lifelong learning lists digital competences as 1 of the 8 key competences for every citizen to enable personal fulfillment, active citizenship, social cohesion, and employability in our modern society [1]. Therefore, it is no surprise that the digital transformation within the health care sector, involving new processes and technologies [2], has completely changed the demands on people working in health care professions. Digital competence in health care is needed [3,4]. According to Vitello et al [5], competence is “the ability to integrate and apply contextually-appropriate knowledge, skills and psychosocial factors (e.g., beliefs, attitudes, values and motivations) to consistently perform successfully within a specified domain.” Salman et al [6] divide competence into 2 aspects: hard and soft. The hard aspects of competence include knowledge, skill, and behavior, whereas the soft aspects include character traits, motives, attitudes, values, and self-image. Together, all these aspects determine the performance or output—both visible and invisible—of an individual in a particular job. Competence, in contrast to competency, is attached to the person rather than to a task or activity [5], which fits better within this work because we are focusing not on specific digital activities but on how professionals deal with digital technologies when working in the health care domain. This is why we concentrate on competence in this work.

The updated version of the digital competence framework for citizens (DigComp 2.2) [7] divides digital competences for private individuals into 5 main dimensions: information and data literacy, communication and collaboration, digital content and creation, safety, and problem-solving. Specific knowledge, skills, and attitudes are assigned to each of these dimensions. Along with the requirements for digital competence in private life, there are certain requirements to be met before one can be considered digitally competent in professional life in the health care sector.

Unfortunately, to date, there is no standard definition for the construct digital competence within the health care domain. Although the topic of interest is digital competence, the term digital literacy was also considered because this term is more common in English-speaking countries, and both concepts are often used synonymously [8]. Currently, for both terms, different understandings exist [9]. In this review, the semantic meaning of the terms is important, that is, the skills and characteristics required to navigate the (professional) digital world.

The lack of a uniform definition also leads to problems in determining digital competence for health professionals: authors criticize the lack of validated and up-to-date instruments to measure digital literacy or digital competence in this field [10,11]. With existing measurement tools, the focus is solely on technical skills; the related aspects that also affect the use of digital technologies are neglected [10].

Therefore, the objective of this research was to create an overview of how digital competence is defined and measured among health care professionals and thus to provide a holistic picture.

Research Questions
Primarily, the following questions will be answered with the help of the literature review:

- What definitions exist of the digital competence of health care professionals?
  - What are the similarities and differences among the various definitions?
  - On which basic models are the different definitions based?

- What possibilities exist for measuring the digital competence of health care professionals?
  - Which dimensions of digital competence are measured?
  - How are the dimensions measured (self-assessment, performance tasks, etc)?
  - Have the assessment tools been validated? What quality criteria have been applied?

Methods

Overview
To provide a systematic overview of existing research literature on digital literacy in health professions, we conducted a scoping review [12]. The review follows the JBI methodology for scoping reviews [13] (based on the works of Arksey and O’Malley [14] and Levac et al [15]), which follows these steps: (1) defining and aligning the objectives and questions; (2) developing and aligning the inclusion criteria with the objectives and questions; (3) describing the planned approach to evidence searching, selection, data extraction, and presentation of the evidence; (4) searching for the evidence; (5) selecting the evidence; (6) analysis of the evidence; (7) presentation of the results; and (8) summarizing the evidence in relation to the purpose of the review, making conclusions, and noting any implications of the findings.

The review was planned beforehand by AM and SM, including choosing the review method, formulating the research questions, selecting the databases, phrasing the search terms, and determining the eligibility criteria. AM screened the search results, during which process there was regular professional exchange with another author, VW. The results were reviewed by SM, VW, and JN. AM, SM, VW, and JN all have experience in conducting scoping reviews.

To ensure the high quality and informative value of the results report, the description of the results is based on the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) checklist [12,16] (Multimedia Appendix 1). In addition, an evaluation protocol was prepared in advance of the review and made publicly available on OSF [17].

Search Strategy
The literature search took place in April 2023 and used the databases ScienceDirect, Scopus, PubMed, EBSCOhost (which provides results from MEDLINE, OpenAIRE, ERIC, and...
The search term used was as follows: (“digital competence” OR “digital literacy”) AND (“medical professional” OR “healthcare professional” OR “healthcare worker” OR “physician assistant” OR “health professional”). Fixed combinations of terms (such as digital literacy) are placed in quotation marks. Parentheses are used to force the right evaluation order of the expression. No adjacent terms were added so as not to make assumptions about the nature of the terms of interest. These were combined with various health worker designations. Neutral terms were chosen for the designation of nonmedical personnel to achieve a neutral and comprehensive understanding for different health professions. The keywords were linked with the Boolean operator “OR” to show results with at least one of the given terms. The operator “AND” ensures that all search results contain both “digital competence” or “digital literacy” and a health worker designation. The search term was developed through several trial cycles of a combination of terms. These were entered into the different databases and, based on the search results, terms were added or removed. The results are shown in Table 1.

Table 1. Results of the database search. The search term (“digital competence” OR “digital literacy”) AND (“medical professional” OR “healthcare professional” OR “healthcare worker” OR “physician assistant” OR “health professional”) was used for each database (N=1682).

<table>
<thead>
<tr>
<th>Database</th>
<th>Results, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ScienceDirect</td>
<td>594 (35.31)</td>
</tr>
<tr>
<td>Scopus</td>
<td>361 (21.46)</td>
</tr>
<tr>
<td>PubMed</td>
<td>15 (0.89)</td>
</tr>
<tr>
<td>EBSCOhost (MEDLINE, OpenAIRE, ERIC, and OAIster)</td>
<td>706 (41.97)</td>
</tr>
<tr>
<td>Cochrane Library</td>
<td>6 (0.36)</td>
</tr>
<tr>
<td>CAMbase</td>
<td>0 (0)</td>
</tr>
<tr>
<td>APA PsycNet</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Psyndex</td>
<td>0 (0)</td>
</tr>
</tbody>
</table>

Eligibility Criteria

This scoping review considered peer-reviewed publications that were research articles, book chapters, review articles, or conference papers published within the last 10 years (2013-2023). Papers in either English or German were included. The articles address the digital competence of health care workers in both outpatient and inpatient care. They come from medical, technical, or educational research fields. Papers from the patient’s perspective or those that address eHealth literacy or digital health literacy, defined as the “skills, knowledge and resources to search for, find, understand, evaluate and apply health information [from the internet]” [18], were excluded because the concept of interest is more concerned with the understanding of information rather than with the professional use of digital technologies. The overall eligibility criteria for this scoping review are presented inTextbox 1.

Textbox 1. Inclusion and exclusion criteria for the scoping review.

Inclusion criteria
- Peer-reviewed publications
- Research articles, book chapters, review articles, or conference papers
- Research field: medical, technical, or educational
- Subject: articles addressing digital competence or digital literacy
- Population: health care workers in both outpatient and inpatient care and students and graduates of health care professions
- Period: articles published from 2013 to 2023
- Language: English or German

Exclusion criteria
- Not peer-reviewed publications
- Research field: any research field other than medical, technical, or educational
- Subject: articles addressing eHealth literacy or digital health literacy
- Population: patients
- Period: articles published before 2013
- Language: other than English or German
Article Screening and Data Extraction

According to the recommendations of Moher et al [19], these steps are followed in the study selection process: first, duplicates are removed from the initial search results, after which the remaining publications are evaluated based on their titles, keywords, and abstracts and, subsequently, checked for suitability based on the full texts. The eligible papers are included in the review [19]. We followed the recommended process and, from the eligible papers, extracted and listed the following data in a Microsoft Excel sheet that was developed a priori but refined iteratively: authors, year of publication, country of origin, type of survey, and target group.

Synthesis of Results

We present the characteristics of the selected studies, with a comparison of the drafted definitions of digital competence. In addition, we report the fundamental frameworks, models, and research papers that originally specified these definitions. We have collected and clustered all competences mentioned in the eligible papers. The structuring of the competences identified in the works was based on the competence categories according to the competence model developed by Hecklau et al [20], who cluster competences into technical, methodological, social, and personal competences to achieve clarity and transparency of the competence model. This clustering was adopted within our work to organize the determined competences. Finally, we explicitly examine the papers in which digital literacy assessment tools are used, with a consideration of the origin of the questionnaires, the form of measurement, and an assessment of their statistical quality.

Results

Selection of Sources of Evidence

The initial search identified 1682 papers (Table 1), of which 1510 (89.77%) remained after duplicates were removed. After applying the inclusion criteria (time period, type, and language) and screening the titles, of the 1510 papers, 428 (28.34%) were available for preselection, which, after the screening of the abstracts, reduced to 119 (27.8%) titles. Finally, after consideration of the full texts, of the 1682 papers identified through the initial search, 46 (2.73%) were included in this scoping review (Figure 1).

Characteristics of Sources of Evidence

The selected papers were largely published from 2020 onward (35/46, 76%), indicating an increase in the perceived relevance of digital literacy among health professionals in the scientific world. In the years prior (2013-2019), only 11 (24%) of the 46 papers were published, with a slightly perceptible increase from 1 (9%) paper in 2014 to 4 (36%) in 2019. Of the 46 papers, the maximum number was published in 2020 (n=15, 33%); in subsequent years, the number of papers decreased to 8 (17%) in 2021 and 6 (13%) in 2022, and in 2023, a total of 6 (13%) papers had been published until May of that year. Table 2 shows the key data of the included papers.
Table 2. Key data of the included papers.

<table>
<thead>
<tr>
<th>Authors</th>
<th>Year</th>
<th>Country</th>
<th>Type of study</th>
<th>Target group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Awami [21]</td>
<td>2020</td>
<td>Libya</td>
<td>Quantitative study</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Barbosa et al [22]</td>
<td>2023</td>
<td>Austria, Belgium, Croatia, Denmark, Finland, France, Italy, Malta, Netherlands, Norway, Poland, Portugal, and United Kingdom</td>
<td>Quantitative study</td>
<td>Radiotherapists</td>
</tr>
<tr>
<td>Brice and Almond [23]</td>
<td>2020</td>
<td>Australia</td>
<td>Scoping review</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Brown et al [24]</td>
<td>2020</td>
<td>Australia</td>
<td>Quantitative study</td>
<td>Nurses</td>
</tr>
<tr>
<td>Burzynska et al [25]</td>
<td>2023</td>
<td>Poland</td>
<td>Quantitative study</td>
<td>Physicians</td>
</tr>
<tr>
<td>Butler-Henderson et al [26]</td>
<td>2020</td>
<td>Australia</td>
<td>Meta-analysis</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Cabero-Almenara et al [27]</td>
<td>2021</td>
<td>Spain</td>
<td>Quantitative study</td>
<td>Health science lecturers</td>
</tr>
<tr>
<td>Cham et al [28]</td>
<td>2022</td>
<td>Australia</td>
<td>Quantitative study</td>
<td>Students of health professions</td>
</tr>
<tr>
<td>Coldwell-Neilson et al [9]</td>
<td>2019</td>
<td>Australia</td>
<td>Framework development</td>
<td>Optometry students</td>
</tr>
<tr>
<td>Evangelinos and Holley [29]</td>
<td>2014</td>
<td>United Kingdom</td>
<td>Qualitative interview</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Faihs et al [30]</td>
<td>2022</td>
<td>Germany</td>
<td>Quantitative study</td>
<td>Medical students</td>
</tr>
<tr>
<td>Golz et al [31]</td>
<td>2021</td>
<td>Switzerland</td>
<td>Quantitative study</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Hallit et al [32]</td>
<td>2020</td>
<td>Lebanon</td>
<td>Quantitative study</td>
<td>Pharmacists</td>
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<tr>
<td>Hilty et al [33]</td>
<td>2021</td>
<td>United States</td>
<td>Scoping review</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Holt et al [34]</td>
<td>2020</td>
<td>Denmark</td>
<td>Quantitative study</td>
<td>Nursing students</td>
</tr>
<tr>
<td>Jarva et al [35]</td>
<td>2022</td>
<td>Finland</td>
<td>Qualitative interview</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Jarva et al [36]</td>
<td>2023</td>
<td>Finland</td>
<td>Questionnaire development</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Jimenez et al [37]</td>
<td>2020</td>
<td>Singapore</td>
<td>Scoping review</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Jose et al [38]</td>
<td>2023</td>
<td>Chile</td>
<td>Scoping review</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Kahlilnen et al [39]</td>
<td>2021</td>
<td>Finland</td>
<td>Quantitative study</td>
<td>Nurses</td>
</tr>
<tr>
<td>Kayser et al [40]</td>
<td>2022</td>
<td>Denmark</td>
<td>Quantitative study</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Kim and Jeon [41]</td>
<td>2020</td>
<td>South Korea</td>
<td>Quantitative study</td>
<td>Nursing students</td>
</tr>
<tr>
<td>Konttila et al [42]</td>
<td>2019</td>
<td>Finland</td>
<td>Systematic review</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Kuek and Hakkennes [11]</td>
<td>2020</td>
<td>Australia</td>
<td>Quantitative study</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Longhini et al [10]</td>
<td>2022</td>
<td>Italy</td>
<td>Systematic review</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>MacLure and Steward [43]</td>
<td>2018</td>
<td>United Kingdom</td>
<td>Qualitative interview</td>
<td>Pharmacists</td>
</tr>
<tr>
<td>MacLure and Steward [44]</td>
<td>2016</td>
<td>United Kingdom</td>
<td>Systematic review</td>
<td>Pharmacists</td>
</tr>
<tr>
<td>Matthews [45]</td>
<td>2021</td>
<td>United Kingdom</td>
<td>Systematic review</td>
<td>Health graduates</td>
</tr>
<tr>
<td>McGregor et al [46]</td>
<td>2017</td>
<td>Australia</td>
<td>Qualitative interview</td>
<td>Health graduates</td>
</tr>
<tr>
<td>Montebello et al [47]</td>
<td>2016</td>
<td>Malta</td>
<td>SWOT® analysis</td>
<td>Students of health professions</td>
</tr>
<tr>
<td>O’Connor and LaRue [48]</td>
<td>2021</td>
<td>United Kingdom</td>
<td>Framework development</td>
<td>Nurses</td>
</tr>
<tr>
<td>Oo et al [49]</td>
<td>2021</td>
<td>Myanmar</td>
<td>Quantitative study</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Poncette et al [50]</td>
<td>2020</td>
<td>Germany</td>
<td>Mixed methods study</td>
<td>Medical students</td>
</tr>
<tr>
<td>Pontefract and Wilson [51]</td>
<td>2019</td>
<td>United Kingdom</td>
<td>Qualitative interview</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Rachmani et al [52]</td>
<td>2020</td>
<td>Indonesia</td>
<td>Quantitative study</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Reixach et al [53]</td>
<td>2022</td>
<td>Spain</td>
<td>Quantitative study</td>
<td>Health care professionals</td>
</tr>
<tr>
<td>Shiferaw et al [54]</td>
<td>2020</td>
<td>Ethiopia</td>
<td>Quantitative study</td>
<td>Health care professionals</td>
</tr>
</tbody>
</table>
The majority of the articles were published in Australia (7/46, 15%), Finland (7/46, 15%), and the United Kingdom (6/46, 13%). The remaining papers were distributed worldwide: Ethiopia (3/46, 7%); Denmark, Germany, Singapore, Spain, and the United States (2/46, 4% each); and Chile, Indonesia, Italy, Lebanon, Libya, Malta, Myanmar, New Zealand, Poland, South Korea, Switzerland, 13 countries in Europe (Austria, Belgium, Croatia, Denmark, Finland, France, Italy, Malta, Netherlands, Norway, Poland, Portugal, and the United Kingdom), and the rest of the world (1/46, 2% each).

The types of papers were mainly distributed between quantitative studies (23/46, 50%) and reviews (scoping reviews, systematic reviews, and meta-analyses; 11/46, 24%). Less represented were qualitative interviews (5/46, 11%) and framework development (3/46, 7%), as well as questionnaire development; mixed methods study; strengths, weaknesses, opportunities, and threats analysis; and historical development report (1/46, 2% each).

The papers’ target group was largely unspecified, with most of them addressing health care professionals (25/46, 54%). Other papers addressed specifically nurses (4/46, 9%), pharmacists (3/46, 7%), health graduates (2/46, 4%), health science lecturers (1/46, 2%), physicians (1/46, 2%), and radiotherapists (1/46, 2%). Some of the papers were aimed at students: students of health professions in general (3/46, 7%), medical students and nursing students (2/46, 4% each), and optometry students and physiotherapy students (1/46, 2% each).

**Definition of Data Literacy**

The main difficulty concerning the literature analysis was that some of the papers used the term digital literacy but actually referred to a different concept (especially eHealth literacy). When selecting the papers for review, articles that dealt, in terms of semantics, with concepts other than data literacy were sorted out.

Most of the papers provided definitions in which digital competence is composed of various dimensions of competence. There was a strong focus on skills in the formulated definitions of digital competence [9,21,22,25-33,35,36,39,40,42,43,45,47,48,50-55,59,60,62]. Many papers (27/46, 59%) also stated in their definitions that certain kinds of knowledge are necessary for competence [4,10,22,23,25-28,30-33,36,39,40,42,47,49-55,59,60,62]. Some of the papers (17/46, 37%) proposed that the attitude toward technical issues should be considered a component of competence [4,10,11,21,24,27,28,30-33,36,42,47,49,54,59]. Other papers (6/46, 13%) added that former experiences with digital topics play a crucial role in forming competence [28,31,40,42,43,46]. According to Konttila et al [42], experiences are the base for the emergence of attitudes. Other works mentioned motivation (7/46, 15%) [31,35,36,40,42,57,59], practices (2/46, 4%) [9,31], consciousness (2/46, 4%) [9,54], fears (2/46, 4%) [11,43], goals (1/46, 2%) [25], identity (1/46, 2%) [9], self-awareness (1/46, 2%) [28], and strategies (1/46, 2%) [54] as part of competence. These competence dimensions provide a framework for the required competence areas, which are described in the Identified Competence Areas and Competences subsection.

The definitions used are either the results of scoping reviews or frameworks where many individual results have been merged (15/46, 33%) [4,10,23,26,28,33,37,42,44,46,48,51,52,59,61]. Alternatively, they are based on other, explicitly named works, such as DigComp 2.2 [7] (4/46, 9%) [22,29,54,56]; the European framework for the digital competence of educators [63] (1/46, 2%) [27]; the technology acceptance model [64] and the unified theory of acceptance and use of technology [65] (1/46, 2%) [11]; the accreditation of competence in information and communication technologies by the government of Catalonia [66] (1/46, 2%) [53]; the Educause Center for Analysis and Research [67] (1/46, 2%) [60]; the General Confidence with Computer Use Scale [68] (1/46, 2%) [32]; the eHealth literacy questionnaire [69] (1/46, 2%) [40]; the eHealth literacy assessment toolkit [70] (1/46, 2%) [34]; the Self-Assessment of Nursing Informatics Competencies Scale [71] (1/46, 2%) [24]; a scale assessing the informatics competencies for nurses [72] (1/46, 2%) [39]; a scale assessing digital literacy with regard to information and communication technology [73] (1/46, 2%) [41]; the definition by Konttila et al [42] (1/46, 2%) [31]; the definition by Ferrari [74] (1/46, 2%) [21]; the definition by Bawden [75] (1/46, 2%) [25]; the definition by Sharpe and Beetham [76] (1/46, 2%) [9]; the definition by Hecklau et al [20] (1/46, 2%) [38]; the definition by Gretton and Honeymen [77] (2/46, 4%) [43,44]; the Health Education England definition [78] (1/46, 2%) [45]; the Jisc 7 elements of digital literacies (1/46, 2%) [47]; the World Health Organization’s Electronic Health Records: A Manual For Developing Countries [79].
Identified Competence Areas and Competences

Overview
Within the included papers, competences in the 4 main competence areas according to the model developed by Hecklau et al [20] were identified: multiple competences could be grouped into technical, methodological, social, and personal competences. All these competences, classified into 4 competence areas, are described in the following paragraphs and depicted in Textbox 2.

Textbox 2. The identified competences grouped into different competence areas.

<table>
<thead>
<tr>
<th>Competence areas and competences</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technical competences</td>
</tr>
<tr>
<td>• Basic computer competence [4,9,11,21-25,27-29,32,33,35-39,41,43-45,47-49,51-54,56,57,62]</td>
</tr>
<tr>
<td>• Basic competence to use wireless devices [21,23-25,37,49]</td>
</tr>
<tr>
<td>• Applied digital health skills [4,10,22,24,26,29,30,33,35,37,39,40,42,43,46,48,50-53,55,57,58,61,62]</td>
</tr>
<tr>
<td>• Anticipation of advanced and future digital competences [30,37,38,41,48,50,57]</td>
</tr>
<tr>
<td>• Administration of technology [4,23,45]</td>
</tr>
<tr>
<td>• Ethical aspects of digitalization [4,36,37,48,50,57,58]</td>
</tr>
<tr>
<td>• Legal aspects of digitalization [4,37,48,50,52]</td>
</tr>
<tr>
<td>Methodological competences</td>
</tr>
<tr>
<td>• Data and information processing competence [4,9,21,22,24-26,29-31,35,37,38,40,41,44,45,47,48,50-57,62]</td>
</tr>
<tr>
<td>• Continuous learning [4,9,23,25,28-30,32,38,41,45-47,49,54,55,57,62]</td>
</tr>
<tr>
<td>• Project management [4,57,61]</td>
</tr>
<tr>
<td>• Research competence [4,37,45,47,57]</td>
</tr>
<tr>
<td>• Problem-solving [22,35,38,41,54,56,62]</td>
</tr>
<tr>
<td>Social competences</td>
</tr>
<tr>
<td>• Working in teams [9,23,29,35,38,41,42,45,47,50,51,53-55,62]</td>
</tr>
<tr>
<td>• Communication competence [4,9,22,29-31,35,36,38,42,43,45,47,49-51,54-57,59,62]</td>
</tr>
<tr>
<td>• Networking skills [38,47,50]</td>
</tr>
<tr>
<td>• Teaching [27,45]</td>
</tr>
<tr>
<td>• Focus on patients [4,10,35-37,48,50,55,57]</td>
</tr>
<tr>
<td>Personal competences</td>
</tr>
<tr>
<td>• Innovative behavior [23,38,45,50]</td>
</tr>
<tr>
<td>• Self-reflection [35,53,54]</td>
</tr>
<tr>
<td>• Critical thinking [22,25,54]</td>
</tr>
<tr>
<td>• Creativity [38,54]</td>
</tr>
<tr>
<td>• Professionalism [23]</td>
</tr>
</tbody>
</table>

Technical Competences
Multiple subcompetences of technical competences were identified: the ones mentioned most often were basic computer competence, meaning knowledge of different computer components and basic computer concepts [21,32,43]; and skills in using hardware (eg, switching equipment on and off and operating input and output devices) [49,62]. Internet use, consisting of navigating the internet, knowledge of various internet sources, and finding and downloading articles, is part of basic computer competence [24,25,28,37,43,52,62]. The users should be able to use and install software [24,28,32,33,37,49,52,62] and especially be able to use information and communication technology, including understanding the basic concepts and components of information and communication technology and designing, creating, integrating, publishing, and revising content [4,9,22,23,27,35-38,41,43-45,47-49,53,54,56,57,62]. Another part of basic computer competence is file management and...
comprehensive knowledge of file formats, the creation of documents and folder structure [37,49], and IT security (e.g., using passwords and antivirus tools) [22,29,37,38,45,52,54,56,62].

Another subcompetence mentioned was basic competence to use wireless devices, consisting of operating hardware [49], using the internet [21,37], managing files [21,37], and using applications [21,37].

Existing competences can be transferred to eHealth contexts to achieve the foundation for applied digital health skills [46]. Here, one of the largest areas is the use of health applications, meaning the use of various digital health solutions for treatment planning, diagnostics, treatment, processing imaging data, and so on [22,24,33,35,40,42,48,57,58]. This includes the management of electronic patient records [22,24,37,43,49,51,57,58,62], the use of wearables and mobile health apps [30,57], the administration of electronic documentation [4,37], and the use of health information systems [37,52,55,57]. In addition, health professionals need skills and knowledge about specific data protection and security requirements of their profession [4,30,48,53]. Furthermore, digitally competent health care workers need to be able to establish new technologies in their work environments and participate in the design, implementation, and evaluation of systems, as well as seek available resources, formulate ethical decisions technical wise, and promote the use of IT in health environments [4,24,42,48,50,57].

A further subcompetence is the anticipation of advanced and future digital competences, where users stay informed about the current state of the art of digital technologies and the competences that are necessary to use these [38,41], as well as how certain technologies will develop in the future, which play a role in the future of health care (e.g., big data, artificial intelligence, robotics, and genomics) [30,37,48,50].

One crucial aspect of technical competence is the administration of technology, which encompasses planning, implementation, optimization, and operation or management, as well as the control of technological products or tools, processes, and services [4,23,45].

Knowledge about ethical aspects [4,36,37,48,50,57,58], such as freedom of choice, privacy, autonomy, and fairness [36], as well as the legal aspects of digitalization [4,37,48,50,52,62], in particular regarding the regulation of medical practice and medical devices [50] and the protection of patient data as well as confidentiality when processing data [52], is equally important when handling new technologies to enable data protection and data security.

**Methodological Competences**

The competence to process data and information consists of finding [4,23,24,26,37,44,47,52,53,62], evaluating [21,23,25,37,43,47,50-53,57,62], creating [23,24,44,49,51], managing [4,23,24,26,29,30,47,49,52,53,57], sharing or communicating [4,23,26,31,44,47,53,57], analyzing [4,26,37,50,53], visualizing [4], and interpreting [24,26,47,49] information or data; deriving actions or decisions [50]; being well versed in data protection and security [50,51]; and knowing the difference among data, information, and knowledge [48].

In addition, the ability to continuously learn is a fundamental component of digital competence. Learning is described as using educational methods such as teaching, training, storytelling, discussion, and targeted research to acquire knowledge, skills, values, beliefs, and habits [23]. It includes the anticipation of service and training needs and, for future digital literacy skills [57], learning how to use new technologies [29,49,62] and acquiring new concepts, methods, and tools [23], especially by using digital teaching and learning resources [4,29,41,47].

Digitally competent health professionals should also be proficient in project management to be able to introduce new operating models and lead IT-based change in their field [4,57,61].

They should be able to use IT for research support and innovations [4] as well as for assessment and continuous improvement of their own skills, their work community skills development, and the development of electronic services [57] through research competence.

**Problem-solving** competence can be interpreted as both dealing with digital problems [22,35,38,54,56] and solving problems through digital means [41,54,56,62].

**Social Competences**

To engage digitally in the social work environment, digitally competent health professionals must be able to work in teams, meaning they should be able to work cooperatively or collaboratively [9,23,38,41,45,47,50,53,62]; take a leadership role [38]; deal with diverse teams consisting of members with different demographics, from different professions, and with different personality traits [38,51]; be willing to compromise for the sake of group harmony [38]; and establish collegial support to create positive digital experiences [35,42].

Another basic requirement to work in (digital) teams is communication competence using a wide range of communication methods [50], including digital communication [4,9,30,38,57,62] (e.g., web-based meetings and consultations and the use of social media [57] within the team [36,57] and with patients [35,36]). Digitally competent health professionals need to know the correct vocabulary [57] and, with this knowledge, the ability to share knowledge [38].

**Networking skills** are evident in the use of knowledge networks, where health professionals participate in digital networks for learning and research and develop an open-access mentality [38,47,50].

Health professionals should not only be able to gain knowledge but also to pass it on: teaching is an important part of digital literacy. Health professionals could impart their knowledge, the ability to share knowledge [38].

Another important part of digital literacy is keeping the focus on patients by considering the patients’ digital needs and evaluating their digital skills, as well as considering their
willingness to use digital services to provide services that they feel safe to use and capable of using [35,57]. In addition, health professionals should promote the use of IT among patients through support and empowerment for self-management, IT guidance (eg, guides and web-based materials), and support in finding information [4,57].

**Personal Competences**

To be digitally competent, health professionals need innovative behavior as a personality trait, meaning they should have the spirit of invention and lifelong determination [23,38,45,50]. The initiative to conceive, consider, try out, or apply new ideas, products, processes, and procedures to their individual work role or their work unit without fear of change [23] is essential to drive the transformation process of health care forward [50].

Another relevant ability for health professionals is self-reflection with regard to their own digital competence [35,53,54] and the identification of personal and professional needs to apply technical solutions [53].

Other personal traits mentioned as relevant for digital competence are critical thinking [22,25,54] and creativity [38,54]. Critical thinking is mentioned in connection with information evaluation [25] or gaining new information within a professional context [22,54]. Creativity is of use when knowledge is built up [54] or a task has to be approached with an innovative mindset [38].

**Professionalism** is defined as the behavior, demeanor, and attitude of a person in a work environment and is considered a useful quality rather than a requirement of a role [23], but it is a characteristic that is beneficial to health professionals wishing to be digitally competent.

**Measurement Instruments**

Of the 46 included papers, 25 (54%) used different questionnaires to evaluate the digital literacy of health professionals. The majority of the questionnaires used (15/25, 60%) [21,22,25,28,30-32,36,49,50,52,53,58,61,62] were developed originally for these papers. Others used existing questionnaires or frameworks (Textbox 3) such as the Self-Assessment of Nursing Informatics Competencies Scale [71] in the study by Brown et al [24]; a scale assessing the informatics competencies for nurses [72] in the study by Kahlilan et al [39]; the eHealth literacy assessment toolkit [70] in the study by Holt et al [34]; the eHealth literacy questionnaire [69] in the study by Kayser et al [40]; the General Confidence with Computer Use Scale [68] in the study by Hallit et al [32]; the attitudes and digital literacy toward information and communication technology scale [73] in the study by Kim and Yeon [41]; the Educause Center for Analysis and Research [67] in the study by Vissers et al [60]; the technology acceptance model [64] and the unified theory of acceptance and use of technology [65] in the study by Kuek and Hakkenes [11]; DigComp 2.2 [7] in the studies by Barbosa et al [22], Shiferaw et al [54], and Tegegne et al [56]; the European framework for the digital competence of educators [63] in the study by Cabero-Almenara et al [27]; and the accreditation of competence in information and communication technologies by the government of Catalonia [66] in the study by Reixach et al [53].
**Textbox 3.** Underlying work for the questionnaires used in the studies.

<table>
<thead>
<tr>
<th>Underlying work and corresponding studies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technology acceptance model [64] and unified theory of acceptance and use of technology [65]</td>
</tr>
<tr>
<td>Kuek and Hakkennes [11]</td>
</tr>
<tr>
<td>Updated version of the digital competence framework for citizens [7]</td>
</tr>
<tr>
<td>Barbosa et al [22], Shiferaw et al [54], and Tegegne et al [56]</td>
</tr>
<tr>
<td>Self-Assessment of Nursing Informatics Competencies Scale [71]</td>
</tr>
<tr>
<td>Brown et al [24]</td>
</tr>
<tr>
<td>Informatics competencies scale for nurses [72]</td>
</tr>
<tr>
<td>Kailhanen et al [39]</td>
</tr>
<tr>
<td>eHealth literacy assessment toolkit [70]</td>
</tr>
<tr>
<td>Holt et al [34]</td>
</tr>
<tr>
<td>eHealth literacy questionnaire [69]</td>
</tr>
<tr>
<td>Kayser et al [40]</td>
</tr>
<tr>
<td>General Confidence with Computer Use Scale [68]</td>
</tr>
<tr>
<td>Hallit et al [32]</td>
</tr>
<tr>
<td>Attitudes and digital literacy toward information and communication technology scale [73]</td>
</tr>
<tr>
<td>Kim and Yeon [41]</td>
</tr>
<tr>
<td>Educause Center for Analysis and Research [67]</td>
</tr>
<tr>
<td>Vissers et al [60]</td>
</tr>
<tr>
<td>European framework for the digital competence of educators [63]</td>
</tr>
<tr>
<td>Cabero-Almenara et al [27]</td>
</tr>
<tr>
<td>Accreditation of competence in information and communication technologies by the government of Catalonia [66]</td>
</tr>
<tr>
<td>Reixach et al [53]</td>
</tr>
</tbody>
</table>

Digital literacy was measured in various forms, and some questionnaires used different combinations of measurement forms (Textbox 4). The specific items of the questionnaires considered in the review are categorized thematically herein. In many surveys, participants provided a self-assessment of specific skills and knowledge. Often, they had to assign certain abilities or confidence levels to themselves [11,22,24,25,27,28,30-32,34,36,39-41,49,52-54,56,58,61,62]. Other questionnaires collected participants’ attitudes toward technical topics [11,21,24,30,31,36,40,41,50,62]. Some items dealt with the experiences or needs of participants with regard to (further) training in digital topics [21,25,30,49,50,53,56,62]. Another way of measuring digital literacy involved requesting access to different technologies, such as smartphones, laptop computers, or tablet devices, for private or professional use [28,32,49,60,62] or the frequency of use of these technologies [11,25,28,40,60]. Other items addressed user behavior: what the devices were used for [24,49,60], and which applications were used [21,24].

The questionnaires differed greatly in their statistical quality. Some have not been validated in any statistical form [21,25,28,39,50,58,60-62], whereas others were only tested on internal consistency [41,49,53], and several were verified with different reliability and validity tests [11,22,24,27,30-32,34,36,40,52,54,56].
Textbox 4. Different measurement forms of digital literacy with item examples.

<table>
<thead>
<tr>
<th>Measurement form and item examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Self-assessment [11,22,25,27,28,30-32,34,36,39-41,49,52-54,56,58,61,62]</td>
</tr>
<tr>
<td>• “I can use the most common computer programs and services (e.g. email, intranet) in my work.” [36]</td>
</tr>
<tr>
<td>• “How well do you feel you master the following skills required to use information systems?” [58]</td>
</tr>
<tr>
<td>• Attitudes [11,21,24,30,31,36,40,41,50,62]</td>
</tr>
<tr>
<td>• “I believe that new digital technologies will fundamentally change medicine in the next few years.” [30]</td>
</tr>
<tr>
<td>• “The transfer to digital services is a positive change.” [36]</td>
</tr>
<tr>
<td>• Experiences, needs of education, or training [21,25,49,50,53,56,62]</td>
</tr>
<tr>
<td>• “I would benefit from additional trainings/courses in the field of shaping digital competences.” [25]</td>
</tr>
<tr>
<td>• “On a personal level, would you like to have specific training in any of the following areas? eg. Digital culture, participation and citizenship using digital tools.” [53]</td>
</tr>
<tr>
<td>• Access to technology [28,32,49,60,62]</td>
</tr>
<tr>
<td>• “Do you think you have internet access in your office?” [62]</td>
</tr>
<tr>
<td>• “Owning a computer.” [32]</td>
</tr>
<tr>
<td>• Frequency of use [11,25,28,40,60]</td>
</tr>
<tr>
<td>• “Please state how often you use the following in your work and in your personal life: computers, Microsoft Office applications, smartphones, tablets, email, the internet, and social media (i.e. Facebook, Twitter and Instagram).” [11]</td>
</tr>
<tr>
<td>• “How often do you use the internet?” [60]</td>
</tr>
<tr>
<td>• User behavior [21,24,49,60]</td>
</tr>
<tr>
<td>• “I use MS Excel for work.” [21]</td>
</tr>
<tr>
<td>• “What is the purpose of [sic] you use a computer?: work, education, communication, entertainment, and playing games” [49]</td>
</tr>
</tbody>
</table>

Discussion

Principal Findings

The selected literature sources show the increasing scientific interest in digital literacy in health care and the worldwide spread of this development. There is a focus on quantitative research, although, because the available survey instruments were considered insufficient to determine digital literacy, researchers often developed their own. The underlying definitions are based on a variety of approaches and sources, which highlights the need for a structured overview. Most of the definitions focused on skills and knowledge as indicators of competence. Soft aspects, as described by Salman et al [6], were also mentioned by authors but less frequently and in many different forms. Attitude, experience, and motivation were mentioned most often. Behavior, which is a hard aspect according to Salman et al [6], was not addressed explicitly in the definitions provided in the included papers.

The identified competences have been categorized according to the competence categories formulated by Hecklau et al [20]. The determined technical competences include basic computer competence, basic competence to use wireless devices, applied digital health skills, anticipation of advanced and future digital competences, administration of technology, ethical aspects of digitalization, and legal aspects of digitalization. Data and information processing competence, continuous learning, project management, research competence, and problem-solving were mentioned in the literature as methodological competences. The following were classified as social competences: working in teams, communication competence, networking skills, teaching, and focus on patients. Personal competences include innovative behavior, self-reflection, critical thinking, creativity, and professionalism.

The results confirm that existing measurement tools focus solely on technical areas [10], and other related aspects, such as the identified competences from the methodological, social, and personal areas in other nonquantitative works, have not been taken into account. Unlike what Longhini et al [10] and Kuek and Hakkennes [11] stated, many of the questionnaires used had high statistical quality and were verified with different reliability and validity tests. The questionnaires largely measure digital literacy via self-assessment. Some also use items relating to attitudes, experiences, access to technology, frequency of use, and use behavior.

The allocation of competences to the categories was sometimes not trivial and not clearly distinguishable; for example, teaching could be categorized as both a social and a methodological competence. How the partial competence areas are connected also remains unanswered in these works. Hurst [81] describes 3 possible dependency relationships: a general factor model where basic competence is composed of equally important subsaspects, an additive model where the individual subsaspects have a juxtaposed relationship, or a hierarchical model where basic subcompetences and higher-level competences exist that build on each other [81]. A more complex consideration of the relationships among the individual competences, for example,
through a factor analysis, would also be conceivable and should be investigated in subsequent research work. Some of the skills identified are specifically linked to digital topics, but others are more general and analog in nature, especially in the social and personal categories. Therefore, mutual influences among the competences are not only conceivable but also probable.

Limitations
One limitation of this literature review is that, because of the very nature of scoping reviews, the quality of the included works was not considered in the review process, and all papers were included in the synthesis, irrespective of quality [14]. This may have led to inferior works being included in the results and being placed on an equal footing with high-quality works. When constructing the search term, no wildcards were used, which limited the search of potential fitting literature, which must be specified as a further limitation. In addition, more variants of the job title medical professional could have been used to maximize the search results. Another limitation could be the practical implementation of the selection of papers and their evaluation by just 1 author. Although the procedure was planned as a team, and the results were discussed extensively, the process was carried out by only 1 person.

Future Directions
This literature review focuses solely on the terms digital competence and digital literacy and provides an overview of the use of these closely related terms. A larger literature review that includes other adjacent topics, such as informatics competences, or refers to specific digital activities in the health care sector, such as telemedicine competences, would heighten the credibility in terms of an overall semantic understanding of the concept of competence when dealing with all sorts of digital technologies. Within this work, which aimed at an understanding of the specifically named term digital competence, the addition of related concepts would not be possible without the development of an initial understanding of this concept, which the authors have developed in the course of this work.

A further enrichment of an in-depth analysis would be the addition of specific medical specialties. The aim of this work was the nonspecific and generalizable consideration of required digital skills in health care, but, of course, every profession has its individual (digital) requirements that are worth considering.

Conclusions
The review shows that the interest in digital literacy as a research topic in health care is currently on the rise but that the understanding of this rather abstract term is widely divergent. A uniform definition and use of terms is needed. The existence of hard and soft aspects of competence, as described by Salman et al [6], was confirmed by many of the used definitions, but which of the identified aspects contribute to what extent needs to be investigated further. Furthermore, the multitude of subcompetences illustrates the complexity of digital competence that needs to be taken into account when developing a measurement instrument. Well-validated questionnaires exist, these focus solely on technical aspects. The competency model identified in this work can be used as a starting point for factor analysis of the identified competences or questionnaire development.

Acknowledgments
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Data Availability
The data sets generated and analyzed during this study are available from the corresponding author upon reasonable request.

Authors' Contributions
All authors contributed to the conceptualization, formal analysis, visualization, validation, and writing of the original and revised drafts. AM and SM developed the methodology design. AM conducted the literature screening and data curation. SM contributed supervision and funding acquisition.

Conflicts of Interest
None declared.

Multimedia Appendix 1
PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) checklist.

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Abbreviations

DigComp 2.2: updated version of the digital competence framework for citizens
PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews

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Review

Global Rate of Willingness to Volunteer Among Medical and Health Students During Pandemic: Systemic Review and Meta-Analysis

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Abstract

Background: During health crises such as the COVID-19 pandemic, shortages of health care workers often occur. Recruiting students as volunteers could be an option, but it is uncertain whether the idea is well-accepted.

Objective: This study aims to estimate the global rate of willingness to volunteer among medical and health students in response to the COVID-19 pandemic.

Methods: A systematic search was conducted on PubMed, Embase, Scopus, and Google Scholar for studies reporting the number of health students willing to volunteer during COVID-19 from 2019 to November 17, 2023. The meta-analysis was performed using a restricted maximum-likelihood model with logit transformation.

Results: A total of 21 studies involving 26,056 health students were included in the meta-analysis. The pooled estimate of the willingness-to-volunteer rate among health students across multiple countries was 66.13%, with an I² of 98.99% and P value of heterogeneity (P-Het)<.001. Removing a study with the highest influence led to the rate being 64.34%. Our stratified analyses indicated that those with older age, being first-year students, and being female were more willing to volunteer (P<.001). From highest to lowest, the rates were 77.38%, 77.03%, 65.48%, 64.11%, 62.71%, and 55.23% in Africa, Western Europe, East and Southeast Asia, Middle East, and Eastern Europe, respectively. Because of the high heterogeneity, the evidence from this study has moderate strength.

Conclusions: The majority of students are willing to volunteer during COVID-19, suggesting that volunteer recruitment is well-accepted.

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KEYWORDS
COVID-19; education; health crisis; human resource management; volunteer
Introduction

The initial outbreak of COVID-19, an emerging and highly infectious respiratory illness, which originated in Wuhan City, Hubei Province, China, occurred in early December 2019 [1]. Subsequently, the situation escalated swiftly, leading to its declaration as a Public Health Emergency of International Concern by the World Health Organization (WHO) [1]. Some of its clinical presentations are fever, cough, dryness, fatigue, dyspnea, and myalgia [2]. The disease also induces prolonged anxiety, chest pain, persistent depression, dizziness, and other lingering symptoms after recovery [3]. In 2020, the WHO reported the rapid spread of the disease to various parts of the world, marking it as a global pandemic, with the number of confirmed cases and deaths escalating worldwide [4]. The pandemic not only affects health but also disrupts various aspects of life, including emotional stability, environmental quality, and the economy [5-7].

The high incidence of COVID-19 has led to an increased demand for health care services and workers [8]. Unlike many other sectors, jobs in health care were not temporarily halted during the COVID-19 pandemic, as health care professionals are essential in combating and preventing viral transmission [9]. However, infections among medical personnel have resulted in an acute shortage of workforce in this sector. Coupled with the increased workload of health care workers, this has led to inadequate patient management [8,10]. A previous study found that nearly half of health care workers exposed to COVID-19 experienced burnout and compassion fatigue, stemming from factors such as excessive workload, emotional exhaustion, personal infection risk, and fear of transmitting the virus to their families [5,11]. Consequently, hospitals faced the challenge of addressing staffing deficits [12].

During health emergencies, it is crucial to bolster the human resource capacity within the health care system. Among the various approaches available, recruiting volunteers is an option worthy of consideration [13]. Volunteering entails participating in activities where individuals dedicate their time to providing services to vulnerable populations without coercion [14,15]. Medical and health students can actively participate in volunteering activities to help manage the COVID-19 crisis. In certain countries and health care institutions, it is suggested that medical and health students voluntarily contribute to crisis management based on their competencies [13,16,17]. Collaborating with volunteers to provide community services could help bridge gaps in human resource capacity and decrease instances of burnout among health care workers during the COVID-19 crisis [18].

Volunteering among health care students has emerged as a valuable resource during outbreaks. A previous study has evaluated the willingness of medical students to volunteer during pandemics and disasters [19]. Furthermore, a previously published systematic review on the willingness of health students to volunteer for COVID-19 reported willingness-to-volunteer rates ranging from 19.5% to 91.5% [20]. Unfortunately, a meta-analysis was not conducted in that systematic review [20]. Data on the global rate of willingness to volunteer are necessary as a basis for evaluating the feasibility of recommending volunteering for health students. Moreover, it is crucial to observe feasibility across different populations, economies, and regions. Therefore, our aim is to conduct a new systematic review with a meta-analysis on the willingness-to-volunteer rate among medical and health students in response to the COVID-19 pandemic.

Methods

Study Design

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) statement was used as the guidance for this study (see Table S1 and S2 in Multimedia Appendix 1) [21]. The research questions were formulated as follows: (1) What is the percentage of COVID-19 volunteer willingness among health care students? (2) What are the demographic factors associated with the willingness of health care students to volunteer? This review was not registered because it did not evaluate direct effects on human health.

Search Strategy

A systematic review search was carried out on PubMed, Scopus, and Embase up to December 10, 2023. Google Scholar was also included as a gray literature source in the search. The keywords used were “health students,” “willingness,” “volunteer OR volunteering OR volunteerism OR voluntary,” AND “COVID-19 OR covid-19 OR SARS-CoV-2 OR COVID-19 pandemic.” The complete search technique is outlined in Table S3 in Multimedia Appendix 2 and searches for the other databases were developed using the Embase search strategy.

Eligibility Criteria, Articles Selection, and Data Extraction

The inclusion criteria were cross-sectional studies aimed at evaluating the rate of willingness to volunteer among medical and health students (encompassing disciplines such as medical, nursing, pharmacy, dentistry, midwifery, public health, and other relevant fields) in response to the COVID-19 situation from December 2019 to December 2023. Willingness to volunteer was defined as a “yes” response to the question “Are you willing to volunteer?” or “Do you want to volunteer?” We only included studies involving undergraduate or diploma students; studies involving other levels of education were excluded. Medical and health students were defined as individuals pursuing higher education degrees (undergraduate or diploma) in medicine, nursing, dentistry, pharmacy, midwifery, public health, and related fields. Exclusion criteria were applied to studies meeting any of the following conditions: (1) qualitative analysis, (2) focused on postgraduate or professional students, (3) non–English language articles, (4) review articles, (5) case reports, (6) randomized controlled trials, (7) clinical trial proposals, and (8) case-control studies.

GT and MI independently screened all duplicate topics, titles, abstracts, and full texts using Zotero version 6.0.30 (Corporation for Digital Scholarship). Duplicate entries were removed, and title and abstract screening were conducted on the remaining records. Subsequently, the selected records were searched for full-text access, and further comprehensive screening was
conducted on the obtained full texts by applying the eligibility criteria. Data extraction was conducted using the tabulation method, covering details such as author and year of publication, country, student population, sample size, gender distribution, academic year of the students, health status, marital status, living arrangements, volunteer experience, and the proportion indicating willingness. GT and MI independently carried out the data extraction process. Continuous data were presented as mean (SD), with conversion from median performed when necessary using an online calculator [22]. Any discrepancies were resolved through consensus.

**Quality Appraisal**

The quality of individual studies was assessed by one reviewer (MM) and independently reviewed for agreement by a second reviewer (SH). In instances of disagreement, a third review author (NN) was consulted. The standardized Quality Assessment Checklist for Survey Studies in Psychology (Q-SSP) tool, consisting of 20 checklist items, was used for the quality assessment of the included studies [23]. High-quality articles were defined as those scoring 70% or higher. The score was determined by the percentage of “yes” responses on the checklist. The utilization of this tool aligns with a previous study [24].

**Statistical Analysis**

The proportion was initially transformed using the logit function \( y = \logit(x) \) before being pooled for meta-analysis with a restricted maximum-likelihood model. The rate was then obtained by multiplying the pooled proportion, following the back transformation from the logit function \( y = 1/(1+exp(-x)) \), with 100%. A rate exceeding 50% was considered the threshold for determining the majority’s willingness to volunteer during the pandemic. The CI was set at 95% (ie, 95% CI), with a \( P \) value of total effect \( (P\text{-tot}) < .05 \) indicating statistical significance. A value of \( I^2 \) greater than 50% or a \( P \) value of heterogeneity \( (P\text{-Het}) < .1 \) was used as the cutoff for determining data heterogeneity in the pooled analysis. Begg’s funnel plot was used to assess the presence of publication bias. The meta-analysis was conducted using jamovi 2.3.21. A moderator analysis was conducted to examine the effects of sample size, age, gender (indicated as male-to-female ratio), academic year (indicated as the ratio of students in second to first year, third to first year, and so on), volunteer experience (indicated as the ratio of students with to without volunteer experience), type of academic program (indicated as the ratio of medical to nursing students and the ratio of medical to dentistry students), country income category, and continent. Country income was categorized based on the World Bank classifications (high income, upper middle income, lower middle income, and low income). The variables used in the moderator effect analysis were also used in the stratification analysis, with the following cutoffs: 22 years old for age, 1 for the male-to-female ratio, 15% for the proportion of first-year students, 1 for the ratio of students with to without volunteer experience, and 5 for the ratio of medical to nursing students. Statistical significance in the stratification analysis was determined using Z-statistics. The statistical analysis adhered to recommendations from previous studies [24-26].

**Results**

**Search Findings**

Collectively, 283 records were identified from PubMed, Scopus, Embase, and Google Scholar in the initial stage. A total of 89 duplicates were automatically detected and subsequently removed. The remaining 194 records underwent screening for relevance based on the title and abstract. Forty records were then selected for full-text access and further thorough screening. During this stage, we identified 1 commentary [27], 1 correspondence [28], and 2 non-English articles [29,30], which were subsequently excluded. One study was excluded because the participants were not specified as medical or health students [31]. Seven studies were found to be qualitative, and therefore data extraction was not feasible; these studies were subsequently removed [32-38]. Additionally, 1 study was excluded because the participants were not pursuing undergraduate degrees [39]. Ten studies were deemed irrelevant to the objective of this review [40-49]. Finally, 21 studies were included in the systematic review and meta-analysis [50-70]. The screening and selection processes are depicted in Figure 1.
Characteristics and Quality of the Included Studies

Characteristics of the included studies along with their quality are presented in Table 1. A total of 21 studies were included, with a combined sample size of 26,024 students [50-70]. The studies were conducted in various countries, including Nigeria (n=3), Pakistan (n=2), Saudi Arabia (n=2), Serbia (n=1), India (n=1), Bulgaria (n=1), Vietnam (n=1), Poland (n=1), Brunei Darussalam (n=1), Australia (n=1), Nepal (n=1), Indonesia (n=1), Romania (n=1), the United Kingdom (n=1), China (n=1), Syria (n=1), and Sudan (n=1). Eligible studies from South and North Americas (including the United States, Canada, and Mexico) were not identified in this systematic review. The average ages of the participants ranged from 22 to 24 years, whereas the proportion of female students varied considerably across studies. Nine studies exclusively recruited medical students [50-56,61,62,67,69], 3 focused on nursing students [55,60,65], and others included a mix of students from different departments. Thirteen studies were categorized as “high quality” based on the Q-SSP [50-62], while others had scores below 70% [63-67], and some even scored 50% or below [68-70]. Detailed assessment results based on the Q-SSP tool are presented in Table S4 in Multimedia Appendix 2 [50-70]. A total of 9/21 (43%) studies did not provide sufficient justification for the sample size. See Table S5 in Multimedia Appendix 2 for the 20 checklist items of Q-SSP and their respective code.
Table 1. Characteristics and quality of the included studies.

<table>
<thead>
<tr>
<th>Author [reference]</th>
<th>Country</th>
<th>Geographic location</th>
<th>Female, n (%)</th>
<th>Age (years), mean (SD)</th>
<th>Department or faculty</th>
<th>Q-SSP*, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Byrne et al [67]</td>
<td>United Kingdom</td>
<td>Western Europe</td>
<td>835 (72.9)</td>
<td>22 (0.61)</td>
<td>Medicine</td>
<td>60</td>
</tr>
<tr>
<td>Gazibara and Pesakovic [62]</td>
<td>Serbia</td>
<td>Eastern Europe</td>
<td>247 (75.8)</td>
<td>23.0 (1.2)</td>
<td>Medicine</td>
<td>75</td>
</tr>
<tr>
<td>Yordanova et al [68]</td>
<td>Bulgaria</td>
<td>Eastern Europe</td>
<td>Not reported</td>
<td>Not reported</td>
<td>Medicine, nursing, physician assistant, medical rehabilitation and occupational therapy, and midwife</td>
<td>45</td>
</tr>
<tr>
<td>Adejimi et al [63]</td>
<td>Nigeria</td>
<td>Africa</td>
<td>211 (62.6)</td>
<td>23.4 (2.6)</td>
<td>Medicine and dentistry</td>
<td>65</td>
</tr>
<tr>
<td>Joseph and Manasvi [69]</td>
<td>Indian</td>
<td>South Asia</td>
<td>119 (58.3)</td>
<td>21.6 (1.1)</td>
<td>Medicine</td>
<td>50</td>
</tr>
<tr>
<td>Nazir et al [61]</td>
<td>Pakistan</td>
<td>South Asia</td>
<td>77 (27.3)</td>
<td>21.9 (1.26)</td>
<td>Medicine</td>
<td>70</td>
</tr>
<tr>
<td>Tran et al [64]</td>
<td>Vietnam</td>
<td>East and Southeast Asia</td>
<td>1192 (58.7)</td>
<td>22.8 (3.7)</td>
<td>General medicine, traditional medicine, pharmacy, medical technique, preventive medicine, nursing, dentistry, public health, midwifery, and medical imaging</td>
<td>65</td>
</tr>
<tr>
<td>Domaradzki and Walkowiak [59]</td>
<td>Poland</td>
<td>Western Europe</td>
<td>116 (27.7)</td>
<td>Not reported</td>
<td>Medicine, nursing, midwifery, pharmacy, electroradiology, medical analytics, dentistry, medical rescue, and others</td>
<td>70</td>
</tr>
<tr>
<td>Hj Abdul Aziz et al [60]</td>
<td>Brunei Darussalam</td>
<td>East and Southeast Asia</td>
<td>16 (22.2)</td>
<td>Not reported</td>
<td>Nursing</td>
<td>80</td>
</tr>
<tr>
<td>Prisca et al [65]</td>
<td>Nigeria</td>
<td>Africa</td>
<td>598 (82.6)</td>
<td>21.5 (2.5)</td>
<td>Nursing</td>
<td>65</td>
</tr>
<tr>
<td>Adejimi et al [58]</td>
<td>Nigeria</td>
<td>Africa</td>
<td>257 (62.5)</td>
<td>23.26 (2.59)</td>
<td>Medicine and dentistry</td>
<td>80</td>
</tr>
<tr>
<td>Al Gharash et al [55]</td>
<td>Australian</td>
<td>Pacific</td>
<td>5 (5.6)</td>
<td>Not reported</td>
<td>Nursing</td>
<td>75</td>
</tr>
<tr>
<td>AlOmar et al [56]</td>
<td>Saudi Arabia</td>
<td>Middle East</td>
<td>3506 (58.3)</td>
<td>22.07 (1.84)</td>
<td>Medicine, nursing, dentistry, applied medical sciences, and public health</td>
<td>90</td>
</tr>
<tr>
<td>Karki et al [57]</td>
<td>Nepal</td>
<td>South Asia</td>
<td>152 (58.2)</td>
<td>Not reported</td>
<td>Medicine and nursing</td>
<td>90</td>
</tr>
<tr>
<td>Khalid et al [53]</td>
<td>Pakistan</td>
<td>South Asia</td>
<td>142 (71.0)</td>
<td>21.5 (1.4)</td>
<td>Medicine</td>
<td>85</td>
</tr>
<tr>
<td>Lazarus et al [54]</td>
<td>Indonesia</td>
<td>East and Southeast Asia</td>
<td>3399 (69.8)</td>
<td>20 (0.27)</td>
<td>Medicine</td>
<td>80</td>
</tr>
<tr>
<td>Magdas et al [70]</td>
<td>Romania</td>
<td>Eastern Europe</td>
<td>805 (78.8)</td>
<td>Not reported</td>
<td>Medicine and nursing</td>
<td>50</td>
</tr>
<tr>
<td>Feng et al [66]</td>
<td>China</td>
<td>East and Southeast Asia</td>
<td>3582 (66.6)</td>
<td>20 (1.5)</td>
<td>Medicine, nursing, public health, medical technology, and health and medical administrative services</td>
<td>60</td>
</tr>
<tr>
<td>AlSaif et al [50]</td>
<td>Saudi Arabia</td>
<td>Middle East</td>
<td>39 (29.1)</td>
<td>Not reported</td>
<td>Medicine</td>
<td>75</td>
</tr>
<tr>
<td>Alsuliman et al [51]</td>
<td>Syria</td>
<td>Middle East</td>
<td>589 (49.1)</td>
<td>Not reported</td>
<td>Medicine</td>
<td>95</td>
</tr>
<tr>
<td>Elsheikh et al [52]</td>
<td>Sudan</td>
<td>Africa</td>
<td>424 (68.2)</td>
<td>23 (2)</td>
<td>Medicine</td>
<td>80</td>
</tr>
</tbody>
</table>


Willingness-to-Volunteer Rate
The forest plot of the pooled analysis on the rate of willingness to volunteer is presented in Figure 2. After being transformed back from the logit function, the pooled proportion of willingness to volunteer was 66.13% (95% CI 56%-72%). The heterogeneity for this pooled estimate was high, with I²=98.99% and P-Het<.001.
Sensitivity Analysis

To observe if a single study affects the entire pooled estimate, a sensitivity test based on a one-leave-out analysis was conducted. The pooled estimates for each study removed are presented in Table 2. The lowest logit proportion was obtained when Adejimi et al [58] was removed (0.59, 95% CI 0.35-0.82), with the $I^2$ value becoming relatively lower (72.06%), although the $P$-Het remained <0.001. The overall rate of willingness to volunteer after the removal of Adejimi et al [58] was 64.34% (95% CI 59%–69%). It is noteworthy that the rate of willingness to volunteer reported by Adejimi et al [58] was the highest among all included studies, at 90.97%.
Table 2. Results from the one-leave-out analysis for the pooled willingness to volunteer among health students.

<table>
<thead>
<tr>
<th>Study removed</th>
<th>Logit proportion</th>
<th>95% CI</th>
<th>P value of total effect</th>
<th>$I^2$, %</th>
<th>P value of heterogeneity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hj Abdul Aziz et al [60]</td>
<td>0.65</td>
<td>0.37-0.94</td>
<td>&lt;.001</td>
<td>99.06</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Prisca et al [65]</td>
<td>0.68</td>
<td>0.39-0.97</td>
<td>&lt;.001</td>
<td>99.05</td>
<td>&lt;.001</td>
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<tr>
<td>Adejimi et al [58]</td>
<td>0.59</td>
<td>0.35-0.82</td>
<td>&lt;.001</td>
<td>72.06</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Adejimi et al [63]</td>
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<td>0.38-0.96</td>
<td>&lt;.001</td>
<td>99.07</td>
<td>&lt;.001</td>
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<tr>
<td>Al Gharash et al [55]</td>
<td>0.71</td>
<td>0.43-0.98</td>
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<td>99.01</td>
<td>&lt;.001</td>
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<td>0.39-0.97</td>
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<td>&lt;.001</td>
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<tr>
<td>AlSaif et al [50]</td>
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<td>0.36-0.93</td>
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<td>&lt;.001</td>
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<tr>
<td>Byrne et al [67]</td>
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<td>0.35-0.89</td>
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<td>0.40-0.97</td>
<td>&lt;.001</td>
<td>99.06</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Gazibara and Pesakovic [62]</td>
<td>0.69</td>
<td>0.40-0.97</td>
<td>&lt;.001</td>
<td>99.06</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Joseph and Manasvi [69]</td>
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<td>0.36-0.93</td>
<td>&lt;.001</td>
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<td>&lt;.001</td>
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<td>0.36-0.92</td>
<td>&lt;.001</td>
<td>99.03</td>
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<td>&lt;.001</td>
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<td>&lt;.001</td>
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<td>&lt;.001</td>
<td>99.03</td>
<td>&lt;.001</td>
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<td>Elsheikh et al [52]</td>
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<td>0.35-0.90</td>
<td>&lt;.001</td>
<td>98.97</td>
<td>&lt;.001</td>
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</tbody>
</table>

Moderator Effect

The effects of moderators were analyzed, and the results are presented in Table 3. The ratio of third- to first-year students significantly affects the overall rate of willingness to volunteer with $P=.02$. Furthermore, the higher statistical significance of the moderator effect was observed on the ratios of fourth-, fifth-, or sixth- to first-year students ($P<.001$, respectively). However, other variables did not moderate the pooled estimate of the willingness-to-volunteer rate ($P$ value ranged from .22 to .70).
Table 3. Moderator effect on the pooled estimates of willingness-to-volunteer proportion (N=21).

<table>
<thead>
<tr>
<th>Moderator</th>
<th>Data type</th>
<th>Study, n (%)</th>
<th>Z</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample size</td>
<td>Continuous</td>
<td>21 (100)</td>
<td>−0.61</td>
<td>.54</td>
</tr>
<tr>
<td>Age</td>
<td>Continuous</td>
<td>14 (67)</td>
<td>0.79</td>
<td>.43</td>
</tr>
<tr>
<td>Male-to-female ratio</td>
<td>Continuous</td>
<td>20 (95)</td>
<td>−1.23</td>
<td>.22</td>
</tr>
<tr>
<td>Second-to-first-year students ratio</td>
<td>Continuous</td>
<td>7 (33)</td>
<td>−2.93</td>
<td>&lt;.001a</td>
</tr>
<tr>
<td>Third-to-first-year students ratio</td>
<td>Continuous</td>
<td>7 (33)</td>
<td>−2.28</td>
<td>.02b</td>
</tr>
<tr>
<td>Fourth-to-first-year students ratio</td>
<td>Continuous</td>
<td>7 (33)</td>
<td>−3.33</td>
<td>&lt;.001a</td>
</tr>
<tr>
<td>Fifth-to-first-year students ratio</td>
<td>Continuous</td>
<td>6 (29)</td>
<td>−2.27</td>
<td>&lt;.001a</td>
</tr>
<tr>
<td>Sixth-to-first-year students ratio</td>
<td>Continuous</td>
<td>4 (19)</td>
<td>−4.01</td>
<td>&lt;.001a</td>
</tr>
<tr>
<td>Single-to-married ratio</td>
<td>Continuous</td>
<td>6 (29)</td>
<td>−0.923</td>
<td>.36</td>
</tr>
<tr>
<td>With-to-without volunteer experience ratio</td>
<td>Continuous</td>
<td>9 (43)</td>
<td>0.946</td>
<td>.34</td>
</tr>
<tr>
<td>Medical-to-nursing student ratio</td>
<td>Continuous</td>
<td>7 (33)</td>
<td>0.671</td>
<td>.50</td>
</tr>
<tr>
<td>Medical-to-dentistry student ratio</td>
<td>Continuous</td>
<td>5 (24)</td>
<td>−0.421</td>
<td>.67</td>
</tr>
<tr>
<td>Country income</td>
<td>Category</td>
<td>21 (100)</td>
<td>0.378</td>
<td>.70</td>
</tr>
<tr>
<td>Continent</td>
<td>Category</td>
<td>21 (100)</td>
<td>−1.16</td>
<td>.24</td>
</tr>
</tbody>
</table>

aSignificant at P<.01.
bSignificant at P<.05.

Stratification Analysis

We further stratified the pooled estimate of the willingness-to-volunteer rate based on several variables, and the results are presented in Table 4. According to Z-statistics, groups with older mean age, a higher number of male participants, and a higher number of first-year students had a significantly higher rate of willingness to volunteer (P<.001). Conversely, a higher number of participants from medical school contributed to a lower rate of willingness to volunteer (P<.001). As compared with the pooled rates of willingness to volunteer in high-income countries, those in upper-middle-income (P<.001) and low-income countries (P=.04) tend to be significantly lower, except for lower-middle-income countries (66.37% vs 69.42%; P<.001). Based on regions, rates of willingness to volunteer were the highest among African and Western European countries (77.38% and 77.03%, respectively). It is worth noting that the heterogeneity of a pooled estimate of studies from Eastern European countries was negligible (I²=0.05%, P=.30), where the rate was 55.23%—the lowest among all regions. The number of samples recruited in studies according to regions and their corresponding rate of willingness to volunteer are presented in Multimedia Appendix 3.
Table 4. Stratification analysis based on the characteristics of participants.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Study, n (%)</th>
<th>Sample, n</th>
<th>Logit proportion</th>
<th>95% CI</th>
<th>Rate, %</th>
<th>P-Z</th>
<th>I², %</th>
<th>P value of heterogeneity</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mean age (years)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≤22</td>
<td>7 (33.3)</td>
<td>12,757</td>
<td>0.51</td>
<td>0.02 to 0.99</td>
<td>62.41</td>
<td>&lt;.001a</td>
<td>98.97</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>&gt;22</td>
<td>6 (21.57)</td>
<td>9744</td>
<td>1.04</td>
<td>0.47 to 1.62</td>
<td>73.89</td>
<td>N/A</td>
<td>99.08</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>Male-to-female ratio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≤1</td>
<td>14 (66.66)</td>
<td>23,528</td>
<td>0.81</td>
<td>0.45 to 1.16</td>
<td>69.21</td>
<td>&lt;.001a</td>
<td>99.31</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>&gt;1</td>
<td>6 (21.57)</td>
<td>2246</td>
<td>0.42</td>
<td>0.01 to 0.83</td>
<td>60.34</td>
<td>N/A</td>
<td>94.12</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>Proportion of first-year students</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≤15</td>
<td>3 (14.28)</td>
<td>1665</td>
<td>0.16</td>
<td>-0.14 to 0.45</td>
<td>54</td>
<td>&lt;.001a</td>
<td>86.11</td>
<td>.006</td>
</tr>
<tr>
<td>&gt;15</td>
<td>4 (19.04)</td>
<td>3510</td>
<td>1.23</td>
<td>0.94 to 1.53</td>
<td>77.38</td>
<td>N/A</td>
<td>88.5</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>With-to-without volunteer experience ratio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≤1</td>
<td>5 (23.80)</td>
<td>7524</td>
<td>0.56</td>
<td>-0.14 to 1.26</td>
<td>63.65</td>
<td>.156</td>
<td>99.22</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>&gt;1</td>
<td>4 (19.04)</td>
<td>2833</td>
<td>0.63</td>
<td>0.17 to 1.10</td>
<td>65.25</td>
<td>N/A</td>
<td>95.25</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>Medical-to-nursing student ratio</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≤5</td>
<td>3 (14.28)</td>
<td>5922</td>
<td>0.67</td>
<td>0.03 to 1.34</td>
<td>66.15</td>
<td>&lt;.001a</td>
<td>97.08</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>&gt;5</td>
<td>4 (19.04)</td>
<td>9513</td>
<td>0.53</td>
<td>0.20 to 0.85</td>
<td>62.95</td>
<td>N/A</td>
<td>97.6</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>Country income</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High income</td>
<td>7 (33.33)</td>
<td>8974</td>
<td>0.68</td>
<td>0.24 to 1.12</td>
<td>66.37</td>
<td>Reference</td>
<td>98.15</td>
<td>.001</td>
</tr>
<tr>
<td>Upper middle income</td>
<td>4 (19.04)</td>
<td>10,857</td>
<td>0.27</td>
<td>-0.05 to 0.59</td>
<td>56.71</td>
<td>&lt;.001a</td>
<td>97.95</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Lower middle income</td>
<td>8 (38.09)</td>
<td>4404</td>
<td>0.82</td>
<td>0.27 to 1.36</td>
<td>69.42</td>
<td>&lt;.001a</td>
<td>97.94</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Low income</td>
<td>2 (9.52)</td>
<td>1821</td>
<td>0.57</td>
<td>0.47 to 0.67</td>
<td>63.88</td>
<td>.041c</td>
<td>99.02</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>Regions</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Africa</td>
<td>4 (19.04)</td>
<td>2096</td>
<td>1.23</td>
<td>0.54 to 1.93</td>
<td>77.38</td>
<td>Reference</td>
<td>97.64</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Eastern Europe</td>
<td>3 (14.28)</td>
<td>1656</td>
<td>0.21</td>
<td>0.12 to 0.30</td>
<td>55.23</td>
<td>&lt;.001a</td>
<td>0.05</td>
<td>.30</td>
</tr>
<tr>
<td>Western Europe</td>
<td>2 (9.52)</td>
<td>1562</td>
<td>1.21</td>
<td>1.00 to 1.24</td>
<td>77.03</td>
<td>.802</td>
<td>98.84</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>East and Southeast Asia</td>
<td>4 (19.04)</td>
<td>12,353</td>
<td>0.64</td>
<td>0.20 to 1.08</td>
<td>65.48</td>
<td>&lt;.001a</td>
<td>99.08</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>South Asia</td>
<td>4 (19.04)</td>
<td>898</td>
<td>0.52</td>
<td>-0.12 to 1.16</td>
<td>62.71</td>
<td>&lt;.001a</td>
<td>94.97</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Middle East</td>
<td>3 (14.28)</td>
<td>7317</td>
<td>0.58</td>
<td>0.24 to 0.91</td>
<td>64.11</td>
<td>&lt;.001a</td>
<td>94.95</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

*a*Significant at *P*<.01.

*b* N/A: not applicable.

*c*Significant at *P*<.05.

**Publication Bias**

Begg's funnel plot for the overall pooled estimate is presented in Figure 3. The symmetrical shape of the funnel plot suggests that publication bias was not detected, with *P*-Begg=.14.
Discussion

Rate of Willingness to Volunteer During the Pandemic

The pooled estimate herein revealed that the overall rate of willingness to volunteer was 66.13%, with the rate being over 50% in almost every individual study. When stratified based on regions, the highest rate of willingness to volunteer was found among students from African countries (77.38%), followed by Western European countries (77.03%). Furthermore, the stratified analyses indicate that being older or female was associated with a higher rate of willingness to volunteer ($P<.001$, respectively). In addition, students in the first academic years were more willing to volunteer compared with those in more senior years ($P<.001$). According to individual studies, students were willing to volunteer due to various motivations, particularly internal factors [50-70]. Studies reported that students are driven by altruistic and duty-driven reasons, where individuals, particularly those aspiring to become future health professionals, feel a sense of responsibility in assisting during the pandemic [35]. They also perceive volunteering activity as an opportunity to learn, gain clinical skills, and enhance personal growth [34].

Research suggests that medical students exhibiting high prosocial motivation are more likely to engage in volunteer activities and persist in such endeavors, even in the absence of prior experience [49]. Moreover, external motivations contribute to such willingness in various forms, notably compensation-related factors. These external motivations include the recognition of academic credit, achievements, receipt of scholarships, and provision of material compensation [49]. Importantly, the willingness of students to volunteer is heightened when such engagement aligns with governmental needs and is endorsed by universities. Students are more likely to engage in volunteering if it is needed by the government and recommended by universities [71].

Despite the positive aspects of volunteering, attention should also be given to the mental health of students. A previous study by Tempski and colleagues [16] revealed a negative association between the mental health problems of medical students (including stress, anxiety, and depression) and their participation as volunteers during the COVID-19 pandemic. Furthermore, many volunteer students express fear of getting infected and spreading the virus to their relatives or friends during their volunteer tasks [72,73]. Students also reported feeling unprepared to deal with the pandemic, citing issues such as personal protective equipment shortages, lack of training and knowledge, role confusion, insufficient information, and a lack of support from social or family networks [71]. As highlighted in a qualitative study, the well-being of volunteers was neglected due to a lack of access to psychological support [36]. Moreover, these challenges are further perpetuated by the academic workload and responsibilities as undergraduate students [74].

In this study, we found that the willingness-to-volunteer rate among first-year students was higher compared with students in the second to sixth year of education. As suggested by a previous study, most first-year students have not yet commenced their involvement in extracurricular activities and are still in the process of selecting the type of activities they wish to pursue...
This further poses a challenge in using student volunteers to overcome the health care workforce shortage, as first-year students lack skills and experience, making them unsuitable for direct clinical assistance. For first-year students, community-based work is more suitable, including but not limited to childcare for health care workers, delivery of medicines to vulnerable populations, mental health checks on children, and other similar tasks. However, aiming to reduce the workload and burnout incidence among health care workers still necessitates recruiting students in higher academic years. Students in higher academic years are more involved in extracurricular activities and more occupied with lecture schedules, making them less willing to volunteer. Moreover, as students are exposed to more medical and health knowledge, they become more considerate of preventive measures. A previous study reported that students were more willing to volunteer if they were assured their grades would not suffer and be compensated, guaranteed coverage of treatment costs if they got infected while volunteering, offered separate accommodation during the duration of their volunteer work, and provided with psychological support. Therefore, addressing these barriers is crucial to encourage students in higher academic years to volunteer during the pandemic.

Herein, we found that female students are more likely to volunteer than male students. This aligns with previous findings, showing a willingness proportion of 60.2% for females compared with 52.3% for males. Consistent with a previous study, women were reported to be more willing to volunteer due to a nurturing inclination to help people in need and their empathetic nature, driven by personal and thoughtful motivations in the long term. However, a study by Lazarus et al. stated that being male was one of the significant demographic factors influencing willingness to volunteer in Indonesia. The differing findings among these studies are indicative of the influence of sociocultural factors on students’ willingness to volunteer during the pandemic.

Our findings indicate that the highest rate of willingness to volunteer is observed in Africa and Western Europe, while the lowest is in Eastern Europe. This aligns with a study revealing significantly lower volunteer rates in Eastern Europe compared with Western Europe, except for the trade union. One of the primary factors contributing to the lower willingness-to-volunteer rate in Eastern Europe is the historical context—having been under communist rule for half a century, memories of mandatory volunteering have imbued the concept of volunteer work with a distinctly negative connotation. This negative perception is further compounded by a postcommunist lack of trust in any public activity. Nowadays, Eastern European countries have progressed beyond acknowledging volunteering to establish a legal framework that actively promotes volunteering. This indicates that certain countries might have to put extra effort into encouraging students to volunteer.

In pandemic settings such as COVID-19, health students play essential roles in addressing the shortage of health care workers and responding to health problems. The students’ activities can be placed into various categories, such as hospital works (triage, admission wards, and emergency rooms), call centers, administrative epidemiological aspects (contact tracing, testing), online or remote consultation (regarding COVID-19 or non–COVID-19 cases, using the phone or internet), laboratory-related works, food or personal protective equipment supply, mentoring juniors, providing childcare for health workers, public education (such as countering hoaxes), and research programs. With the help of volunteers, health care providers express appreciation for their valuable contributions. There are many significant advantages to volunteering, including helping provide more services and clinical care, reducing the workload for local staff, improving the quality of care, and shortening waiting times for patients. In return, it enhances how the community views and uses health care services.

Recommendations and Considerations

Based on the findings of this study, we propose several recommendations to increase the willingness-to-volunteer rate among medical and health students during the pandemic. First, we suggest implementing a robust encouragement program that integrates volunteering activities into curricula and offers psychological and accommodation support. Second, schools should prioritize the provision of high-quality training, promote knowledge, ensure clear role distribution, and effectively disseminate information to enhance the overall volunteering experience. Third, it is imperative for schools to ensure the complete safety of health care students by implementing measures such as preventing shortages of personal protective equipment, facilitating grade conversion, and guaranteeing coverage of treatment costs in case of infections incurred during volunteering.

Last but not least, although deploying students as volunteers could help overcome the health care worker shortage during the pandemic, it is important to consider potential drawbacks. The risks of contracting the disease and consequently experiencing death or long COVID-19 symptoms are high, especially during the early stages of the pandemic when managing the disease is significantly challenging. This further implicates liability issues for universities, colleges, or academic health centers. Therefore, it is crucial to actively inform students who are willing to volunteer regarding the aforementioned risks. Moreover, during volunteering, students might not be able to study optimally. The additional burden on health care workers to supervise volunteers should also be considered, implying the necessity to prepare students with volunteering skills beforehand and to establish a specific body tasked with managing the volunteers.

Limitations

Our study is the first to calculate the global rate of willingness to volunteer during the pandemic among medical and health students. We obtained data from countries across different regions, namely, Africa, Eastern Europe, Western Europe, East and Southeast Asia, South Asia, and the Middle East. However, the study has several limitations, including being unable to retrieve data from sources other than scientific publications. We did not collect data from reports published by government or nongovernmental organizations. Additionally, we did not contact experts who might have unpublished data regarding the willingness-to-volunteer rate. The rate was calculated from...
heterogeneous data, which indicates the moderate strength of evidence. More than 40% of the included studies did not sufficiently justify the sample size, raising caution about the representativeness of the data. Moreover, moderator effects might be influenced by confounding factors that could not be controlled in this study. For example, as the effect of gender was observed based on the male-to-female ratio, the numbers might be influenced by differences in baseline demographics across countries and the composition of medical and other health professional schools. It is, therefore, important to confirm the findings through primary research.

Conclusions
The overall rate of willingness to volunteer among medical and health students during COVID-19 was 66.13%. This number indicates that the recommendation for medical and health students to volunteer can be pursued, as the majority of students are willing to volunteer, although efforts to increase willingness remain necessary. Higher rates of willingness to volunteer were observed among studies with more first-year students and female participants. According to the region, students from African and Western European countries were more willing to volunteer during the pandemic. Unfortunately, the interpretation of the pooled estimate is limited by high heterogeneity, which is expected due to the variability in different countries, settings, and populations. However, this study can serve as a basis for managing medical and health students in volunteering during health crises.

Acknowledgments
We acknowledge the collaboration between Universitas Islam Negeri Syarif Hidayatullah Jakarta, Institut Teknologi dan Bisnis Ahmad Dahlan Jakarta, Universitas Syiah Kuala, and Universitas Muhammadiyah Aceh during the study and the preparation of this article.

Data Availability
All data underlying the results are available as part of the article and no additional source data are required.

Authors' Contributions
MM contributed to the conceptualization, investigation, resource allocation, and drafting of the original manuscript. SH, NN, and MF contributed to the validation, review and editing of the manuscript, and supervision. GT contributed to the investigation and drafting of the original manuscript. MI contributed to the conceptualization, validation, methodology development, and drafting of the original manuscript. All authors have reviewed and approved the final version of the manuscript for publication.

Conflicts of Interest
None declared.

Multimedia Appendix 1
PRISMA 20-item checklist and PRISMA abstract checklist.
[DOCX File , 34 KB - mededu_v10i1e56415_app1.docx ]

Multimedia Appendix 2
Search strategy and combination of keywords used in each database; detailed assessment of the included studies using the Q-SSP tool; and the 20 checklist items of Q-SSP and their respective code. Q-SSP: Quality Assessment Checklist for Survey Studies in Psychology.
[DOCX File , 26 KB - mededu_v10i1e56415_app2.docx ]

Multimedia Appendix 3
(A) Number of samples and (B) rate of willingness-to-volunteer based on regions.
[PNG File , 194 KB - mededu_v10i1e56415_app3.png ]

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Abbreviations

P-Het: P value of heterogeneity
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses
P-tot: P value of total effect
Q-SSP: Quality Assessment Checklist for Survey Studies in Psychology
WHO: World Health Organization
Curriculum Frameworks and Educational Programs in AI for Medical Students, Residents, and Practicing Physicians: Scoping Review

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Abstract

Background: The successful integration of artificial intelligence (AI) into clinical practice is contingent upon physicians’ comprehension of AI principles and its applications. Therefore, it is essential for medical education curricula to incorporate AI topics and concepts, providing future physicians with the foundational knowledge and skills needed. However, there is a knowledge gap in the current understanding and availability of structured AI curriculum frameworks tailored for medical education, which serve as vital guides for instructing and facilitating the learning process.

Objective: The overall aim of this study is to synthesize knowledge from the literature on curriculum frameworks and current educational programs that focus on the teaching and learning of AI for medical students, residents, and practicing physicians.

Methods: We followed a validated framework and the Joanna Briggs Institute methodological guidance for scoping reviews. An information specialist performed a comprehensive search from 2000 to May 2023 in the following bibliographic databases: MEDLINE (Ovid), Embase (Ovid), CENTRAL (Cochrane Library), CINAHL (EBSCOhost), and Scopus as well as the gray literature. Papers were limited to English and French languages. This review included papers that describe curriculum frameworks for teaching and learning AI in medicine, irrespective of country. All types of papers and study designs were included, except conference abstracts and protocols. Two reviewers independently screened the titles and abstracts, read the full texts, and extracted data using a validated data extraction form. Disagreements were resolved by consensus, and if this was not possible, the opinion of a third reviewer was sought. We adhered to the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) checklist for reporting the results.

Results: Of the 5104 papers screened, 21 papers relevant to our eligibility criteria were identified. In total, 90% (19/21) of the papers altogether described 30 current or previously offered educational programs, and 10% (2/21) of the papers described elements of a curriculum framework. One framework describes a general approach to integrating AI curricula throughout the medical learning continuum and another describes a core curriculum for AI in ophthalmology. No papers described a theory, pedagogy, or framework that guided the educational programs.

Conclusions: This review synthesizes recent advancements in AI curriculum frameworks and educational programs within the domain of medical education. To build on this foundation, future researchers are encouraged to engage in a multidisciplinary
approach to curriculum redesign. In addition, it is encouraged to initiate dialogues on the integration of AI into medical curriculum planning and to investigate the development, deployment, and appraisal of these innovative educational programs.

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**KEYWORDS**

artificial intelligence; machine learning; curriculum; framework; medical education; review

### Introduction

The field of medicine is constantly evolving with new technologies and discoveries [1]. One of the emerging technologies is artificial intelligence (AI), a simulation of human intelligence powered by machines, specifically computer systems that use machine learning and deep learning [2]. AI allows for complex decision-making and the ability for human capabilities such as tasks done by physicians and other health care providers [2]. Through recent advancements, AI has begun to become an innovation to be adopted in the field of medicine [3]. Current fields using this type of technology are radiology [4], pathology [5], dermatology [6], primary care [7], and surgery [8], among other fields of medicine [9]. These AI-related medical innovations can be seen through different ways, including robot-assisted surgical procedures, diagnosis and risk assessments, as well as the development and customization of drugs [3,10]. However, to move forward with the implementation of AI in clinical practice, physicians need to have a better understanding of AI and how to use it in clinical practice [11].

Although medicine has seen major changes over the last decades, medical education is still largely based on traditional curricula [12]. It often lacks fundamental concepts and even basic familiarization with AI and other emerging technologies [13]. A recent survey by Stanford Medicine found that 44% (230/523) of physicians and 23% (48/210) of medical students and residents reported that their education had not been helpful in preparing for new technologies in health care [14]. Currently, there are no accreditation requirements related to AI [15]. The knowledge gap between engineers, clinicians, and scientists continue to grow as health care moves to a more digital environment, which will ill-prepare young physicians who will work with AI-enabled tools and technologies [16,17].

At the moment, AI is beginning to enter the field of medical education through its uses in learning support, assessments of students’ learning, and curriculum review [2]; however, there are several publications urging institutes and clinical educators to begin integrating AI educational concepts into their medical curricula [12,13,15-20]. There have been efforts to include AI education globally within each level of medical training. These efforts are led by national medical associations such as the UK National Health Service [21], the US American Medical Association [22], and Canada’s Royal College of Physicians and Surgeons [23]. They have released documents recommending policies for integrating AI within their respective medical educational institutions [21-23]. This highlights the importance of the work on the intersection of medical education and AI around the world. Surveys of medical trainees have also supported the need to incorporate the teaching of AI in the undergraduate medical curriculum [24].

To our knowledge, there are no medical schools with formal required courses on AI in health care. While still uncommon, the importance of AI medical education has been identified and acted on at some institutions, such as Duke University, which offers a training course called Machine Learning School for the School of Medicine [12]. Other institutions have also developed elective courses to teach AI to residents, such as in radiology [25]. As AI is being used in a variety of fields within medicine [9], it is important to have a structured and validated curriculum framework because future medical providers will be exposed to these types of technologies depending on their chosen fields.

A curriculum framework is a document which describes “the educational environment in which syllabuses (or subject-specific outlines of objectives, outcomes, content and appropriate assessment and teaching methodologies) can be developed” [26]. Curriculum frameworks can be described as educational road maps to teaching and learning. For example, a curriculum framework was created for global health concepts in family medicine education [27]. Medical educators work regularly with frameworks to inform the appropriate learning, assessment, and performance of the health care workforce [28]. Frameworks are tools that can inform the delivery of teaching and curricula development as well as inspire innovation in health care education. There are various aspects that can be included in curriculum frameworks and how they may be used for other disciplines. Obadeji [29] clearly describes the common elements of curriculum frameworks for health professional education, which include (1) the need and the purpose of a curriculum or a program, (2) learning objectives and outcomes, (3) course content that will facilitate the accomplishment of the objectives or learning outcomes, (4) organization of the content, and (5) implementation of curriculum—educational strategies and methods of assessment.

Due to the broad nature of this topic and its prospective limited data, a scoping review is the most appropriate method. Previous reviews exploring topics surrounding AI and medical education have focused on the application of AI in medical education [2,30], attitudes of medical students toward AI [31], and gaps of AI learning within medical education [32]. A recent review of AI educational programs and competencies for health care professionals was published [33]; however, due to the increase in attention on this topic, further reviews must be conducted. Furthermore, the previous reviews had some limitations, such as the exclusion of continuing professional education and the lack of investigating learning theories, pedagogies, and frameworks of their identified AI educational programs. Our review will cover these limitations by focusing on the medical
education continuum as the developed AI educational programs for medical students, residents, and practicing physicians can help medical educators navigate the learning pathway for current and future physicians. Moreover, no review has focused on examining curriculum frameworks that guide AI concepts within medical education.

Thus, we conducted a scoping review of published literature on AI curricula being used in medical education. Overall, the main aim of this scoping review is to synthesize knowledge from the literature on curriculum frameworks and current educational programs that focus on the teaching and learning of AI for medical students, residents, and practicing physicians. More specifically, we aim to investigate the details of the current educational programs including (1) the framework, pedagogy, or theory used; (2) the delivery of the educational program; (3) the curricular content; and (4) the evaluation of the program, to inform future research on developing or adopting AI curriculum frameworks for use in medical educational institutions.

Methods

Protocol and Registration

The protocol for this review was developed in accordance with the Joanna Briggs Institute (JBI) Reviewers Manual for Evidence Synthesis [34] and guided by the methodological framework developed by Arksey and O’Malley [35], supplemented by Levac et al [36]. The PRISMA-SeR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews) [37] was used when reporting results, and is reported in Multimedia Appendix 1. The protocol was registered on Open Science Framework Registries and published on JBI Evidence Synthesis [38].

Eligibility Criteria

Participants

To be eligible for inclusion, the participants of the studies had to fall under the population that provided medical education or received medical education, which includes medical students. This includes undergraduate medical education (UME), residents or postgraduate medical education (PGME), and practicing physicians (continuing medical education [CME]) at any health care setting (ie, primary, secondary, and tertiary care).

Exposure

Included studies must describe either a curriculum framework or programs for AI education within medicine. The frameworks and programs must focus on learning about AI and how to use AI-specific tools for the medical profession.

Outcome

For the purpose of this review, all elements of a curriculum framework described by Obadeji [29], either in part or as a whole, were considered and reported. Included papers may also describe current and developed educational programs for AI training in medicine. These educational programs have already been developed or evaluated, and papers describing recommendations of what to teach or programs not yet developed were not considered. This review focused on any framework, theory, or pedagogy mentioned within the program; the delivery of the educational program (eg, course and workshop); and curricular content (eg, learning topics and learning objectives); if the educational program was evaluated, it was described according to the model of training evaluation developed by Kirkpatrick et al [39].

Information Sources

All types of studies were included, such as theoretical work, program descriptions, and empirical studies. Commentaries, reviews, perspectives, opinions, as well as position papers and any companion papers associated were also included. All study designs for empirical studies using qualitative, quantitative, or mixed methods studies were eligible for inclusion. These include experimental and quasi-experimental studies (such as randomized controlled trials, quasi-randomized controlled trials, nonrandomized clinical trials, interrupted time series, and controlled before-and-after studies), observational studies (such as cohort, case control, cross-sectional, and case series studies), qualitative studies (such as ethnography, narrative, phenomenological, grounded theory, and case studies), and mixed methods studies. Conference abstracts and protocols were excluded. Conference abstracts often contain preliminary findings that may not be as comprehensive or validated as full-text articles. As they are brief summaries of studies, they may lack the detailed methodology and results needed for a thorough understanding and synthesis in our scoping review. Furthermore, as protocols are plans of how to conduct the research, they do not provide findings or results that are necessary for a scoping review’s goal to map the extent, range, and nature of research activity in a given field. Therefore, considering the provided justifications, we decided to exclude conference abstracts and protocols.

Search Strategy

The following search strategy has been developed by a specialized librarian. The text words contained in the titles and abstracts of relevant papers and the index terms used to describe the papers were used to develop a full search strategy. The search strategy took an iterative approach, initially using general terms such as “artificial intelligence,” with the later addition of variations and synonyms such as “deep learning” and “machine learning.” In addition, terms for the concepts of medical education and curriculum were added. An initial limited search of MEDLINE (PubMed) was conducted to identify relevant papers on this topic. An information specialist (GG) performed a comprehensive search in the following bibliographic databases: Ovid MEDLINE, Ovid Embase, CENTRAL (Cochrane Library), CINAHL, and Scopus. To identify any unpublished frameworks, web searches of Google, New York Academy of Medicine Grey Literature Report, and medical learning institutional websites were searched. Reference lists of all included research papers and all relevant reviews were back searched, and Google Scholar was used for forward citation tracking to identify further studies. Papers were restricted to English and French due to the constraints of the research team. Papers were also restricted by date beginning in the year of 2000, as during the 1950s to the late 1990s AI was in its early phase with reduced funding and
interest of AI in medicine [40]. The initial search was conducted in November 2021 and later updated in May 2023.

Selection of Sources of Evidence

Following the search, all identified records were collated and uploaded into a reference management system, EndNote (version 20.3; Clarivate Analytics), where duplicates were removed. Following a pilot test with 2 reviewers (RT and AB) using 10% (510/5104) of the studies, titles and abstracts were then screened using Rayyan, a web-based research platform, by 2 independent reviewers (RT and AB) for assessment against the inclusion criteria for the review. The full text of selected citations was assessed in detail against the inclusion criteria by 2 independent reviewers (RT and AB). Any disagreements that arose between the 2 reviewers were resolved by a third reviewer (SAR).

Data Extraction

Data were extracted by 2 reviewers (RT and AB) using a data extraction tool on an Excel (Microsoft Corp) sheet developed and validated by the team. The data extraction tool was created and validated using previously validated data extraction tools [32-34] and input from experts in the field. It focuses on key characteristics related to curriculum framework elements and educational program details. Any disagreements that arose between the 2 reviewers were resolved by a third reviewer (SAR). Data on paper characteristics (eg, authors, title, country of origin, type of study, and year of publication), curriculum framework elements, and educational program details were extracted.

Synthesis of Results

The results of the review are presented as a table of the data extracted from the included literature to highlight the key findings with respect to the aims of this scoping review. Descriptive statistics (eg, frequency) was used when reporting paper characteristics and education program details. For curriculum frameworks described, reviewers presented main elements, including (1) the need and purpose of curriculum, (2) the learning objectives and outcomes, (3) course content that will facilitate the accomplishment of the objectives or learning outcomes, (4) the organization of the content, and (5) implementation of curriculum. For current educational programs described, reviewers independently recorded and presented data on the framework, theory, or pedagogy that may have been used; the delivery of the educational program; and curricular content; and if the educational program was evaluated, it was described according to the model of training evaluation developed by Kirkpatrick et al [39].

The model of training evaluation developed by Kirkpatrick et al [39] was used to categorize educational outcomes evaluations (Figure 1 [39]). Level 1 describes the degree to which learners find the training favorable, engaging, and relevant; level 2 describes the degree to which learners acquire the intended knowledge, skills, confidence, and commitment based on their participation in the training; level 3 describes the degree to which learners apply what they learned during training when they are back to work; and level 4 describes the degree in whether the targeted outcomes resulted from the training program at an organizational level [39]. A narrative summary accompanied [41] the charted results and described what and how AI curriculum content is being delivered to trainees of various medical education stages.

Quality Appraisal of Included Studies

Due to the nature of this review, the methodological quality or risk of bias of the included papers was not appraised, which is consistent with scoping reviews guidelines [34,37].

Results

Search Results

From the systematic search, 5076 total papers were identified. These papers were extracted from web-based databases, and the computer software EndNote was used to manage these
references. Following removal of duplicates on EndNote, 2458 papers were uploaded to Rayyan software and screened by title and abstract. After abstract and title screening, 60 papers remained for full-text screening. A gray literature search identified 60 papers from Google Scholar and reference lists, from which 28 (47%) papers were retrieved for full-text screening, and 32 (53%) papers were not retrieved or were irrelevant. Following full-text screening of databases and gray literature, 21 papers were included for further analysis [12,25,31-33,42-57]. Refer to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) diagram (Figure 2) [58].

Figure 2. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flowchart.

Characteristics of the Included Studies

Data was collected from 21 included studies and summarized in Multimedia Appendix 2 [12,25,31-33,42-57]. A total of 12 studies were published in the United States [12,31,32,42-45,48,51,52,54,57]; 6 in Canada [33,46,47,49,50,55]; and 1 each in Germany [25], Korea [53], and Oman [56] (Multimedia Appendix 3). The earliest publication retrieved was from 2016, with 77% (15/21) of the papers published in the last 3 years since the pandemic began (Multimedia Appendix 3). From the 21 studies, 6 (29%) were reviews [31-33,45,53,54], 4 (19%) were commentaries [44,47,50,51], 4 (19%) were opinions [12,48,52,56], 3 (14%) were perspectives [43,55,57], 3 (14%) were empirical studies using a cross-sectional survey design [25,42,49], and 1 (5%) was a position paper [46].

In terms of setting, 43% (9/21) of the papers mentioned multiple levels of education ranging from UME, PGME, to CME [12,31-33,46,50,51,54,56], while 24% (5/21) of the papers specified on UME [42,44,47,53,55], 19% (4/21) of the papers specified on PGME [48,49,52,57], and 14% (3/21) of the papers were focused on CME [25,43,45]. Across the 21 included studies, 19 (90%) altogether described 30 current or previously offered educational programs [12,25,31-33,42-55] and 2 (10%) described elements of a curriculum framework [56,57].

Curriculum Framework Elements

Two papers described the main elements of a curriculum framework (Table 1) [56,57]. The first paper was an opinion paper by Masters [56], which mentions 3 of the 5 elements of a curriculum framework. The paper describes the need and purpose of a curriculum, course content, and brief descriptions in terms of organization of content. The second paper to describe elements of a curriculum framework was the study by Valikodath et al [57], which provides information for all 5 elements. This includes the main purpose of an ophthalmology AI curriculum, the learning objectives, course content topics, a 4-year resident organization plan, and implementation of the curriculum, as outlined in Table 1. We noticed similarities in relation to what medical trainees should learn, as emphasized in Figure 3 [56,57].
### Table 1. Curriculum framework studies’ characteristics (n=2).

<table>
<thead>
<tr>
<th>Masters [56]</th>
<th>Valikodath et al [57]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Program audience</strong></td>
<td><strong>Need or purpose</strong></td>
</tr>
<tr>
<td>• Multiple (undergraduate medical education, PGME, and continuing medical education: general)</td>
<td>• PGME: ophthalmology</td>
</tr>
<tr>
<td><strong>Learning objectives</strong></td>
<td><strong>Course content</strong></td>
</tr>
<tr>
<td>• This general framework will</td>
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<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td><strong>Learning objectives</strong></td>
<td><strong>Course content</strong></td>
</tr>
<tr>
<td>• Learning objective 1: To understand the basic components of AI</td>
<td></td>
</tr>
<tr>
<td>• Learning objective 2: To identify the limitations of AI, especially in health care and research</td>
<td></td>
</tr>
<tr>
<td>• Learning objective 3: To summarize current uses of AI in ophthalmology and evaluate the primary literature</td>
<td></td>
</tr>
<tr>
<td>• Learning objective 4: To know how to potentially apply AI into clinical practice, including telemedicine and web-based visits</td>
<td></td>
</tr>
<tr>
<td><strong>Course content</strong></td>
<td><strong>Course content</strong></td>
</tr>
<tr>
<td>• “...we need now to teach AI literacy and a basic understanding of Data Management and AI concepts, models and terminology (such as big data (and the growing number of Vs), data mining, machine learning, deep learning, supervised and unsupervised learning, natural language processing and neural networks) [...]”</td>
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<td></td>
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<tr>
<td>• Option A: the basics</td>
<td>• Topic 2. AI in medical systems</td>
</tr>
<tr>
<td></td>
<td>• “In all cases where AI is taught, the current limitations of AI need to be identified [...] Understanding these systems will be necessary to evaluate the applicability and appropriateness of solutions. [...]”</td>
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<tr>
<td>• Option B: more advanced</td>
<td></td>
</tr>
</tbody>
</table>
From our comparisons, we found that the main curricular topics presented by Masters [56] appropriately corresponded to the curricular topics presented by Valikodath et al [57], for example, a main curricular topic of “AI in Medical Systems,” which describes the way in which students should learn the structures and processes of AI systems that they will be using in the future. This corresponds to “Clinical Applications” and “Surgical Applications” in which the content is targeted into learning how to use AI applications for ophthalmology. It appears that Masters’ [56] framework on course content can work as the foundation on what curricular concepts a program should include. This is because previous reviews have detailed similar curricular topics currently being taught.

**Current Educational Programs**

From the 19 papers that describe an educational program, 30 current or previously offered educational programs were identified (Table 2) [12,25,31-33,42-55]. A total of 13 papers

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**Figure 3.** The comparison between the course content described by Masters [56] and Valikodath et al [57].
described, mentioned, or presented 24 educational programs [12,31-33,43,45-47,50-54], while 6 papers described and assessed 6 educational programs using evaluation methods (eg, survey and test scores) [25,42,44,48,49,55]. No papers described a theory, pedagogy, or framework that guided the educational program.

Table 2. Educational program characteristics (n=30 educational programs described in 19 papers).

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Frequency, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Type of educational program</strong></td>
<td></td>
</tr>
<tr>
<td>Course</td>
<td>15 (50)</td>
</tr>
<tr>
<td>Project</td>
<td>4 (13)</td>
</tr>
<tr>
<td>Lecture (dedicated to artificial intelligence)</td>
<td>4 (13)</td>
</tr>
<tr>
<td>Webinar</td>
<td>3 (10)</td>
</tr>
<tr>
<td>Educational summit or conference</td>
<td>2 (7)</td>
</tr>
<tr>
<td>Workshop</td>
<td>2 (7)</td>
</tr>
<tr>
<td><strong>Pathway of education and program audience</strong></td>
<td></td>
</tr>
<tr>
<td>Undergraduate medical education</td>
<td></td>
</tr>
<tr>
<td>General topics</td>
<td>16 (94)</td>
</tr>
<tr>
<td>Radiology</td>
<td>1 (6)</td>
</tr>
<tr>
<td>Postgraduate medical education</td>
<td></td>
</tr>
<tr>
<td>Radiology</td>
<td>5 (100)</td>
</tr>
<tr>
<td>Continuing medical education, n (%)</td>
<td></td>
</tr>
<tr>
<td>General topics</td>
<td>4 (50)</td>
</tr>
<tr>
<td>Radiology</td>
<td>3 (34)</td>
</tr>
<tr>
<td>Cardiology</td>
<td>1 (13)</td>
</tr>
<tr>
<td><strong>Delivery setting</strong></td>
<td></td>
</tr>
<tr>
<td>Medical school</td>
<td>23 (77)</td>
</tr>
<tr>
<td>National or international medical association</td>
<td>7 (23)</td>
</tr>
</tbody>
</table>

Educational Program Delivery

Of the 30 educational programs described collectively in the 19 remaining papers, 15 (50%) programs were courses, 4 (13%) were project-related initiatives, 4 (13%) were didactic lectures dedicated to AI, 3 (10%) were webinars, 2 (7%) were an educational summit or conference, and 2 (7%) were 1-day workshops. "AI courses were defined as elective courses focused on AI-based education. Didactic lectures dedicated to AI are 1 or 2 lectures that mention AI education but not a full course. There were 77% (23/30) educational programs delivered from a medical school, while 23% (7/30) were delivered from recognized national or international medical associations. Furthermore, it is important to clarify that some papers used multiple educational program delivery approaches. For example, an included paper explained their educational intervention was a course, but this course included didactic lectures, mentorship, and a final project. However, the reporting of this educational program’s delivery is classified as only a course and not counted as another delivery approach to minimize confusion.

Of the 30 educational programs described collectively in the 19 remaining papers, 17 (57%) UME educational programs were targeted toward medical students. Of these 17 programs, 16 (94%) were UME educational programs focused on general topics of AI in medicine and 1 (6%) was an UME educational program focused on radiology concepts. In total, 17% (5/30) of the postgraduate educational programs were for residents who were in the radiology specialty. Of the 30 educational programs, 8 (26%) were specified for practicing physicians (n=4, 50% were CME educational programs focused on general topics of AI in medicine, n=3, 37% were radiology for CME education, and n=1, 13% was in cardiology for CME). The educational program characteristics are provided in Table 2.

Curricular Content

The following curricular concepts were adapted and framed from previous similar reviews [32,33]. The curricular content and concepts were divided into 2 types: theoretical curricular concepts and application-based curricular concepts. The subcategories and their descriptions are outlined in Table 3. The following describe the theoretical curricular concepts: fundamental of AI for using AI systems (15/19, 79%) [12,25,31-33,42-47,49,51-53]; fundamentals of health care data science for using AI systems (10/19, 53%) [12,25,31-33,45,47,49-51]; strengths and limitations of AI (9/19, 47%) [31-33,45-49]; and ethical, legal, and economic considerations of AI systems (11/19, 58%) [12,25,31-33,42,45-48,52]. The following describe the application-based curricular concepts: applications of AI systems
(19/19, 100%) [12,25,31-33,42-55], operating AI systems in health care settings (10/19, 53%) [12,25,31-33,46,47,52,55], impact of AI on clinical reasoning and medical decision-making (7/19, 37%) [12,25,31-33,43,55], communication of AI results to patients (4/19, 21%) [12,31-33], and critical appraisal of AI systems (7/19, 37%) [12,31-33,50,53,54].

Table 3. Curricular concepts mentioned in the educational program papers (n=19).

<table>
<thead>
<tr>
<th>Theoretical curricular concept</th>
<th>Description of curricular concept</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fundamental of AI for using AI systems</td>
<td>Providing an overview of AI definitions and concepts, including machine learning; natural language processing; and the basics of data acquisition, cleaning, analysis, and visualization</td>
<td>[12,25,31-33,42-47,49,51-53]</td>
</tr>
<tr>
<td>Fundamentals of health care data science for using AI systems</td>
<td>Providing an overview of the environment supporting AI, which includes biostatistics, big data, and the use and processing of data by algorithms and machine learning</td>
<td>[12,25,31-33,45,47,49-51]</td>
</tr>
<tr>
<td>Strengths and limitations of AI</td>
<td>Promoting learners’ comprehension of the advantages and limitations of various AI systems, such as factors that affect AI accuracy (eg, sources of error and bias)</td>
<td>[31-33,45-49]</td>
</tr>
<tr>
<td>Ethical, legal, and economic considerations of AI systems</td>
<td>Developing a comprehensive understanding of ethics, equity, inclusion, patient rights, and confidentiality, alongside regulatory frameworks, policy considerations, liability, and intellectual property issues related to using AI systems as well as grasping the potential alterations to business or clinical processes resulting from the integration of AI technologies</td>
<td>[12,25,31-33,42,45-48,52]</td>
</tr>
<tr>
<td>Application-based curricular concepts (learning how to use AI for clinical practice)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Applications of AI systems</td>
<td>Familiarizing with clinical application of AI systems in clinical practice to understand how they are used</td>
<td>[12,25,31-33,42-55]</td>
</tr>
<tr>
<td>Operating AI systems in health care settings</td>
<td>Understanding how to embed and engage with AI tools into clinical settings and workflows (eg, learning to engage in data mining tools or how to properly communicate with AI systems to receive meaningful results)</td>
<td>[12,25,31-33,43,46,47,52,55]</td>
</tr>
<tr>
<td>Impact of AI on clinical reasoning and medical decision-making</td>
<td>Having the ability to understand, interpret, and apply results of AI systems in clinical practice</td>
<td>[12,25,31-33,43,55]</td>
</tr>
<tr>
<td>Communication of AI results to patients</td>
<td>Communicate findings to patients in a personalized and meaningful manner and engage in discussions regarding the use of AI in the medical decision-making process</td>
<td>[12,31-33]</td>
</tr>
<tr>
<td>Critical appraisal of AI systems</td>
<td>Acquiring proficiency in assessing diagnostic and therapeutic algorithms powered by AI to ensure safe and effective integration and use in clinical practice</td>
<td>[12,31-33,50,53,54]</td>
</tr>
</tbody>
</table>

AI: artificial intelligence.

The mentioned concepts encompass foundational learning that serves as the basis of medical artificial intelligence educational philosophy and clinical practice.

The mentioned concepts prioritize the practical applications of artificial intelligence knowledge and skills in a clinical context.

Assessment of Educational Outcomes

Of the 19 papers, 6 (32%) presented the results of their evaluation of an educational program (Table 4) [25,42,44,48,49,55]. Two papers described only level 1 evaluation outcomes (eg, learner reaction and satisfaction with the educational program) in which participants were overall very satisfied with the AI content learned [42,48]. Four papers described level 2 evaluation outcomes (eg, change in attitude, knowledge, or skill) in which learners demonstrated acquisition of a variety of competencies (linear algebra pertaining to AI and basics of AI) and skills (eg, incorporate medical decisions given by an algorithm and implementing AI in clinical practice) [25,44,49,55] where two of these papers also evaluated level 1 outcomes [25,49]. There were no outcomes that could be categorized as level 3 or level 4; thus, the program evaluations did not comment on the change in behavior or affect at the organizational level or on patient outcomes.
This is the first review to identify curriculum frameworks for AI in medical education. Their frameworks remain dissimilar in all aspects, except in how their course content was described. As seen with these 2 papers, the lack of curriculum frameworks in the current state of curriculum framework in medical education are very limited. Although the literature is abundant in terms of recommendations and potential plans of actions for integrating AI education within medical education, there is an inadequate amount of formal curricula or frameworks. For example, curricular recommendations lack specific learning outcomes and are not based on a particular education theory, as they usually focus solely on the content or competencies that should be taught. Although understanding what concepts should be taught in AI is important, curriculum frameworks must be as comprehensive as possible. From the identified frameworks, Masters outlines a broad framework for any level of education, while Valikodath et al outlines a complete framework for ophthalmology residency education. Their frameworks remain dissimilar in all aspects, except in how their course content was described. As seen with these 2 papers, the lack of curriculum frameworks in the literature is staggering. Further studies should focus on the development of these frameworks and start thinking on how to plan for the impending changes in medical education. As Valikodath et al demonstrated their AI curriculum framework for ophthalmology, other specialties should follow suit, as AI affects each specialty differently.

Current State of Curriculum Frameworks for AI Medical Education

This is the first review to identify curriculum frameworks for AI medical education, and our findings demonstrate that they

### Discussion

#### Principal Findings

The development and implementation of AI in medical education has greatly increased within the last decade, specifically since the COVID-19 pandemic where there was a global shift into the digital world accelerating the development of AI technology. This can be seen as the majority of included papers within this review were published since COVID-19 pandemic. Although there is a growing field within research and practice, AI medical education, specifically within curricula development, is still limited. We found that the current curriculum frameworks for AI medical education are limited, indicating a need for further research. We also found that the current state of AI educational programs lack the use of a theory, framework, or pedagogy. In addition, we uncovered alternative methods and different levels of in-depth curriculum planning for AI in medical education.

### Table 4. Studies describing evaluation outcomes (n=6).

<table>
<thead>
<tr>
<th>Study</th>
<th>Educational program</th>
<th>Levels and outcomes of the model of training evaluation developed by Kirkpatrick and Kirkpatrick [39]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alderson et al [42], 2021</td>
<td>Course</td>
<td>Level 1: “...satisfaction scores of 4.4/5.0 (n=13) [...]”</td>
</tr>
<tr>
<td>Barbour et al [44], 2019</td>
<td>Educational summit</td>
<td>Level 2: “...there was a general belief [about 70% from the figures] that AI would make health care less humanistic.”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Level 2: “...did not observe a meaningful shift in attitudes regarding the desire to take a leadership role in developing or implementing AI [...]”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Level 2: “...attended believing they had a poor baseline understanding of AI’s role in health care, and left the summit with an enhanced understanding of the topic [...]”</td>
</tr>
<tr>
<td>Hedderich et al [25], 2021</td>
<td>Course</td>
<td>Level 1: “The participants were overall very satisfied with the study material and the organization of the course, and deemed the content of the course important for their work as a clinician or scientist.”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Level 2: “...self-perceived skills improved in all areas, for understanding Python code as well as for understanding concepts of linear algebra pertaining to AI.”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Level 2: “...participants felt more confident to analyze a research paper in the field, to implement an AI algorithm in a clinical environment, and to incorporate the decisions given by an algorithm into their clinical decision making.”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Level 2: “Most of the participants felt more competent at dealing with AI in medical imaging after the course.”</td>
</tr>
<tr>
<td>Kang et al [48], 2017</td>
<td>Workshop</td>
<td>Level 1: “Ninety percent of the residents... reported that the course was helpful or very helpful [...]”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Level 1: “...94% of the participants...felt that the lectures were of high or very high quality.”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Level 1: “Eighty-two percent...reported that they planned to pursue additional educational or research training in CER or big data analytics after the course [...]”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Level 1: “[...] 98% of the respondents felt that health services and big data research are important or very important for the future of radiology.’”</td>
</tr>
<tr>
<td>Lindqwister et al [49], 2021</td>
<td>Course</td>
<td>Level 1: “Exit surveys demonstrated a high degree of learner satisfaction, with an aggregate rating of 9.8/10.”</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Level 2: “There is a statistically significant difference between all pre- and postlecture question results (P&lt;.04) by Wilcoxon Sign-rank test.”</td>
</tr>
<tr>
<td>Tschirhart et al [55], 2022</td>
<td>Workshop</td>
<td>Level 2: “...considerable improvement in the first independent dataset, with further improvement in subsequent datasets [...]”</td>
</tr>
</tbody>
</table>
appears to be far from sufficient in the existing literature, and further research is needed.

**Current State of AI Medical Educational Programs**

**Overview**

In comparison to curriculum frameworks, educational programs in this field have been reviewed recently, specifically in the past 3 years [31-33]. However, research in AI medical education evolves quickly, and thus, a further identification of programs was carried out. We specifically looked at the framework, pedagogy, or learning theory described; the content and its audience; and if the program was evaluated for outcomes, which were used to assess its effectiveness, according to the model developed by Kirkpatrick et al [39].

**The Lack of Learning Theories and Pedagogies**

There were no papers that referenced a framework, pedagogy, or learning theory that guided the existence of the educational program. However, the use of frameworks, pedagogies, or learning theories is important for informing the development of valid, accurate, and competent educational programs [62-64]. By using frameworks, pedagogies, or learning theories, educators can choose the most effective instructional tactics, learning objectives, assessment, and evaluation approaches that can best help their students to learn [65]. A recent paper that fell outside the scope of our search date describes the use of constructivist theory and backward design learning principles that guided the development of their AI course [66]. Further papers should implement and report on a learning theory, framework, or pedagogy, as they have a role in medical education [65].

**The Generalized AI Medical Content**

The integration of AI concepts and topics within medical education remains generalized throughout the different levels of medical education, as seen with the educational programs described in our review. A total of 20 educational programs were described as focusing on general topics such as introductions to AI or information on AI and its application to medicine. The only postgraduate and continuing educational programs that had an AI-specific educational material were radiology, ophthalmology, and cardiology. This can be attributed to various reasons, including the constant evolution and novelty of AI technology, which may describe why generalized educational programs for AI appear across the medical educational continuum [67]. Radiology had the highest number of educational programs and was seen in all levels of medical education because AI in medicine was first applied in the field of radiology as it detected microcalcifications in a mammography during the year of 1992, or it could be due to the field being highly technological [68]. It is encouraging to see that specialties such as ophthalmology and cardiology have increased interest in AI education; other specialties and medical institutions should begin to follow suit. This is encouraging as it demonstrates that other specialties besides the highly technological field of radiology have been learning AI within medical education. This is especially important as more fields of medicine besides radiology are integrating AI within their practice, such as cardiology, pathology, and ophthalmology [3]. Furthermore, most of the educational programs were found in UME and within medical schools, which is ideal as it introduces a large audience of medical students to the concept of AI and its applications early in their careers.

**The Success of Current AI Educational Programs**

The included literature demonstrates that current efforts are being made to evaluate the outcomes of AI-related educational initiatives. According to the model developed by Kirkpatrick et al [39], an internationally recognized tool for evaluating and analyzing the results of educational, training, and learning programs, current AI programs have overall been positively received by medical learners. This was represented by the positive reactions, opinions, and attitudes toward AI after completing an educational program (level 1) as well as the acquisition of AI-related knowledge, skills, and confidence (level 2). These findings were also presented in a similar review in which the AI educational programs they identified also had positive outcomes, which were categorized as level 1 or level 2 [33]. However, further studies must assess educational programs for outcomes in relation to behavioral changes (level 3), specifically if there has been a transfer of AI-related knowledge, skills, and abilities into their daily work.

Further studies should also assess how the acquisition and application of these AI-related knowledge, skills, and abilities has affected the organization as a whole (eg, Has the increase in AI-educated physicians improved overall efficiency at the hospital?) or on patient outcomes (eg, Has there been an improvement in the patient’s functional status or safety because of AI-educated physicians? [level 4]). By assessing for these additional outcomes, educators and medical organizations can understand how current AI educational programs have affected physician performance with AI technology. Increased research on the evaluations of educational programs can help further validate current educational tools and be used as inspiration for other institutions to create their own educational material. As seen in the review [33], there is a lack of consistency in the measures of these outcomes, as self-constructed and nonvalidated instruments were also used. Future studies should develop a validated tool to evaluate educational outcomes for a comprehensive synthesis.

**Curriculum Planning and Framework Development of AI Medical Education**

Curriculum planning of AI educational initiatives within medical education is insufficient. Although limited studies of curriculum frameworks were published, other forms of curriculum planning can be seen in the literature. Some medical institutions have conducted AI perception surveys [69,70], curriculum needs assessment surveys [71-73], and an interview [74] to understand what should be integrated into the AI medical curriculum. These studies are promising and contribute to the overall efforts to understanding how current educators, medical students, residents, and physicians consider AI within their educational system.

The absence of curriculum frameworks is staggering, especially given that AI competence is likely to become a required skill for medical graduates [75]. The development of AI curricula
and frameworks have already been gaining traction across other fields of education and levels. This can be seen as early as childhood education; for example, Su and Zhong [76] present their own curriculum framework, which outlines their concepts, teaching methods, teaching activities, projects, and assessment suggestions for AI education.

From a global perspective, the United Nations Educational, Scientific, and Cultural Organization, a specialized agency of the United Nations, released a document outlining the current practices of developing and implementing AI curricula in primary and secondary school education (K-12) [77]. From their report, several types of frameworks for AI literacy have been suggested, such as the AI Literacy Competency Framework, the AI4K12: 5 Big Ideas Framework, and the Machine Learning Education Framework. These recent reports and papers suggest increased efforts to integrate AI education before postsecondary school, which further stresses the importance of developing AI curricula and frameworks in medical education. Although there are current educational frameworks for AI education, each target audience must have their own specialized curricula to tailor the educational needs of the learners.

Medical educators can develop their curriculum through several different methodologies, such as the 10 key questions to be addressed while developing a curriculum [78] and the 6-step approach for curricular design [79]. However, curriculum frameworks allow a visual and detailed road map to implement a curriculum. Through this detailed format, educators are able to easily navigate the curriculum and its implementation, especially for new concepts in medicine, such as AI. To develop curriculum frameworks for AI in medicine, there must be an interdisciplinary team consisting of medical educators, AI experts and users, researchers, and curriculum designers due to the multiple fields incorporated.

The introduction of AI in medicine must be properly structured and organized within UME, PGME, and CME. Therefore, curriculum frameworks should be properly established through different levels of education and specialties. This has been emphasized by other reviews that call for integration of AI education in all levels and, thus, all specialties of medicine [17,33]. For example, a curriculum framework for UME will be different than a curriculum framework for PGME in dermatology. Curriculum frameworks can be adapted and they most likely will be, especially since AI education in medical education is still in its infancy. This is where leaders in UME, PGME, and CME organizations (eg, policy makers, medical educators, and researchers) must communicate effectively to eliminate any crossover education and repeated information. New technology and innovations in relation to AI and medicine will inevitably occur; however, it is important to be cognizant of the fundamentals of AI and how it will affect a physician’s practice at the time. Sufficient planning of an AI curricula will deliver effective education for physicians who will increasingly be using AI technology in the near future; therefore, medical educators and institutions must begin to consider curriculum planning.

Incorporating and Advocating for AI Into the Medical Curriculum

The literature emphasizes the need to introduce AI in the medical education curriculum [12,13,15-20]; however, there are several challenges that have been discussed in terms of implementing this type of education. This includes insufficient time, insufficient resources (eg, lack of teaching staff or knowledge), and variable aptitude and interest in AI [80-82]. However, this review details several approaches to implementation as well as 6 studies that have evaluated their educational program. These successful educational programs can provide medical schools and national and international medical organizations with examples of current AI content topics and implementation methods that have worked for others. These medical education institutions can view how AI-based medical education is currently being offered around the world and understand any challenges, opportunities, and strengths about these programs. Although the content and provision of AI education is heterogenous, this heterogeneity can allow educators and students to view the many types of programs that were offered. As AI education for medicine is still in its infancy, educators should explore these programs where they can then potentially modify an educational program that best suits their needs. As seen in this review, there are several ways to incorporate AI material into the current curriculum seamlessly, such as an AI fundamentals lecture or module, an AI elective, or a research project.

Medical students, residents, and practicing physicians also have the opportunity to advocate for the inclusion of AI education at their respective institutions [46]. For example, there are several North American university chapters of the Artificial Intelligence in Medicine Student Society, such as the University of Toronto and University of Alberta, which organizes workshops, conferences, and multiple speaker sessions throughout the year [46]. These student interest groups demonstrate the increased interest for AI and can potentially build momentum and advocate for AI education at their respective institutions. As some of the offerings at these student interest groups include brief educational material for AI, medical institutions can work with these students as a starting point.

Strengths and Limitations

The strengths of this review include the comprehensive search strategies, the inclusion of a variety of information sources, and rigorous methodological approaches that are replicable. For example, study selection was completed by 2 reviewers, and disagreements were resolved by discussion or consensus involving a third investigator. Furthermore, a scoping review protocol was registered and published to improve transparency of the methodological process.

Although this study was conducted in a structured and systematic manner, there are some limitations that are important to consider. A limited number of papers were retrieved during the search and selection process. Only 2 papers reported having a curriculum framework, with 1 reporting a full curricula plan related to AI in medicine. This can be because AI technology is emerging and continuing to change within medicine and it has been limiting in terms of educational advances. Because of
the nature of the scoping review, the quality of each identified study was not assessed.

**Conclusions**

Medicine is rapidly evolving from the information age to the age of AI, where machines will become an integral part of medical practice. Thus, medical education needs to keep pace with changes in medical practice. This review synthesized knowledge from the literature on curriculum frameworks and current educational programs that focus on the teaching and learning of AI for medical students, residents, and practicing physicians. To better integrate AI curricula into the continuum of medical education, discussions surrounding curriculum planning of AI should begin where institutions are recommended to work collaboratively with teams of curriculum designers, data scientists, and medical educators to develop AI curricula and educational programs. There is a need to (1) develop a general AI education curriculum framework for UME; (2) develop a specific AI education curriculum framework for each specialty within PGME and CME; and (3) design, implement, and evaluate current educational programs. Overall, institutions must begin equipping current and future physicians with the knowledge, skills, and confidence to effectively use AI applications as it will continue to grow within the field of health care.

**Acknowledgments**

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**Authors' Contributions**

RT, SAR, and PP conceived the idea, developed the research protocol and methods, and drafted and edited the final manuscript. GG helped develop and run the search strategy. AB, PP, and SAR helped to refine and develop the research question and study methods and helped with drafting and editing of the manuscript. All authors except PP approved the final manuscript submitted; however, the authors would like to acknowledge that the late PP provided many meaningful contributions to this work before his passing.

**Conflicts of Interest**

None declared.

Multimedia Appendix 1

PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) checklist.

[DOCX File, 107 KB - mededu_v10i1e54793_app1.docx ]

Multimedia Appendix 2

Study characteristics (N=21).

[DOCX File, 41 KB - mededu_v10i1e54793_app2.docx ]

Multimedia Appendix 3

Countries and years of publications included in the review.

[PDF File (Adobe PDF File), 824 KB - mededu_v10i1e54793_app3.pdf ]

**References**

15. Pucchio A, Papa JD, de Moraes FY. Artificial intelligence in the medical profession: ready or not, here AI comes. Clinics (Sao Paulo) 2022;77:100010 [FREE Full text] [doi: 10.1016/j.clinsp.2022.100010] [Medline: 35176642]
Abbreviations

AI: artificial intelligence  
CME: continuing medical education  
PGME: postgraduate medical education  
PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses  
PRISMA-ScR: Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews  
UME: undergraduate medical education

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Time for Medicine and Public Health to Leave Platform X

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Abstract

For more than 50 years, digital technologies have been employed for the creation and distribution of knowledge in health services. In the last decade, digital social media have been developed for applications in clinical decision support and population health monitoring. Recently, these technologies have also been used for knowledge translation, such as in the process where research findings created in academic settings are established as evidence and distributed for use in clinical practice, policy making, and health self-management. To date, it has been common for medical and public health institutions to have social media accounts for the dissemination of novel research findings and to facilitate conversations about these findings. However, recent events such as the transformation of the microblog Twitter to platform X have brought to light the need for the social media industry to exploit user data to generate revenue. In this viewpoint, it is argued that a redirection of social media use is required in the translation of knowledge to action in the fields of medicine and public health. A new kind of social internet is currently forming, known as the "fediverse," which denotes an ensemble of open social media that can communicate with each other while remaining independent platforms. In several countries, government institutions, universities, and newspapers use open social media to distribute information and enable discussions. These organizations control their own channels while being able to communicate with other platforms through open standards. Examples of medical knowledge translation via such open social media platforms, where users are less exposed to disinformation than in general platforms, are also beginning to appear. The current status of the social media industry calls for a broad discussion about the use of social technologies by health institutions involving researchers and health service practitioners, academic leaders, scientific publishers, social technology providers, policy makers, and the public. This debate should not primarily take place on social media platforms but rather at universities, in scientific journals, at public seminars, and other venues, allowing for the transparent and undisturbed communication and formation of opinions.

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KEYWORDS
internet; social media; medical informatics; knowledge translation; digital technology; clinical decision support; health services research; public health; digital health; perspective; medicine

Introduction

Digital technologies have been used for the creation and distribution of knowledge in medicine and public health for more than 50 years. In addition to their applications for clinical decision support and population health monitoring [1-5], in the last decade, digital social media have been used for knowledge translation [6] such as in the process of establishing research findings as scientific evidence and distributing these findings for use in clinical practice, policy making, and health self-management. However, in May 2023, an editorial in Lancet Digital Health, a leading digital health journal, stated that the social media industry serves as “a commercial determinant of health due to the indirect health consequences of its business practices and actions” [7]. Eight months earlier, the entrepreneur Elon Musk had taken control of the microblog Twitter with a US $44 billion deal. At the time, Twitter was the social media platform most frequently used for knowledge translation and opinion formulation in the fields of medicine and public health. In one of his first actions as Chief Operating Officer, Musk laid off approximately 80% of the company’s employees [8] and phased out most of the content moderation work that countered disinformation and misbehavior [9]. In addition, Musk allowed previously suspended users such as Russian state actors to reactivate their accounts [10]. Changes to the platform also made it essentially impossible for researchers to study the activities occurring on Twitter [11]. Users with verified (paid) accounts were only allowed to read 6000 posts per day, those with unverified accounts could read 600 posts, and new users with unverified accounts could read 300 posts per day. This action exposed that the rationale for the verification and dissemination procedures on the platform is based on financial rather than social capital; consequently, the possibilities for external observers to inspect interactions had been made almost nonexistent. The dismantling of Twitter was manifested by renaming the service X in July 2023, thereby completing the transformation of the platform.
To date, it has been considered standard practice for academic and health service institutions as well as for individual researchers and practitioners to have social media accounts for the dissemination of research findings, access to topical information, and participation in debates about novel discoveries. However, the transformation of Twitter to platform X highlights new threats to the presence of health institutions on social media platforms; in particular, the rational translation of scientific knowledge to health action is currently at stake. In this viewpoint, it is argued that a redirection of social media use is needed with respect to the translation of knowledge to action in medicine and public health.

Social Media Platforms as Transformative Technologies

More than 60 years ago, mass communication researchers pointed out that the introduction of any novel information technology has the potential to change the shape and character of the affected community [12,13]. Without much forethought or debate, in many countries, social media platforms have become organic components of the information infrastructure. For instance, in Sweden, the proportion of the population regularly following national news broadcasts on the radio and television remained constant between 2009 and 2020, while the proportion of social media users increased from 33% to 78% and the proportion subscribing to printed morning newspaper decreased from 70% to 24% during this same time period [14].

Public institutions active on social media typically choose a platform that they consider generally agrees with the content they want to disseminate; universities and scientific journals share research findings on microblogs such as platform X, whereas cultural authorities tend to use TikTok to share visual content and elementary schools share information in Facebook groups. Even before Twitter was rebranded as platform X, the microblog was associated with several problems and challenges that could have a potential impact on knowledge translation, especially concerning the verification of posted and shared information [15]. The decision made by Elon Musk and his managerial team to reduce the possibility for researchers to analyze the content and interactions occurring on the platform brings to light the fact that a large share of these issues can be traced back to the need for the social media industry to exploit user data to generate revenue.

The logic underpinning such user and customer misuse can be explained by the “life cycle” model of social media platforms [16]. Initially, while financed by seeding financial capital, the platforms produce value for their primary users; the platforms then exploit the users to produce value for business customers and then finally also exploit their business customers to maximize the value for the owners, which eventually leads to death of the platform. The life cycle model thus highlights that small efforts needed to change the operation of social media platforms can serve to rapidly redistribute value between stakeholders in a “two-sided market,” where the platforms sit between users and producers of information. For example, user value is downplayed to produce value for business customers when platform algorithms are tuned to reward conflict-making and fragmentation with the goal of generating more views of posts, which, by extension, increases the display of ads paid for by business customers [17]. A recent study of news dissemination on Facebook [18] reported the greater circulation of conservative than liberal news domains, and indicated that a larger share of the news content was labeled as “false” in the conservative domains than in the liberal domains. The explanation provided by the authors for the faster propagation of conservative content, which has also been observed in other studies [19,20], was that false news stories disseminate faster on social media than true stories because false news items have more “novelty” and tend to arouse more emotions such as fear, disgust, and surprise than true news [21]. The authors argued that the Facebook functions Pages and Groups constitute a news curation and dissemination machine [22], which could then be available to any interest group for manipulation of public opinion [19] or intentionally fracturing an information ecosystem [23].

The Fediverse and Open Social Media

The problems associated with current social media platforms indicate that if social technologies are to be used for knowledge translation in medicine and public health, this translation should only take place on digital platforms where users are not exploited to create value for the platform’s business partners and investors. The fediverse concept denotes an ensemble of open social media that can communicate with each other while remaining independent platforms [24]. With the emergence of open microblogs such as Mastodon [25] and Bluesky [26], the photo-sharing service Pixelfed [27], and the video service PeerTube [28], users can choose how they want to participate and own their data. Users sign up to specific instances in the fediverse and these instances host their data. The instances are operated by various actors, ranging from the Mastodon project to public institutions, for-profit corporations, nonprofit organizations, and groups of individual users. Technically, the fediverse consists of interconnected network servers running software applications that can read and write the same content.

The open architecture of the fediverse can be compared to that used for email messaging. The email user does not have to compose, organize, and read messages in the same software application, and two users do not have to use the same tools to communicate. The underlying idea is that email simply represents a source of data, and thus many software applications should be able to understand and manipulate these data. In other words, although email applications can have different interfaces, privacy policies, and purposes, every email application can interpret the meaning of an email address and every email address can send messages to every other email address, regardless of the application used. Similarly, if a user posts on Mastodon in the fediverse, another user can see the post in their Pixelfed feed.

The key enabler of the fediverse has been ActivityPub, a communication protocol overseen by the World Wide Web Consortium. More recently, other similar protocols have appeared, including AT managed by Bluesky. In Germany, government institutions, universities, and newspapers have
already begun using such forms of open social media [29]. This enables these organizations to control their own channels while still being able to communicate with other platforms through the open standards. In several other countries, many institutions, ranging from public service organizations such as the BBC in England to civil society organizations, have chosen to establish themselves with official accounts at alternative digital platforms. However, reliable data on the magnitude of the migration to alternative digital platforms remain scarce. One early study estimated that approximately 2% of Twitter users deleted their accounts and left the platform for the Mastodon project within the first weeks following the Musk takeover [30]. Approximately 15% of the followers of these users migrated to the exact same Mastodon instance as that of the users they follow. While the larger Mastodon instances attracted more users (the 25% largest instances on Mastodon attract 96% of users), the smaller instances, directed toward specific topics, attracted the more active users.

**Translation of Health Knowledge on Social Media**

Based on their responsibility for the peer review, verification, and distribution of research findings, scientific journals play a central role in knowledge translation. Medical and public health journals currently use social media platforms for the promotion and dissemination of content, branding, and facilitating conversation [31,32]. Although the number of social media posts shows a positive correlation with journal Altmetric scores and impact factors [33,34], there is no evidence for causal associations between social media activity and improved knowledge translation. Typically, approximately 40% of all scientific literature is posted on social media [35]; however, half of these posts draw no clicks to the underlying research, whereas an additional 20% of the posts receive only one or two clicks [36]. Moreover, the citation of articles by other researchers will not benefit from social media posting [37]. Instead, the social media presence of scientific journals may indirectly impede rational knowledge translation by luring potential users of new health knowledge to digital environments where research evidence is not necessarily discriminated from unrestrained streams of disinformation. Therefore, medical and public health journals have multiple motivations for reevaluating their social media presence and considering movement to open platforms or even leaving social media altogether. Reconsidering their social media presence is also relevant for the academic and health service institutions that produce and use the knowledge managed by scientific publishers. Establishing accounts and developing the ability to communicate on open microblogs such as Mastodon and Bluesky have become a technically viable alternative along with the use of open standards and protocols such as ActivityPub and AT. By moving to open social media platforms, health institutions can create a digital community that owns and operates their own channels for communication with each other, policy makers, and the public. Open platforms are not susceptible to the capriciousness of private companies and can also provide channels for the dissemination of unaltered health knowledge required during contingencies such as a pandemic. However, moving only one or a few health institutions from platform X to open platforms will not suffice in creating such digital environments.

**Toward a Social Internet for Medicine and Public Health**

A new kind of social internet is currently forming. As of February 2024, approximately one-fifth of daily Twitter/X users had left the platform since the Musk takeover in 2022 [38,39]. Considering the status of the social media industry, a short-term goal of medical and public health institutions should begin with contemplating the purpose of their social media presence and explaining how they protect health science beneficiaries from being misled by disinformation (eg, whether and how they promote science literacy [40]) among their followers.

In parallel, a broad discussion is needed about the use of social technologies for knowledge translation in medicine and public health. Examples of translation of medical knowledge in social media platforms where users are less exposed to disinformation are beginning to appear [41]. However, the new social internet also offers possibilities for novel, innovative forms of knowledge translation (eg, in demanding settings such as global health contingencies). For instance, as grounding for a synchronized response to a future pandemic, social media instances with purposive interaction rules [42] can proactively be created in interpandemic periods. Here, instances can be created for separate professional disciplines (from virologists to modelers) and policy-maker categories (from public health officers to politicians) [43]. In parallel, a set of orthogonal instances, organized as multidisciplinary networks, can be created where the professionals and policy makers can collaborate in local and regional response programs [44].

Continued discussion about the use of social media for knowledge translation in medicine and public health should involve researchers and health service practitioners, academic leaders, scientific publishers, social technology providers, policy makers, and the public. This debate should not primarily take place on social media platforms but also at universities, in scientific journals, at public seminars, and other venues, enabling the transparent and undisturbed communication and formation of opinions.

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Authors' Contributions

TT conceptualized the idea and wrote the manuscript.

Conflicts of Interest

None declared.

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Evidence-Based Learning Strategies in Medicine Using AI

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Abstract

Large language models (LLMs), like ChatGPT, are transforming the landscape of medical education. They offer a vast range of applications, such as tutoring (personalized learning), patient simulation, generation of examination questions, and streamlined access to information. The rapid advancement of medical knowledge and the need for personalized learning underscore the relevance and timeliness of exploring innovative strategies for integrating artificial intelligence (AI) into medical education. In this paper, we propose coupling evidence-based learning strategies, such as active recall and memory cues, with AI to optimize learning. These strategies include the generation of tests, mnemonics, and visual cues.

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KEYWORDS
artificial intelligence; large language models; ChatGPT; active recall; memory cues; LLMs; evidence-based; learning strategy; medicine; AI; medical education; knowledge; relevance

Introduction

e-Learning has revolutionized the way medicine is taught and learned through the use of different internet-based technologies that enhance education [1]. Among these technologies, artificial intelligence (AI) tools, especially large language models (LLMs), have notably garnered significant attention in recent years, given their promising implications for medical education. LLMs are algorithmic models that are trained by extensive data sets, and they have the capability to comprehend text and generate natural-language text in response to a given prompt (input). This allows for interactive engagement with these technologies in a conversational format akin to a “chat” [2,3]. One of the most known LLMs is ChatGPT (owned by OpenAI), and its latest version, ChatGPT-4, was recently released to the public.

Recent studies have demonstrated the great achievements of LLMs in relation to medical knowledge and reasoning, such as ChatGPT-4 scoring 90% when answering USMLE (United States Medical Licensing Examination)-type questions [4], ChatGPT-4 passing a neurosurgery written board examination [5], and ChatGPT outperforming physicians in terms of providing empathic responses [6]. The educational potential of this technology is immense, encompassing a wide variety of applications. These include but are not limited to tutoring (personalized learning), patient simulation, generation of examination questions, and streamlined access to information [7-9]. The revolutionary potential of LLMs has resulted in researchers and medical students exploring the integration of AI into medical school curricula [10,11]. The rapid advancement of medical knowledge and the need for personalized learning underscore the relevance and timeliness of exploring innovative strategies for integrating AI into medical education [12].

Although numerous publications have examined the implications of LLMs for medicine and medical education, few have explored, in detail, specific strategies whereby LLMs can be used to optimize learning. In this paper, we propose strategies based on active recall, mnemonics, and the use of ChatGPT-4 [13] and DALL·E 3 (through ChatGPT-4) for enhancing learning outcomes regarding factual knowledge and thus help fill this gap of information. These strategies include the creation of pretests and posttest quizzes, the development of mnemonics, and the use of visual cues and mnemonics. Pretests and posttests serve as effective tools for active recall—a proven method for improving memory retention. Mnemonics simplify complex information into more digestible and memorable formats. Visual cues provide a graphical representation of information, aiding in better understanding and recall.

Active Recall–Based Strategies

Medical school requires a significant amount of time spent on reading. Research indicates that medical students typically dedicate an average of 1.5 to 6 hours per day to reading [14,15]. Moreover, teacher-centered lectures, which predominantly focus
on passive learning, persist as one of the most used strategies despite challenges in the medical education community with regard to encouraging integration with active learning methods that enhance the retention and application of knowledge [16-18]. This may be because medical school students might prefer classic didactic lectures over demonstrations, small group discussions, feedback activities, group work (generating test questions and coming up with solutions to a problem), and other active learning methods that have been reported to better enhance memory and retention [19].

It is essential to adopt evidence-based strategies to enhance learning efficiency, especially considering the substantial academic workload and the ongoing reliance on passive learning methods. One such strategy is active recall, which involves actively retrieving information that was initially acquired passively through lectures, articles, or videos. This strategy is known to enhance learning significantly in comparison with passive learning strategies [20,21]. In this context, it is beneficial for readers to approach their reading proactively. This can be achieved by prefacing their reading with self-directed inquiries, understanding the main topics of the material, consistently formulating questions, and recognizing key concepts of high significance. Some related techniques include elaborative interrogation, which consists of answering “why” questions about a given concept to enhance medium- to long-term associative memory; self-explanation to relate new information to known information or explain steps taken for solving a problem to improve memory, comprehension, and transfer; and practice testing, which can improve memory, is not as time consuming, and can be applied at different times of the learning process [20].

One application of an active recall–based strategy involving the use of AI is illustrated in Figure 1, which shows ChatGPT being instructed to generate questions about cellulitis, as an example. Students are encouraged to attempt such questions before starting lectures or reading text. Answering questions before attending a lecture or reading a text (pretesting) is a strategy that enhances the learning process [22]. Interestingly, making mistakes during the study process can enhance learning by improving later memory; generating correct feedback; facilitating active learning; and stimulating the learner to redirect attention appropriately, especially when a mistake is followed by corrective feedback [23,24].
Taking tests has been proven to enhance learning in various studies [25-28]. Repeated test-taking increases the transfer of learning [25] and improves long-term recall [28], and it even outperformed concept mapping for long-term retention in a previous study [26]. This strategy can be integrated with AI, as shown in Figure 2, which depicts our attempt to extract information from a StatPearls article on cellulitis [29] and request ChatGPT to generate relevant questions. The AI system can produce various question formats, such as multiple-choice, true-false, and fill-in-the-blank questions, when given the appropriate prompts. These questions may be stored and reviewed days or weeks after the initial review to successfully apply spaced repetition, which has been demonstrated to improve learning and the consolidation of knowledge [21].

By using this method, one can input answers to questions and prompt ChatGPT to evaluate the answers’ accuracy against the provided text. For instance, using questions from Figure 2, we tested ChatGPT’s response by answering a query about common causative bacteria of cellulitis. We intentionally incorporated broad, correct concepts (gram-positive bacteria) and specific yet erroneous details (emphasizing staphylococci, particularly *Staphylococcus aureus*, as primary causatives instead of the correct streptococci) (Figure 3). ChatGPT feedback was tested again to contrast it with the feedback on a completely wrong answer (Figure 4).
Figure 2. Example of the use of ChatGPT for creating a posttest.
Figure 3. Feedback from ChatGPT on a partially correct answer to a question provided by ChatGPT.
Memory Cues

Memory cues are learning strategies in which a process of metacognition transforms information in a way that makes the information easier to recall or understand. Cues can be self-generated or generated by external agents, other people, or AI. Evidence has long suggested that self-generated cues are superior to cues generated by other people [30,31]. Nonetheless, there is available evidence that indicates that memory cues generated by others can still enhance recall [32].

Memory cues are effective because they make difficult-to-remember information into something simpler or meaningful, which facilitates recall [32,33]. For example, a classic memory cue in medical school for remembering descriptors of pain is the use of the mnemonic “SOCRATES” (site, onset, character, radiation, associations, time course, exacerbating factors, and severity). In this context, the name of the great philosopher is repurposed to recall how to properly assess pain in a patient, with the name becoming an acronym. In a recent meta-analysis, a statistically significant effect was found for cueing decreasing the learners’ perceived cognitive load and promoting learning outcomes, namely retention, and the transfer of knowledge [34].

Other modalities of memory cues that are commonly used include pictures, short stories, songs, and rhymes [32]. Evidence indicates conflicting conclusions regarding the superiority of a specific modality of cues over another. For instance, in a study
conducted by Pearson and Wilbiks [35], the authors attempted to evaluate the effect of the number of self-generated memory cues and aimed to test the findings of previous research that showed that the use of multisensory memory cues (i.e., audiovisual cues) had a greater effect on recall than the use of one modality (i.e., either visual cues [written words] or auditory cues [spoken words]). Their findings were that a greater number of cues led to higher recall, with statistical significance, but the modality of the cues did not have an effect on recall.

As previously indicated, one way to enhance the creation of an effective mnemonic is by using a common word as a cue to recall information [33]. This is one of the various ways that learners attempt to encode new vocabulary, abstract concepts, and master knowledge.

Figure 5 is an example of ChatGPT generating a mnemonic, using the word “brains” to recall the absolute contraindications of thrombolysis. Other examples are shown in Figure 6, in which ChatGPT creates a short story, and in Figure 7, in which ChatGPT creates a poem.

Figure 5. Acronym created by ChatGPT.
Figure 6. Short story created by ChatGPT.
Visual Mnemonics

A visual mnemonic or cue is a tool that uses visual imagery to improve the recall of information. This differs from verbal mnemonics, which use words, phrases, or songs, as visual mnemonics use pictorial cues to forge memorable links. Their effectiveness stems from the incorporation of visual representations, analogies, or symbolism, which fortifies the associations and makes them more distinct. Visual mnemonics aid in recalling abstract or intricate information and facilitate both the sequential and the immediate retrieval of memorized material [36,37]. The use of mnemonics can be highly useful for learning difficult or abstract information [30], which is often found in the field of medicine [38]. Multiple studies have demonstrated that using visual or pictorial mnemonics can enhance learning outcomes [35,39].

DALL·E 3 is an AI system created by OpenAI that generates images based on prompts provided by the user and can be used for the creation of visual mnemonics. An example is given in Figure 8; a prompt was given to DALL·E 3 to create an image. For this example, which we created via DALL·E 3, the prompt “Fat purple man with long hair falling into a trap in a dry desert” was used to help recall some important features of hairy cell leukemia. “Fat” was used to recall the massive splenomegaly seen in patients with this condition; “purple” was used to make an association with lymphocytes, which are commonly seen as purple cells via hematoxylin and eosin staining and are involved in the pathogenesis of this neoplasm; “long hair” helps with
recalling the filamentous projections of cells in hairy cell leukemia; “trap” was used to remember that this disease stains positively in tartrate-resistant acid phosphatase staining; and “dry desert” was used to recall that bone marrow fibrosis leads to dry tap on aspiration.

**Figure 8.** DALL·E 3 creation with the prompt “Fat purple man with long hair falling into a trap in a dry desert.”

**Discussion**

**Active Recall**

Active recall is a highly effective learning strategy and significantly outperforms passive restudying when it comes to certain learning outcomes, such as conceptualization and long-term retention [21]. It has yielded better evaluation testing performance than traditional studying or rereading. Kornell et al [22] reviewed recall when participants were presented with fictional and nonfictional information, modifying the time for pretesting and read-only strategies. The testing strategy yielded a greater amount of correct answers than the read-only strategy, with statistical significance when equal or more time was allocated to the testing condition when the final test was performed more than 24 hours after the learning exercise, as well as in the fictional topic scenarios (P<0.01). Other studies supporting the use of pretesting have been reported [22,40,41]. This highlights the role of pretesting in learning new information.
The benefits of active learning through testing have also been supported by other authors. Butler [25] tested students’ recall ability when they were either passively restudying or studying via repeated testing. Butler [25] found that repeated testing resulted in better performance on a recall test than passive learning strategies and concluded that repeated test-taking increases the transfer of learning. In another study performed by Karpicke and Blunt [26], when retrieval practice (testing) was evaluated against passive learning strategies and even concept mapping, it proved to be better for verbatim and inference question answering, resulting in an improvement of about 50% in long-term retention scores ($d=1.50$; $F_{1,38}=21.63$; $\eta_p^2=0.36$). Additionally, the superiority of retesting over passive restudying for long-term retention has even been proven in a randomized controlled trial, wherein pediatric and emergency medicine residents were randomized to study the same text passages either via testing or repeated studying (ie, rereading). They were then tested on day 1, week 2, week 4, and month 6. The test results showed that the scores of participants who studied via testing were, on average, 13% higher than the scores of participants who performed repeated studying ($P<.001$), with an effect size of 0.91 [28]. Spaced testing (taking tests on different days between study sessions) has an even better effect on retention, long-term memory, and evaluation performance than repeated test-taking [27]. On the other hand, research indicates that spaced repetition (regardless of whether studying is done actively or passively) promotes more efficient and effective learning [42]. The previously mentioned studies highlight the importance of leveraging evidence-based techniques for studying rather than passive learning strategies. As we exemplified, these strategies can be coupled with AI. This approach addresses the limitation of relying solely on teacher-provided tests or textbook tests [20]. Moreover, ChatGPT is available on different platforms (web application and mobile app), and it can save chats (interactions) across these platforms. Therefore, students can easily access ChatGPT wherever it is needed and space their study sessions. Further, self-testing with AI reduces the pressure of graded assessments and leverages errors as learning opportunities [23,24], which research has shown to be particularly effective when the learner is confident in their incorrect answers [23]. This could be related to the effect of feedback.

Several articles on active recall and learning emphasize the role of feedback in enhancing learning processes, which is a characteristic that passive studying lacks. Roediger and Butler [27] compared traditional studying with test-taking studying without feedback and test-taking studying with differently timed feedback to determine whether test-taking studying results in better retention and whether retention is enhanced by feedback. They tested participants at different times and highlighted the efficiency of test-taking as a studying strategy, which was superior to that of traditional reading and restudying (22%, 32%, and up to a 43% difference between traditional studying and test-taking studying without feedback, test-taking studying with immediate feedback, and test-taking studying with delayed feedback, respectively). Since feedback has a clear impact on learning, especially when coupled with active recall strategies, non–AI-mediated active learning strategies could be limited by the lack of opportunities to offer feedback. Feedback generally comes from a reliable source, such as a teacher or an expert, or is obtained through an appropriate literature search, which can be time consuming. Sometimes, it is not possible to have the timely intervention of a teacher or an expert if there is a lot to study, and it may not be possible for a student to conduct a proper literature search if the student is new to a given topic. Furthermore, there are different types of feedback; some feedback is self-directed (ie, obtained through an introspective process). Feedback in the learning process can be used to enhance or develop skills for setting goals, monitoring one’s own learning process, and assimilating input (feedback) toward enhancing performance [43]. All of these are important skills to have when one attempts to obtain feedback on their own, such as when using LLMs for feedback.

AI can enhance medical education by offering feedback and explanations to clarify incorrect responses, thereby increasing study efficiency. By using AI tools like ChatGPT, students can receive detailed feedback on their answers, including the identification of errors and the provision of correct information, as we have shown. ChatGPT presents promising implications in providing technically accurate medical feedback, given the exceptional knowledge it has exhibited, as we previously described. This process, however, should not replace thorough literature research or foundational knowledge acquisition. AI models can also serve as tutors to facilitate discussions on specific knowledge areas, similar to existing models in other fields, such as Khan Academy’s Khanmigo, which serves as a fully personalized tutor [44]. One limitation of AI systems like ChatGPT is their character limit for inputs, which can be managed by breaking text into sections or using multiple prompts. Additionally, web searching is only available with ChatGPT’s paid subscription; for the free version, one should provide ChatGPT with the reference text by copying and pasting it. Further research is needed to explore the potential of AI-assisted tutors in medical education, especially in education on basic subjects.

**Memory Cues**

Memory cues can be used as effective learning tools that ease the studying experience for a student attempting not only memorization but also mastery of complex concepts and new vocabulary. Evidence has described the superiority of self-generated memory cues over cues created by others [30,31]. The explanations behind the superiority of self-generated memory cues are (1) the generation effect of creating such cues, that is, the act of generation requires significant cognitive effort, which boosts memory, and (2) the cue selection process itself and the consequential metamnemonic effect. This means that students who identify the learning formats that work best for them are able to create their own memory cues by using a modality that is tailored to their needs [31]. For example, if a student prefers to have a visual representation of the ideas that they are attempting to memorize, they might lean toward the creation of mnemonics that create a mental picture to integrate information. Tullis and Fraundorf [31] proposed evidence that the benefits of self-generated cues come in great part from the correct selection of a cue from a list of candidates. If students
can create multiple cues, they can, with greater effectiveness, select the cue that best benefits retrieval. Tullis and Fraindhoven [31] further suggested that allowing a learner to select from multiple options of cues requires less cognitive work, takes less time, and may not hinder memorization.

As we described, the act of generation is effortful and may be time consuming. AI tools like ChatGPT can help students as a result of their seemingly tireless and effortless generative capacity. In addition, these tools can create multiple cues with different modalities (textual-based cues and pictorial cues) when prompted to do so, thereby allowing learners to focus on understanding the material and selecting the most appropriate cue that fits their educational needs. The downside to the use of this method is that multiple attempts may be required for ChatGPT to produce a mnemonic that is subjectively good or fitting enough for a particular student. In addition, it is our opinion that these tools are best used when the user has an idea of what they should learn or memorize, and the user should prompt the AI tool to create a mnemonic device that facilitates the recall of the information they wish to encode. This is because there is abundant evidence of ChatGPT not only making errors but also blatantly providing false information [45], which is known as “artificial hallucination.”

Visual Mnemonics

Previous research has explored the effectiveness of visual mnemonics in improving learning outcomes. An experimental study that compared pictorial mnemonic use to traditional study methods found that pictorial mnemonics aid in learning from text passages by improving the recall of factual knowledge and long-term memory retention in college students [46]. Additionally, a randomized trial compared audiovisual mnemonics against traditional text-based learning for retaining medical knowledge; participants who used mnemonics demonstrated significant improvements in free-recall tests, with scores improving by 65%, 161%, and 208% immediately, after 1 week, and after 1 month, respectively, when compared to those who used text materials (P<.001). Moreover, the group that used mnemonics outperformed the group that used text materials by 55% in a 1-week-delayed multiple-choice test that focused on higher-order thinking (P<.001) [47]. In a comparative study of visual mnemonics versus traditional lectures for learning the porphyrin pathway, there was no significant difference in quiz scores immediately or 1 week after the intervention; however, the mnemonic group exhibited a 20% higher score 3 weeks later (P=.02) [48]. In another randomized trial that compared story-based audiovisual mnemonics with traditional text reading for memory retention among medical students, the audiovisual mnemonics group demonstrated significantly better performance in multiple-choice tests immediately after the intervention (P=.04), as well as at 1 week, 2 weeks, and 4 weeks after the intervention [49]. These results underscore story-based mnemonics’ superior effectiveness in enhancing immediate and long-term memory retention in medical education. Although there is some variation in the visual mnemonic techniques across studies (eg, the studies by Yang et al [47] and Abdalla et al [49] used some audiovisual mnemonics), they consistently demonstrated that factual knowledge can be represented visually and that the use of this type of mnemonic enhances both the recall and long-term retention of knowledge, with large effect sizes.

The visual mnemonic proposed in our study highly resembles the strategy used in the experiment by Rummel et al [46], in which visual mnemonics were created from texts about psychologists, incorporating elements for recalling both the psychologists’ names and the key aspects of their theories. In our mnemonic, “long hair” aids in recalling the name of the disease (hairy cell leukemia), and the other elements in the image are used to help recall the disease’s main features. The Picmonic System, which uses mnemonics from a web-based educational platform [50] that was used in the studies by Yang et al [47] and Abdalla et al [49], also adopts the visual mnemonic approach by combining visual elements and storytelling to enhance the recall of information; this is also highly similar to our approach. Thus, using DALL·E 3 for mnemonic generation shows promise for improving different learning outcomes, such as test performance, long-term retention, and free recall. Future studies should experimentally investigate the effectiveness of visual mnemonics generated by text-to-image models in learning processes. A significant limitation of using DALL·E 3 for medical mnemonic generation is its restriction on explicit content, prohibiting prompts with terms like “blood.” By recognizing this limitation, knowledge area–specific text-to-image models can be developed to more accurately describe the information needed and enable the use of words that are commonly used in a knowledge area but are censored in current models. Another limitation is that creating stories that accurately reflect the intended factual knowledge for mnemonic cues can be complex, particularly for certain subjects. Effective prompt engineering techniques could help in creating more relevant and coherent visual mnemonics.

Conclusions

LLMs, as a form of AI, are transforming the landscape of medical education. They offer a vast range of applications, and their potential has sparked discussions about integrating them into medical school curricula. Active recall–based learning strategies can be integrated with AI and can promisingly improve the recall and retention of information. This integration can be effectively applied by using AI to generate pretests and posttest quizzes. Memory cues, including self-generated mnemonics and mnemonics created by AI, can effectively simplify and transform complex information, thereby enhancing recall and optimizing learning. ChatGPT can create multiple types of memory cues, such as acronyms, short stories, and even poems. Moreover, AI tools, like DALL·E 3, can create images based on text and thus can be used to create visual mnemonics. However, crafting the right prompts can be challenging and time consuming, and results may vary. Thus, we believe that the use of new AI-based technologies, such as ChatGPT and DALL·E 3, is a highly useful strategy for learning, especially when these technologies are used with evidence-based principles. Further research is warranted to elucidate the impact of these strategies within the context of medical education.
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Abbreviations

- **AI**: artificial intelligence
- **LLM**: large language model
- **SOCRATES**: site, onset, character, radiation, associations, time course, exacerbating factors, and severity
- **USMLE**: United States Medical Licensing Examination

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Development of a Novel Web-Based Tool to Enhance Clinical Skills in Medical Education

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Abstract

A significant component of Canadian medical education is the development of clinical skills. The medical educational curriculum assesses these skills through an objective structured clinical examination (OSCE). This OSCE assesses skills imperative to good clinical practice, such as patient communication, clinical decision-making, and medical knowledge. Despite the widespread implementation of this examination across all academic settings, few preparatory resources exist that cater specifically to Canadian medical students. MonkeyJacket is a novel, open-access, web-based application, built with the goal of providing medical students with an accessible and representative tool for clinical skill development for the OSCE and clinical settings. This viewpoint paper presents the development of the MonkeyJacket application and its potential to assist medical students in preparation for clinical examinations and practical settings. Limited resources exist that are web-based; accessible in terms of cost; specific to the Medical Council of Canada (MCC); and, most importantly, scalable in nature. The goal of this research study was to thoroughly describe the potential utility of the application, particularly its capacity to provide practice and scalable formative feedback to medical students. MonkeyJacket was developed to provide Canadian medical students with the opportunity to practice their clinical examination skills and receive peer feedback by using a centralized platform. The OSCE cases included in the application were developed by using the MCC guidelines to ensure their applicability to a Canadian setting. There are currently 75 cases covering 5 specialties, including cardiology, respirology, gastroenterology, neurology, and psychiatry. The MonkeyJacket application is a web-based platform that allows medical students to practice clinical decision-making skills in real time with their peers through a synchronous platform. Through this application, students can practice patient interviewing, clinical reasoning, developing differential diagnoses, and formulating a management plan, and they can receive both qualitative feedback and quantitative feedback. Each clinical case is associated with an assessment checklist that is accessible to students after practice sessions are complete; the checklist promotes personal improvement through peer feedback. This tool provides students with relevant case stems, follow-up questions that probe for differential diagnoses and management plans, assessment checklists, and the ability to review the trend in their performance. The MonkeyJacket application provides medical students with a valuable tool that promotes clinical skill development for OSCEs and clinical settings. MonkeyJacket introduces a way for medical learners to receive feedback regarding patient interviewing and clinical reasoning skills that is both formative and scalable in nature, in addition to promoting interinstitutional learning. The widespread use of this application can increase the practice of and feedback on clinical skills among medical learners. This will not only benefit the learner; more importantly, it can provide downstream benefits for the most valuable stakeholder in medicine—the patient.

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KEYWORDS

medical education; objective structured clinical examination; OSCE; e-OSCE; Medical Council of Canada; MCC; virtual health; exam; examination; utility; usability; online learning; e-learning; medical student; medical students; clinical practice; clinical skills; clinical skill; OSCE tool

Introduction

In 2020 and 2021, over 5000 final-year medical students graduated from a Canadian medical program and were matched to a residency program [1]. For these cohorts, portions of in-person clinical learning were limited due to the COVID-19 pandemic. Alongside clinical learning, the COVID-19 pandemic also caused numerous academic and health care institutions to
adopt more web-based learning platforms [2], thus emphasizing the importance of remote learning in the current day.

Prior to 2021, final-year Canadian medical students were required to pass an objective structured clinical examination (OSCE) held by the Medical Council of Canada (MCC) in order to progress to a residency training program [3]. Although this requirement has ceased for Canadian medical graduates, OSCEs remain integral within the medical education curriculum by serving as assessment tools for clinical skills. The goal of these OSCEs is to assess the candidate’s clinical judgment, reasoning, knowledge, and skills. The examination is typically divided into twelve 11-minute-long stations, with a 2-minute break between each station. Stations can include clinical problems within the following fields: internal medicine, surgery, pediatrics, obstetrics and gynecology, psychiatry, and preventative medicine and public health [3].

The resources available to medical students for OSCE preparation and the real-world clinical setting are few and far between. Although such resources exist, they are limited by one or more factors. One of the biggest limitations for existing OSCE resources is that they are not specific to the MCC objectives, thus restricting their use in a Canadian medical education setting. Another major limitation is that they are often not directed at medical students but rather at students in other health care disciplines, such as pharmacy students and nursing students. Although these resources are beneficial for practice purposes, other professions have different scopes of practice, and the OSCE feedback generated for students via such resources may not always be translatable. Additionally, many of the existing OSCE preparation tools require user setup with platforms such as Zoom or Microsoft Teams; there are few that exist as stand-alone applications through which students can access feedback, clinical prompts, and OSCE assessments within a single centralized platform.

Another important limitation of existing resources is the inability to provide users with feedback regarding their clinical performance, specifically through formative learning experiences. Clinical educators often utilize quantitative scores and feedback in the form of checklists in order to provide students with assessments of their performance. However, this may not always be possible, given the time constraints of clinicians and staff. A possible solution to this is the utilization of peer feedback through formative learning experiences [4]. Unlike summative assessments and examinations, formative learning experiences provide students with opportunities in which they are able to focus on skill development as opposed to percentages and grades. Several studies have demonstrated the benefits of formative experiences, such as encouraging reflective review, reducing test anxiety, and advancing the learners’ self-regulation skills [5,6]. Moreover, the remote nature of web-based platforms for formative learning can contribute to interinstitutional learning, in which peers who have additional knowledge or exposure within certain medical fields can enhance the clinical skills of those whose training lacks in these areas.

Given the emphasis on web-based learning and the fact that few formative learning experiences exist for students, it is evident that there is a need for an electronic OSCE (e-OSCE) preparation tool that fills the aforementioned gaps in the medical education system. Thus, the beta version of the MonkeyJacket application for OSCE practice was developed with these gaps in mind [7]. The e-OSCE tool was piloted among a group of 6 medical students and resident physicians at Western University and McMaster University, with the goal of providing direct feedback to the software development team to refine the utility of the application. The primary research objective of this study was to describe the approach to the development and dissemination of the MonkeyJacket e-OSCE application tool. This paper also aims to describe the platform itself, the potential utility of the application as a tool that provides scalable formative feedback for learners, and how the application serves as a valuable tool in Canadian undergraduate medical education.

**Development**

**Purpose of Development**

The MonkeyJacket platform was built for the purpose of developing a formative learning experience (ie, rather than a summative one) in which the goals are to practice with various clinical cases and receive feedback through peer evaluations.

**Tool Development**

The backend of the MonkeyJacket platform was developed by a team of software engineers, project managers, and data scientists. The platform, including the video chat functionality, was custom coded by using a combination of Jitsi (8x8 Inc) and JavaScript Node.js (OpenJS Foundation). Through numerous rounds of user testing and quality control, the application was consistently reviewed and improved by the development team to ensure a smooth experience for users.

**Development and Testing of the Application**

The cases for the MonkeyJacket application were created by medical students and resident physicians. The trialing and testing of the application were conducted by a group of 6 medical students and resident physicians over a span of 3 months. Group members were encouraged to practice with everyone in the group to allow for diversity in perspectives and promote intragroup learning during the testing period. In addition to seeking group feedback regarding the practice cases and feedback checklists, the user study group was encouraged to provide feedback regarding functionality and ease of use. Comments were then relayed to the development team, and appropriate changes to the application were made.

**Inclusion of Cases**

The goal was to build practice cases that address CanMED (communicator, collaborator, leader, health advocate, scholar, professional, and medical expert) roles and provide formative feedback in the following disciplines: cardiology, respirology, gastroenterology, neurology, and psychiatry [8-10]. Within each discipline, cases were developed based on common and vital red-flag clinical presentations across patient demographics. Additionally, some uncommon and highly fatal conditions were also included within the data set to represent the diversity of cases seen in clinical settings. There are a total of 75 cases in

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(page number not for citation purposes)
Building the Physician Candidate Prompts

The next step was developing the clinical prompt and task for each case, for both the student presenting as the “patient” and the student practicing as the “physician.” We followed the MCC guidelines in ensuring that prompts were written in a clear and unambiguous manner and tasks could be completed in real time. For example, we avoided prompts such as “explore this further with the patient” and instead replaced them with prompts such as “take a thorough history, with a focus on GI symptoms and summarize your findings.” We also avoided time-defining phrases, such as “the symptoms started at 9am,” and instead replaced them with more definite timelines, such as “2 hours ago.” All clinical stems included the patient’s name, age, gender, and presenting symptoms and the task(s) that must be completed by the physician. The cases were framed such that it was the candidate’s first time assessing the patient, rather than assuming that they had a pre-existing relationship with the patient.

Compiling Information for the Standardized Patient and Trainers

All patient case stems included the following demographic data: the patient’s name; age; occupation; opening statement or history of the presenting illness, including symptoms with qualifications (onset, duration, quality, severity, timeline, alleviating factors, etc); associated symptoms; past medical history; medication history; family history; and social history. For the latter items, only positive histories (eg, if the patient has a history of past illnesses or a family history) were given. Nonverbal cues were also indicated on the patient’s prompt so that they could be communicated to the physician, especially in psychiatry stations (eg, “I avoid eye contact, either looking at the ground or focusing on my hands. I give limited information making it obvious that I’m holding something back.”).

Developing the Feedback Checklists

In deciding the number of checklist items for each clinical prompt, we included items that were relevant to assessing the candidate’s abilities and ensured that the checklists were not exhaustive. The number of items on each checklist depended on the complexity of the case, but most checklists consisted of 30 to 40 items. The checklist items all began with an action verb to guide the standardized patient, who is also the examiner, on what was expected from the physician.

Using the MCC guidelines, we ensured that the items were discrete, observable, and dichotomous. Toward ensuring that items were discrete, each checklist item assessed for 1 concept or grouped concepts together; the candidate could get the full score even if they asked about 1 concept within the group. For example, a checklist item for qualifiying pain was “Elicits character of pain – sharp, dull.” For this checklist item, the candidate would get full marks for asking about any character of pain. In ensuring that items were observable, we avoided terminology including “understands” and “appreciates” and instead used terms like “asks about” and “gives reasonable differential diagnoses.” Toward ensuring that items were dichotomous, the candidate either received the full mark for the item or did not; the checklist did not have any rating scales or instructions regarding part marks.

Review, Revise, and Pilot

The MCC states that case development is an iterative process requiring thought, review, and revision, and thus one should be open to feedback. The first step of the review involved the medical development team, which consisted of medical students and resident doctors, piloting the application in an iterative process to continue to refine the platform. This allowed us to identify missing information from the patient script and review the checklist to reduce ambiguity. Additionally, the cases were also reviewed by attending physicians in order to increase the validity of the clinical situations.

Ethical Considerations

This study did not contain or capture any human information or data. Therefore, as per Article 2.4 from the Tri-Council Policy Statement Research Ethics Board, this study was exempt from research and ethics review and did not require research ethics board approval [14].

Application Interface and Features

Description of the Application

Upon entry into the platform, students land on a home page in which they are able to enter their email and password credentials (Figure 1). Prior to the start of an OSCE station, the student completing the station as the acting physician receives a brief prompt that introduces the patient’s name, age, and chief complaint (Figure 2).
Once both students press “Begin station,” the practice OSCE station starts, and the session begins. In this example, student A is practicing their skills as the “physician,” and student B is providing feedback as the “patient.” During this time, student A is only able to see the brief clinical prompt entailing the chief complaint. However, student B is able to view a more extensive patient history, along with behavioral cues, and the feedback checklist for items that student A should inquire about during the patient interview. While student A takes the history, student B is responsible for completing the checklist along with answering clinical questions, which are asked by student A, based on the history provided (Figure 3). At the end of the practice OSCE station, student B is responsible for completing the assessment checklist for student A in order to successfully save and submit the practice session.

Figure 1. Main log-in screen of the MonkeyJacket platform. OSCE: objective structured clinical examination.
Figure 2. Example screen of the student in the role of the physician. The student physician is able to see the student patient on the left side of the screen and a blank clinical note that may be filled during the encounter.
Figure 3. Example of the MonkeyJacket platform screen as seen by the student in the role of the standardized patient. The case details are shown on the left, and the checklist assessment is shown on the right.

Feedback Checklists

Checklist items can be divided into two categories: (1) generic items and (2) items relevant to the presenting concern. Examples of general checklist items can be found in Textbox 1.

Relevant checklist items are those that are pertinent to the primary presenting concerns of the patient. For example, if the patient presents with shortness of breath, some relevant checklist items could include those listed in (Table 2).

At the end of all assessment checklists, the student is also asked to state the top 2 or 3 differential diagnoses based on the history presented. After stating the differential diagnoses, the student is asked for their top diagnosis. There are also other pertinent clinical questions that the student must answer. Examples of other clinical questions include questions about deciding on the most appropriate imaging modality, other diagnostic tests, and the initial management of the clinical presentation.

After assessment checklists are completed and submitted on the platform, a percentage score is calculated based on the total number of check marks received. The score is recorded and stored within the MonkeyJacket platform. Students are able to review all personal case attempts that they have completed within the platform. Additionally, audio files are also captured so that students can later review the session and reflect on not just their medical expert knowledge but also the soft skills of
communication and rapport building that they must demonstrate (Figure 4).

**Textbox 1.** Examples of general objective structured clinical examination checklist items.

- Introducing self
- Confirming patient’s name and age
- Explaining reason for consult
- Building initial rapport
- Gaining consent
- Asking open-ended questions
- Asking about medications and allergies
- Exploring social history (including cigarettes, alcohol, recreational drugs, diet, occupation, and physical activity)
- Exploring and responding to ideas, concerns, and expectations
- Showing empathy
- Avoiding jargon
- Summarizing issues back to patient
- Global score
- Answering follow-up questions correctly

**Table.** Examples of relevant objective structured clinical examination checklist items, with the primary presenting concern being shortness of breath.

<table>
<thead>
<tr>
<th>Assessment checklist items</th>
<th>Examples of what should be asked about</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asking qualifying questions about presenting symptoms</td>
<td>Onset, duration, site, character, severity, duration, and timeline of pain</td>
</tr>
<tr>
<td>Asking about relevant associated symptoms</td>
<td>Coughing, recent calf pain, palpitations, fever, and chest pain</td>
</tr>
<tr>
<td>Asking about recent illnesses and past medical history</td>
<td>Heart disease, stroke, diabetes, hypertension, etc</td>
</tr>
<tr>
<td>Asking about relevant family history</td>
<td>Heart disease among family members aged younger than 55 y, diabetes, high cholesterol, autoimmune disease, history of atopy, etc</td>
</tr>
</tbody>
</table>
Discussion

Overview

The MonkeyJacket application is a novel, innovative, and unique tool for medical students seeking additional practice regarding the development of clinical skills. The overarching goal of the MonkeyJacket application is to fill the gap that exists within medical education—a lack of scalable formative feedback for clinical skill development for learners. The MonkeyJacket application addresses this gap through the focus on peer feedback and the technological features built within the platform. Additionally, the application keeps track of participants’ scores so that individuals may review the trend in and learn from their performance after practice sessions.

The biggest advantage of this platform is the potential for scalability it provides for medical learners. According to Medical Education Statistics 2020, there were 14,967 faculty members and 11,865 medical learners across Canadian medical schools by the beginning of 2020 [15]. On top of the clinical responsibilities of faculty members, they are also responsible for fulfilling teaching and academic requirements. As such, it is not feasible for faculty members to provide additional feedback to learners outside of the designated OSCE preparation time. The MonkeyJacket platform allows students to receive an abundance of feedback from peers, should they wish for...
additional practice. The scalability of the platform also decreases the administrative load on medical schools, as students would have simple access to additional clinical skills feedback that does not require constant faculty supervision.

Another significant advantage of the MonkeyJacket application is the remote nature of the web-based platform. Traditionally, practice OSCE examinations have been conducted in person, often with a student’s peer or friend. The utilization of the MonkeyJacket application is simple, in that it allows a student to share the link with anyone that has access to a computer and internet connection, thus allowing students to practice regardless of their geographical location. Moreover, medical students would be able to practice with students from other schools, thus promoting interinstitutional learning. A medical student residing in British Columbia could easily practice history-taking skills with a fellow student in Ontario, thus allowing both students to learn from each other and teach each other strategies that they have learned within their respective curricula. It is known that medical education institutions across Canada place emphasis on different areas of focus. For example, it was found that preclerkship pediatric clinical skills training greatly varied across the 17 Canadian medical schools, with 6 schools dedicating less than 7 hours and 8 schools dedicating over 10 hours—a total difference of 30% [16]. The development of a remote-based platform allows medical students to learn from their peers, who may have had more exposure within certain areas when compared to students’ own training, thus enhancing their knowledge.

In addition to the remote nature of the application, it also poses a great advantage in terms of its accessibility with respect to cost. A significant barrier to finding accessible practice resources for medical students is the cost associated with purchasing resources. It was found that, on average, osteopathic medical students spend US $4129 on resources exclusively in preparation for their board examinations [17]. Although this finding is specific to medical students in the United States, where there are different board examinations, Canadian medical students are not exempt from such costs. Canadian medical graduates, on average, finish medical school with CAD $164,688 (US $84,612 as of the time of writing) of debt, including education-related and non–education-related expenses [18]. Although numerous companies offer preparation courses, these can vary in cost from a few hundred dollars to several thousands of dollars. Thus, costs associated with expensive preparation courses and resources can be a significant barrier for students seeking resources. The MonkeyJacket platform is completely open access and free of charge. For medical students looking to gain extra practice, the MonkeyJacket platform provides a simple and accessible option, with multiple opportunities for peer evaluation and progress tracking.

Limitations

To ensure that the MonkeyJacket web application was serving its intended population, relevant feedback from medical students and residents was taken into consideration when developing the functions and design of the web application. Nonetheless, there were some limitations to this study.

One limitation of this study is the sample size of students included in the feedback process. In this study, there were 5 medical students and 1 medical resident involved throughout the testing process. At the time of writing, the 6 participants have completed over 200 practice case scenarios via the MonkeyJacket platform. Future studies should include a larger sample size of participants in order to obtain more diverse feedback regarding the functionality and usability of the application.

Another limitation of this study is that all participants were from either Western University or McMaster University. This application originated from researchers based in Western University, and thus all students were recruited from the same institution for ease of organization and planning. Although this was advantageous, as the knowledge and OSCE skills were standardized among study participants, this can also reflect a lack of diversity in perspectives with respect to OSCE skills.

Lastly, traditional OSCE examinations are extensive, in that they also evaluate a candidate’s ability to perform relevant physical examination and procedural skills in response to a primary patient concern. Given the web-based nature of the MonkeyJacket platform, it was not possible to integrate such assessments. However, one way to assess a candidate’s knowledge regarding relevant physical examination skills is to add it to the checklist and ensure that the candidate knows the rationale for why certain physical examination components would be used.

Future Directions

In the future, the MonkeyJacket application will be preparing for extensive nationwide deployment across Canadian medical institutions. Through partnership with major Canadian medical student groups, the application will be disseminated for widespread use. This will allow us to collect a vast amount of quality improvement feedback. Ideally, we will be able to test if the use of the application leads to improved medical examination scores.

At the time of writing, the cases included within the platform are tailored toward scenarios that can help medical learners, who will become competent resident physicians, develop clinical skills. The expansion of the application in the future can include more specialized cases for specific residency subspecialties. In addition, MonkeyJacket is useful not only for Canadian medical students but also for medical trainees globally, as clinical skills examinations are part of many international medical education programs. This can be explored in the future, once the application is successfully deployed in Canada.

Conclusions

The MonkeyJacket OSCE tool is a comprehensive and accessible learning resource for medical learners. This innovative tool offers medical learners a solution that addresses the lack of practice tools and formative feedback within the realm of clinical skill development. As medical students proceed through their training, OSCEs remain an integral component of assessments ensuring that learners are demonstrating required competencies for safely practicing medicine upon graduation. The development of comprehensive and accessible OSCE
practice tools with built-in evaluations eases the stress associated with preparation for clinical examinations and promotes a more competent medical workforce, with the latter benefiting the most important stakeholders in medicine—the patients.

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Authors’ Contributions
CS oversaw the direction of the publication and was the senior author and organizer of the project. AA and FF wrote the manuscript. AA created the figures. EA provided a summary of Medical Council of Canada (MCC) objectives. AA, FF, EA, TB, AK, and EW conducted the practice OSCE sessions. All authors reviewed the final manuscript.

Conflicts of Interest
The MonkeyJacket application is owned by GoodLabs Studio. CS and TL are part of the GoodLabs Studio development team; however, there is no conflict of interest that affected this work.

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3. NAC Examination. Medical Council of Canada. URL: https://mcc.ca/examinations-assessments/nac-examination/ [accessed 2023-01-03]


Abbreviations

CanMED: communicator, collaborator, leader, health advocate, scholar, professional, and medical expert

e-OSCE: electronic objective structured clinical examination

MCC: Medical Council of Canada

OSCE: objective structured clinical examination

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Proposing a Principle-Based Approach for Teaching AI Ethics in Medical Education

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Abstract

The use of artificial intelligence (AI) in medicine, potentially leading to substantial advancements such as improved diagnostics, has been of increasing scientific and societal interest in recent years. However, the use of AI raises new ethical challenges, such as an increased risk of bias and potential discrimination against patients, as well as misdiagnoses potentially leading to over- or underdiagnosis with substantial consequences for patients. Recognizing these challenges, current research underscores the importance of integrating AI ethics into medical education. This viewpoint paper aims to introduce a comprehensive set of ethical principles for teaching AI ethics in medical education. This dynamic and principle-based approach is designed to be adaptive and comprehensive, addressing not only the current but also emerging ethical challenges associated with the use of AI in medicine. This study conducts a theoretical analysis of the current academic discourse on AI ethics in medical education, identifying potential gaps and limitations. The inherent interconnectivity and interdisciplinary nature of these anticipated challenges are illustrated through a focused discussion on “informed consent” in the context of AI in medicine and medical education. This paper proposes a principle-based approach to AI ethics education, building on the 4 principles of medical ethics—autonomy, beneficence, nonmaleficence, and justice—and extending them by integrating 3 public health ethics principles—efficiency, common good orientation, and proportionality. The principle-based approach to teaching AI ethics in medical education proposed in this study offers a foundational framework for addressing the anticipated ethical challenges of using AI in medicine, recommended in the current academic discourse. By incorporating the 3 principles of public health ethics, this principle-based approach ensures that medical ethics education remains relevant and responsive to the dynamic landscape of AI integration in medicine. As the advancement of AI technologies in medicine is expected to increase, medical ethics education must adapt and evolve accordingly. The proposed principle-based approach for teaching AI ethics in medical education provides an important foundation to ensure that future medical professionals are not only aware of the ethical dimensions of AI in medicine but also equipped to make informed ethical decisions in their practice. Future research is required to develop problem-based and competency-oriented learning objectives and educational content for the proposed principle-based approach to teaching AI ethics in medical education.

Keywords

artificial intelligence; AI; ethics; artificial intelligence ethics; AI ethics; medical education; medicine; medical artificial intelligence ethics; medical AI ethics; medical ethics; public health ethics

Introduction

Background

Artificial intelligence (AI) and its applications have been of interest in both the scientific and societal domain for many years. AI has the potential to improve medical care through more accurate diagnosis and to reduce the burden on the health care system by reducing costs and workload [1,2]. Although AI in medicine has the potential to reduce the burden on medical staff, uncertainty about its capabilities raises concerns regarding job displacement [3]. The use of AI is expected to pose significant ethical challenges. AI algorithms are often trained on unrepresentative data, leading to potential discrimination and disadvantages for certain patient groups. Bias on the part of developers can also result in inequitable treatment [4].
use of AI in medicine can also lead to erroneous diagnoses such as unnecessary treatment, which violates the basic principles of medical ethics [5].

Research recommends teaching AI ethics early in medical education to prepare for its potential impacts and challenges [6-8]. In addition to the technical and legal aspects of the use of AI in medicine, recent publications emphasize the importance of teaching AI ethics in medical education [9-11]. Recent studies have indicated that medical students anticipate significant ethical challenges from the use of AI in medicine [12,13]. Furthermore, research suggests limited knowledge and understanding of AI among medical students [14]. Despite the need for early teaching of AI ethics, there is a lack of guidance on specific content and methods for integrating AI ethics into medical curricula [10].

Definitions of AI

Although the term artificial intelligence dates to the 1950s, there is inconsistency regarding its definition within the scientific community and the public [15]. On the basis of current scientific definitions, AI can be subdivided into “artificial general intelligence,” referred to as “strong AI” and “artificial narrow intelligence,” commonly referred to as “weak AI” [16]. Artificial general intelligence refers to the development of systems with “general intelligence,” capable of performing intellectual tasks comparable with humans. The term “artificial narrow intelligence” refers to an AI that has the capability to perform specific intellectual tasks comparable with humans without possessing general intelligence [17]. Artificial narrow intelligence can be subdivided into 2 main fields of current research: “symbolic AI” and “statistical AI.” On the basis of the idea of representing knowledge or certain intelligent behaviors using symbols and rules, “symbolic AI” commonly refers to rule-guided expert systems [16,18]. The term “statistical AI” refers to the development of systems that can find correlations and patterns within the analyzed data sets using statistical methods, without being explicitly programmed to do so or following predefined rules. Examples of “statistical AI” include “machine learning” (ML) with its subfield, “deep learning,” or “natural language processing” (NLP) [18]. While the ability to learn from data independently and increase their capabilities lies at the heart of ML, the subfield of deep learning focuses on the development of artificial neural networks that mimic the human central nervous system to process information. The subfield of NLP focuses on the analysis and processing of human language–based information by computer systems to enable improved human-computer interactions [16]. Advanced NLP techniques are, for example, used in large language models such as the AI-based chat applications available to the public, for example, ChatGPT (OpenAI, LLC) or Bard (Google LLC).

In medicine, AI and its respective subfields and specializations have attracted increased scientific interest in recent years [19]. For example, “symbolic AI” is used to develop rule-based expert systems such as “clinical decision support systems” (CDSSs) [20]. CDSSs aim to assist with diagnosis and selection of the best treatment for patients by providing information based on the current guidelines and information provided by experts. CDSSs follow rules and instructions predefined by experts and are therefore susceptible to ethical challenges such as the transfer of bias by experts or developers [21]. Because of their ability to analyze large amounts of data, systems based on ML are used to identify and process image-based data in medical specializations such as radiology or dermatology. An extensive study published in Nature in 2017 showed that systems based on ML are capable of detecting certain types of skin cancer (eg, malignant melanomas) with an accuracy comparable to that of dermatologists using image-based data [22].

As the data used to train ML-based systems and applications represent the basis of any subsequent analysis and therefore significantly influence accuracy, the data need to be representative of the target population [23]. This is especially important in the medical context, where demographic disparities in data can lead to systematic misdiagnoses or treatment recommendations that are less effective for underrepresented groups [24]. Unrepresentative data can potentially lead to bias and discrimination, with significant effects on patients [21,24]. To avoid any discrimination or negative effects for patients, the sources and composition of data sets used for AI development are of paramount importance. Ensuring the representation of the data is crucial, as the diversity and comprehensiveness of the data determine the system’s ability to generate reliable and valid outputs across different patient demographics [23]. Furthermore, acknowledging and addressing potential limitations and errors in AI products is essential for maintaining the validity of AI outputs, which directly affect the scope of their applicability in clinical settings [21]. AI systems trained on narrow or biased data sets may not only perform inadequately in diverse real-world scenarios but also misinform clinical decision-making, undermining the trust and credibility essential in medical practice [25]. The low accuracy and validity of AI, potentially leading to a lack of trust and credibility, could severely impact the utility of AI in the medical context. Utility refers to not only the performance of AI on a technological level but also how it translates into meaningful and practical advantages in health care settings. Therefore, the utility of AI in medicine is intrinsically linked to its ability to provide actionable, accurate insights that directly inform and enhance clinical decision-making [26]. It is therefore imperative to rigorously evaluate and validate AI systems against a variety of data sets that reflect the full spectrum of clinical cases and patient populations to ensure the utility, generalizability, and accuracy of AI tools in a broad range of health care contexts.

Although becoming broadly available rather recently, AI-based chat applications such as ChatGPT have rapidly emerged as significant tools with the potential to revolutionize various aspects of medicine, including the education and training of future physicians [27,28]. For example, these applications could be deployed for simulated patient-physician interactions, providing medical students with a low-risk environment to practice diagnostic skills and ethical decision-making [28]. The potential and broad availability of AI-based chat applications raise new ethical questions that necessitate comprehensive teaching in medical education.

AI Ethics

The field of AI ethics was an area of interest for both scientific and governmental communities, even before the emergence of
AI applications such as ChatGPT, which has gained widespread public attention [29,30]. However, there remains a lack of consensus on the definition of AI ethics, which can be attributed to several factors, including the novelty and interdisciplinary nature of the field as well as the absence of a widely accepted definition of AI [31].

Despite the current lack of consensus on the definition of AI ethics, some definitions are available. For example, AI ethics can be defined as “the emerging field of practical AI ethics, which focuses on developing frameworks and guidelines to ensure the ethical use of AI in society (analogous to the field of biomedical ethics, which provides practical frameworks for ethical practice in medicine)” [32]. This definition emphasizes the novelty of the field, further highlighting the importance of biomedical ethics.

The emphasis on biomedical principles is consistent with current scientific and governmental efforts aimed at developing AI ethics frameworks and guidelines to ensure the ethical development, deployment, and use of AI technologies [29,33]. The biomedical principles mentioned in the definition of AI ethics refer to the well-known and established principles of medical ethics initially proposed by Beauchamp and Childress [34]. The 4 principles of autonomy, beneficence, nonmaleficence, and justice are considered fundamental to medical ethics, while most guidelines and frameworks on AI ethics do not specifically focus on ethical considerations regarding the development, implementation, or use of AI in medicine; the emphasis on these principles further reinforces their importance [30,35].

Although existing guidelines and frameworks aim to address various ethical concerns related to AI, such as privacy, bias, accountability, and transparency, it should be noted that they fail to provide a clear definition of AI ethics [30]. Given the rapid pace of advancements in AI technology and its increasing impact on society, the need for clear and consistent definitions of AI and AI ethics is becoming increasingly urgent [30]. To specifically address ethical considerations related to AI in medicine and medical practice, a definition of “medical AI ethics” has been proposed, which “is an interdisciplinary subfield of AI ethics concerned with the application of ethical principles and standards to the research, development, implementation, and use of AI technologies within the practice of medicine” [10]. This definition emphasizes the importance of principles regarding the use of AI in medicine, which is fundamental to this study.

**AI Ethics in Medical Education**

Although the need for teaching AI ethics in medical education is emphasized in scholarly literature, there is a lack of specification on relevant teaching content for AI ethics. In a recent scoping review, only a limited number of publications specifically focusing on the teaching of AI ethics as part of medical education were identified [10]. Although other publications acknowledge the importance of ethics in AI education, they do not provide specific content or guidance [36-39].

In one of the 2 identified publications specifically addressing AI ethics teaching content for medical education, 6 potential topics were defined: informed consent, bias, safety, transparency, patient privacy, and allocation [9]. The 6 teaching subjects were proposed to address the potential challenges related to the application of AI in medicine. For example, the anticipated challenge of informed consent highlights the importance of patient autonomy, potentially impeded by the lack of transparency or explainability in the decision-making of AI-based applications. Besides these 6 potential teaching subjects, the importance of teaching fairness and responsibility is emphasized by another publication that focuses on AI ethics education [11]. Furthermore, the importance of empathy has been emphasized in relation to the use of AI in medicine and the associated need to teach AI ethics [6].

A recurrent theme related to the teaching of AI ethics as part of medical education focuses on the principles of medical ethics according to Beauchamp and Childress (autonomy, beneficence, nonmaleficence, and justice) [10]. This emphasis is also echoed by existing guidelines and frameworks regarding AI ethics [30]. Additional recommendations on AI ethics teaching content include “explainability,” “liability,” and “accountability,” which are also considered important by available guidelines [30,40].

On the basis of the analysis of existing publications on teaching AI ethics in medical education, 12 potential subjects were considered for teaching AI ethics. The 12 identified potential teaching subjects for AI ethics in medical education are listed in Textbox 1.
Textbox 1. Recommended artificial intelligence (AI) ethics teaching content with specific descriptions.

**Informed consent**
Informed consent in the context of AI in medicine requires that patients be fully informed about treatment options and risks, necessitating a comprehensive understanding and explanation of AI technologies by physicians.

**Bias**
The use of AI in medicine may exhibit biases stemming from nonrepresentative data or structural conditions, leading to potential discrimination based on sex, age, or socioeconomic status.

**Safety**
The use of AI in medicine can have potentially harmful consequences for patients, necessitating a critical examination of the accuracy of AI-based applications and clear communication of their limitations.

**Transparency**
Transparency in AI-based medical applications is essential for understanding decision-making processes, influencing the quality and ethics of patient care, and maintaining trust, particularly in critical scenarios.

**Privacy**
Privacy not only refers to implementing technical data protection measures but also comprehensively understanding the ethical implications of handling sensitive patient data.

**Allocation**
In the context of AI in medicine, allocation refers to equitable access to technology and the impact of AI on equitable access to care.

**Fairness**
Fairness in AI ethics within medicine refers to ensuring equitable treatment for all patients regardless of their background. This encompasses the need for AI systems to be free from biases that may affect diagnosis, treatment recommendations, or patient outcomes.

**Responsibility**
Responsibility in the context of AI ethics in medicine emphasizes the importance of health care professionals and AI developers to using AI tools responsibly. This includes ensuring that these tools are safe, reliable, and used in a manner that benefits the patients.

**Empathy**
Empathy in the context of AI underscores the importance of maintaining the human aspect of health care, especially as AI technologies become more prevalent.

**Explainability**
Explainability in AI in medicine is closely linked to transparency and is important for understanding the AI-based decision-making process, affecting physician-patient relationships, and shared decision-making.

**Liability**
Liability in medical AI ethics concerns the potential for treatment errors related to the use of AI in the medical context. Questions on liability extend from potential users to health care institutions and AI developers.

**Accountability**
Accountability in medical AI involves understanding the associated limitations and competent oversight by medical professionals. This includes critically assessing AI errors and biases and ensuring accurate, informed, and ethical applications within medical decision-making. In addition, this accountability extends to continuously monitoring AI performance and adapting to evolving ethical and clinical standards in medical practice.

**Objective**
On the basis of a discussion and reflection theoretical analysis of the recommended teaching subjects on AI ethics informed by existing literature (as specified in the AI Ethics in Medical Education section), this study aims to introduce a set of ethical principles for “medical AI ethics.” As the proposed AI ethics teaching subjects for medical education in the existing scientific literature primarily focus on the challenges associated with the use of AI in medicine, they fail to acknowledge the broader implications of foundational ethical principles. By concentrating on a principle-based approach to AI ethics, this paper aims to address the gap in the existing scientific literature, serving as a foundational framework for AI ethics teaching content in medical education.

**Theoretical Analysis of Recommended AI Ethics Teaching Subjects in Medical Education**

**Overview**
Ethics commonly relies on principles as foundational guidelines for decision-making and behavior. The 4 foundational principles of medical ethics—autonomy, beneficence, nonmaleficence, and justice—are highly relevant in the context of teaching ethics in medical education [41].

While these 4 principles have been an integral part of current scientific publications on AI ethics in medical education, the
recommended teaching subjects are mainly derived from the anticipated challenges associated with the use of AI in medicine [10]. Addressing these challenges is important for fostering a comprehensive understanding regarding the use of AI in medicine. However, this approach does not fully capture the multidisciplinary and interdisciplinarity nature of this field. The complexity of AI ethics in medicine extends beyond these anticipated challenges, encompassing a wide range of disciplines such as law, medicine, ethics, and computer science. For example, the proposed teaching subject of “informed consent” warrants a detailed analysis to exemplify the high level of interdisciplinarity present in AI ethics, intersecting with each of the other proposed teaching subjects. This interconnection results in a substantial overlap, which can challenge the establishment of clear distinctions between the different areas of AI ethics.

The methodology of this study is anchored in a theoretical approach, building upon a previous comprehensive scoping review of the existing literature on teaching AI ethics in medical education [10]. This also includes the consideration of relevant guidelines and frameworks regarding the ethics of AI, resulting in the identification of 12 potential teaching subjects for AI ethics as detailed in Textbox 1. To exemplify the high level of interdisciplinarity present in AI ethics by focusing on the subject of “informed consent,” the publications included in the scoping review, including the proposed challenges associated with the use of AI in medicine, were re-evaluated. This theoretical analysis provides the foundation for the development of the principles of medical AI ethics presented in the Medical AI Ethics section. The theoretical basis of the proposed principle-based approach to AI ethics is further strengthened by our expertise as we specialize in the ethical use of AI in medical and public health contexts. This background informs the depth and rigor of the analysis, ensuring that the developed framework is both relevant and grounded in practical ethical considerations in these fields. The theoretical methodology we used is characterized by a focus on conceptual development and theoretical insights rather than empirical testing or data collection.

Informed Consent

Overview

Informed consent represents an important development in medical ethics and patient rights, representing a departure from the historically paternalistic nature of medical practice [42]. In earlier medical paradigms, decision-making was predominantly physician driven, with minimal patient involvement. This approach, often paternalistic, assumes the primacy of the physician’s judgment, potentially leading to interventions conducted without comprehensive patient understanding or consent [42].

The development and integration of informed consent into medical practice represents a substantial cultural and ethical transition toward acknowledging and upholding patient autonomy. Central to this evolution is the concept of shared decision-making (SDM), a collaborative process that involves physicians and patients jointly making treatment decisions. SDM encompasses a thorough discussion of available treatment options, including their benefits and risks, and considers patient values, preferences, and circumstances [42,43]. This method positions patients as active participants in their health care journey rather than as passive recipients of medical decisions.

In this context, informed consent is pivotal in facilitating SDM, as it ensures that patients are not only informed of their medical choices but also engaged in selecting options that resonate with their personal health goals and values. This approach transforms the traditional physician-patient relationship into a partnership, where decisions are mutually agreed upon, thereby honoring the patient’s right to self-determination. It also fosters a deeper level of trust and respect within the physician-patient relationship.

As a result, informed consent serves more than just a legal requirement to minimize liabilities; it is a crucial aspect of patient-centered care and a fundamental element of ethical medical practice. This signifies the transition from a paternalistic approach to one that emphasizes patient autonomy and upholds the principles of SDM.

Informed Consent in the Context of AI in Medicine

Regarding the development, implementation, and use of AI in medicine, the concept of informed consent warrants a comprehensive introduction owing to the technical complexities inherent to AI. AI systems, particularly those used in diagnostics and treatment recommendations such as ML, often involve algorithms that might be nontransparent to both patients and health care professionals. This lack of transparency presents a substantial challenge to the conventional process of informed consent, complicating the task of understanding and communicating how an AI-based application formulates recommendations [44].

Moreover, the development of AI-based applications involves extensive data sets, raising concerns regarding data privacy and the potential for expropriation of personal health data [9]. These issues necessitate clear communication with patients throughout the physician-patient relationship and during the process of ensuring informed consent. It is imperative that patients are adequately informed about not only the advantages and risks associated with AI-assisted treatments but also the manner in which their data are used, protected, and stored [45]. With the increasing integration of AI in medicine and health care, the process of obtaining informed consent must be adapted to meet these challenges, thereby ensuring that patients retain control over their health care decisions in an environment increasingly influenced by AI.

Intersections of Informed Consent With Key AI Ethics Teaching Subjects

Overview

This section aims to underscore interdisciplinarity and intersectionality among the recommended teaching subjects in AI ethics, as outlined in the Informed Consent section, with informed consent serving as a representative example. Focusing on these intersections, this section highlights the importance of an integrated educational approach in the context of medical AI ethics. Such an approach acknowledges that topics such as
bias, privacy, and transparency, among others, are not merely isolated subjects but instead require a comprehensive, holistic evaluation. Embracing this integrated perspective is important for a comprehensive understanding of AI ethics in medical practice and education, underscoring the need to re-evaluate and potentially refine current teaching recommendations. To effectively illustrate the interdisciplinarity and interconnectedness of frequently recommended teaching subjects for AI ethics in medical education, “informed consent” should be discussed in the context of 5 frequently proposed teaching subjects: bias, safety, transparency, privacy, and liability.

Bias
To enable patients to make informed decisions when AI-based applications are used in their treatment, it is important to address the possibility of bias inherent in these technologies. Informed consent in this context requires the awareness and understanding of potential biases in AI decision-making processes [46]. For instance, a diagnostic AI-based application might exhibit varying levels of accuracy across different demographic groups, potentially owing to data representation issues [21]. Patients must be informed of such disparities in accuracy as this information is vital for them to consent to the use of AI in their treatment.

Safety
The safety of AI-based applications in medicine is a critical component of informed consent for medical treatment recommendations involving AI. Patients must be clearly informed about the potential risks associated with AI-driven medical decisions, including the possibility of erroneous outcomes such as false positives or negatives [47]. This comprehensive understanding of the safety profile of AI-assisted treatments is essential for patients to make informed decisions about their care. Being informed and knowledgeable about the limitations and risks of AI technologies ensures that patients can weigh these factors against potential benefits when consenting to AI use in their treatment.

Transparency
Transparency in AI systems is important not only for patients but also for physicians, who serve as the primary receivers and communicators of AI-driven medical information. A clear understanding of how AI-based applications work, particularly how decision-making processes are performed, is required for physicians to effectively communicate with their patients [48]. Such informed communication is a fundamental aspect of the informed consent process, fostering a deeper understanding and trust within the physician-patient relationship [49]. When patients receive comprehensive and transparent information from their trusted health care providers, they enhance their engagement and participation in decision-making. Therefore, transparency in AI goes beyond technical clarity and is crucial for fostering a strong physician-patient relationship, ensuring that informed consent is based on a shared understanding of the potential risks and benefits associated with AI-assisted treatments [50].

Privacy
The process of obtaining informed consent for AI-based medical treatment recommendations should include data privacy. It is important for patients to be informed about the use, access, and protection of their data. Ensuring that patients understand how their personal health data are used, who has access to it, and the measures in place to protect it is a key component of the informed consent process [51]. This comprehensive disclosure and transparency regarding data handling are vital for maintaining the integrity of the physician-patient relationship and for upholding the ethical standards of medical practice in the era of AI.

Liability
Regarding the use of AI in medicine, it is imperative to address the concept of liability in the informed consent process. Patients should be clearly informed of the potential for errors and liability issues associated with AI-driven medical decisions [52]. This conversation should entail a discussion on who bears responsibility, including the liability of physicians, if an AI system malfunctions or leads to incorrect medical outcomes such as misdiagnoses or inappropriate treatment plans. The explicit clarification of liability, particularly the role and responsibility of health care providers in conjunction with AI, is important for helping patients understand the potential risks involved [53]. This understanding is a key component of a comprehensive informed consent process that directly affects the patients’ trust in AI and their treating physicians. By transparently addressing these liability concerns, including the physicians’ responsibilities, health care providers can reinforce the integrity of the physician-patient relationship and uphold the ethical standards of medical practice in an AI-integrated health care environment [53].

Medical AI Ethics

Overview
The high degree of interdisciplinarity and intersectionality in AI ethics, as detailed in the previous section, highlights potential conflicts in teaching AI ethics based solely on the anticipated challenges associated with the implementation and use of AI in medicine. This complexity underscores the necessity of adopting a principle-based approach to AI ethics education, mirroring established pedagogical frameworks in medical ethics education [41].

In the context of traditional medical ethics education, the emphasis on foundational principles provides a broad and adaptable framework that is essential for understanding and addressing complex ethical dilemmas. This approach facilitates the holistic comprehension of ethical issues, offering the flexibility to accommodate the diverse and evolving nature of medical scenarios. Similarly, when considering AI in medicine, a focus on core ethical principles rather than solely on specific challenges lays the groundwork for a robust and comprehensive educational strategy. Future medical professionals should be equipped with a deeper and more nuanced understanding of ethical decision-making by emphasizing ethical principles in the context of implementing and using AI in medicine. This principle-based approach ensures that medical ethics education...
remains relevant and responsive to the dynamic landscape of AI integration in medicine. The goal is for medical students to be able to effectively navigate the ethical complexities associated with AI technologies in medicine, not just focusing on potential challenges but also emphasizing the ethical values that are essential to medical practice.

Owing to the paramount importance and relevance of the 4 principles of medical ethics formulated by Beauchamp and Childress [34], the principles of autonomy, beneficence, nonmaleficence, and justice should provide the essential foundation for medical AI ethics. These 4 principles are subsequently introduced based on existing scholarly discourse, focusing on the use of AI in medicine, with an emphasis on medical education.

Traditional medical practices have predominantly focused on individual relationships between physicians and patients. However, modern health care increasingly necessitates considering broader aspects such as cost-effectiveness, resource allocation, and proportionality, especially in light of financial constraints. A prominent illustration of these evolving dynamics in medical practice is the COVID-19 pandemic. This global health crisis underscored the critical importance of public health considerations and highlighted extensive interdisciplinarity and interconnectivity within the field of medicine. The COVID-19 pandemic has highlighted the importance of balancing individual patient care with broader public health measures [54]. It demonstrated how medical decisions are not made in isolation but are profoundly influenced by factors such as resource availability, health care infrastructure, and broader societal implications. This scenario emphasizes the crucial role of public health principles in informing medical practices, particularly in crises. The pandemic also illustrates the necessity of integrating insights from various disciplines, including epidemiology, health economics, and ethics into medical decision-making.

Given the anticipated impact of AI on the field of medicine, which extends beyond the traditional concept of medical practice owing to its inherent interdisciplinarity and complexity, ethical considerations must be adapted accordingly. The scope of AI in medicine introduces novel ethical dimensions that require a broader framework for ethical analysis. Therefore, the integration of 3 principles of public health ethics—efficiency, common good orientation, and proportionality—is proposed along with the established principles of medical ethics to form a comprehensive foundation for medical AI ethics [55-58]. Similar to the principles of medical ethics outlined by Beauchamp and Childress [34], each principle of public health ethics is examined in subsequent sections with a specific focus on its relevance to AI in medical practice and education. While the principles of public health ethics may not be as established or universally agreed upon as those of medical ethics, their inclusion provides a suitable framework to address the unique challenges posed by AI in medicine and health care. This extended ethical framework aims to provide a more comprehensive understanding of the role and implications of AI in medicine, ensuring that future medical professionals are equipped to make ethically sound decisions in increasingly AI-integrated medical practice. The proposed principles of AI ethics for medical education are presented in Figure 1.

**Figure 1.** The principles of medical artificial intelligence (AI) ethics for medical education.

![Principles of medical AI ethics](Figure_1.png)

**Autonomy**

The principle of autonomy in medical ethics emphasizes the right to make independent decisions regarding health care [34]. This principle recognizes an individual’s capacity for self-determination and personal choice, affirming that patients have the authority to provide or withhold consent for medical treatment. Respecting autonomy in medical practice involves providing patients with sufficient information, ensuring comprehension, and facilitating independent decision-making [59]. This respect for autonomy is closely tied to the principle of informed consent, which ensures that patients actively participate in decisions regarding their care and treatment.
In the context of using AI in medicine, particularly in diagnostics and treatment recommendations, technology introduces new challenges and opportunities to maintain patient autonomy [60]. For example, when using AI-based diagnostic applications, it is crucial to inform patients about how these tools impact their health care decisions, ensuring that informed consent is comprehensive. Equally important is equipping physicians with the knowledge to balance AI-generated insights with their clinical expertise, thus upholding both patient and physician autonomy in decision-making processes. The incorporation of AI into health care decision-making can affect the presentation and comprehension of options by patients. Ensuring that patients retain their autonomous decision-making power in an AI-driven environment requires the careful consideration of how the information is communicated and understood [60]. Autonomy in this context extends to ensuring that patients have a clear understanding of AI interventions and their capabilities, limitations, and impact on personal health decisions. Moreover, the principle of autonomy extends to physicians. If AI increasingly assists in medical decision-making, it is imperative that physicians remain empowered to make independent professional judgments, balancing AI insights with their clinical expertise and ethical considerations.

The principle of autonomy addresses several anticipated challenges and recommends teaching subjects on AI ethics in medical education. For example, in the context of informed consent, autonomy ensures that patients are fully aware of the role and limitations of AI in their treatment, including potential bias and safety concerns. Autonomy also involves clear communication regarding data privacy, ensuring that patients understand how their data are used in AI systems. In the context of using AI in medicine, autonomy is not limited to the patient’s understanding and decision-making; it also encompasses the physician’s ability to make independent judgments informed by, but not solely reliant on, AI-driven data. This dual focus preserves the integrity of clinical decision-making and respects both the patient’s and the physician’s autonomous roles. Furthermore, transparency and explainability in AI systems are fundamental to ensure that patients autonomously understand and evaluate AI-driven health care choices. Autonomy acts as a guiding principle that addresses these challenges, ensuring that patient rights and self-governance remain central to the increasingly AI-integrated landscape of medical practice. This principle also extends to the equitable allocation of medical resources and fairness in treatment decisions, where an autonomous choice must be informed by unbiased AI recommendations. This comprehensive approach to autonomy in AI ethics education underscores the need for a balanced consideration of both patient and physician perspectives to ensure ethical integrity in the application of AI in medicine.

**Beneficence**

The principle of beneficence, a fundamental aspect of medical ethics, underscores the responsibility of health care providers, including physicians, to act in the best interests of patients [61]. This principle is the basis of the ethical framework guiding health care delivery and promoting actions that enhance patient well-being and welfare [34]. In medical practice, beneficence guides physicians to consider the actual benefits of medical interventions, extending from the sole minimization of potential harm. Therefore, this principle encompasses a broader responsibility toward enhancing the overall quality of life of the patient, affirming that every medical decision should contribute positively to the holistic well-being of the patient [50].

The principle of beneficence is paramount in the application of AI in medicine, such as through predictive analytics and personalized medicine. Although promising, AI-based applications must be critically evaluated for their efficacy and safety to ensure alignment with the overarching goal of promoting patient well-being, which reflects the true essence of beneficence in medical practice [62]. In addition, it is crucial to ensure that AI-based applications align with the broader goals of patient care, emphasizing not only clinical outcomes but also patient quality of life and overall well-being. Such an approach should consider individual social backgrounds and personal circumstances, ensuring that AI-driven health care focuses on the diverse needs of each patient [50].

In the context of AI ethics and medical education, beneficence emphasizes the importance of developing, implementing, and using AI applications designed with the primary aim of improving patient outcomes. This includes addressing potential biases in AI algorithms that could negatively impact patient care, ensure patient safety, and maintain transparency in the AI decision-making processes. Therefore, the principle of beneficence guides the ethical application of AI in medicine, ensuring that these advancements aim to maximize patient benefits and well-being, consistent with the overarching goals of medical practice.

**Nonmaleficence**

Although the principle of nonmaleficence also focuses on ensuring the best possible treatment for patients and aligning all actions accordingly, it emphasizes that health care professionals should do no harm [34]. This principle is complementary to the principle of beneficence, and it aims not only to prevent harm but also to proactively avoid and reduce risks associated with medical care. Nonmaleficence requires that the risks of any medical intervention are carefully weighed against their potential benefits and actions that could cause harm are avoided. This principle underlines the responsibility of health care providers to ensure that any treatment or medical advice does not adversely affect a patient’s health.

The potential risks of using AI in medicine, such as misdiagnosis, algorithmic biases, and data security breaches, reinforce the relevance of the principle of nonmaleficence. To ensure nonmaleficence, the rigorous testing and validation of AI systems, ongoing monitoring for adverse outcomes, and commitment to addressing any safety concerns are crucial [62]. Moreover, this commitment extends to the ethical development and deployment of AI technology. It involves actively working to mitigate risks, such as biases in training data, that could lead to unequal or unfair treatment outcomes [50].

To raise the awareness of potential conflicts with the principle of nonmaleficence regarding the use of AI in medicine, medical education should focus on the ethical design, development, and
deployment of AI applications in medicine. Therefore, nonmaleficence is an important part of medical AI ethics, emphasizing the need to ensure the accuracy and reliability of treatment recommendations originating from the use of AI-based applications in medicine. Teaching content on nonmaleficence addresses various anticipated challenges regarding the use of AI in medicine, such as safety, privacy, bias, and transparency. By adhering to the overarching principle of nonmaleficence, physicians can navigate the ethical challenges posed by AI in medicine, ensuring that the technology is used in ways that prioritize patient safety and harm reduction.

Justice

The principle of justice in medical ethics, as outlined by Beauchamp and Childress [34], is concerned with ensuring fair and equal treatment for all patients regardless of their socioeconomic status, background, or circumstances. This principle emphasizes the importance of fairness in the distribution of resources and access to health care services. In practical medical settings, justice can be translated into unbiased decision-making, equal opportunity for treatment, and eradication of any form of discrimination.

Justice is an important aspect regarding the use of AI in medicine. Owing to the risk of bias due to unrepresentative training data, for example, treatment recommendations from the use of AI in medicine could lead to disadvantages for different groups or individuals, directly conflicting with the principle of justice [50]. Furthermore, access to the technology itself could be limited, for example, by economic means, thereby potentially perpetuating existing inequalities in access to advanced medical technologies [35]. This potential for injustice can be further exacerbated if an increasing prevalence of AI in medical practice is anticipated.

Owing to the substantial risk of injustice with the use of AI in medicine, medical education should include teaching the principle of justice in the context of AI. Focusing on the equitable availability and use of AI technologies, future physicians should be trained to recognize and address the potential inequities that AI might introduce or perpetuate. Therefore, teaching the principle of justice, extending from traditional medical ethics education, can serve as a foundation to address anticipated challenges such as allocation, bias, fairness, liability, and accountability. For instance, when considering liability and accountability, justice refers to ensuring that patients are not disproportionately affected by errors or failures in AI systems. It involves advocating for systems that hold developers and health care providers responsible for potential technological malfunctions, ensuring that accountability measures are in place to protect all patients from potential harm or injustice, especially those in vulnerable or marginalized groups [53].

Efficiency

Efficiency within public health ethics underscores the strategic use of resources to maximize health benefits for the population [57]. This principle is not only solely an economic concern but also a moral imperative to ensure the equitable and judicious use of medical technologies and services. Ethical considerations regarding the principle of efficiency are especially relevant in health care settings where resources are limited and demand is high, as exemplified in the context of the COVID-19 pandemic.

Owing to the capabilities of AI in medicine with the potential to enhance the efficiency of medical services through faster and more accurate diagnostics, it is crucial to consider the ethical implications of these developments [19]. The ability of AI to rapidly analyze large data sets can greatly enhance the speed of diagnostic procedures, which could result in more timely patient care and improved treatment choices that are more precise. However, this benefit is contingent on the data quality. Poor-quality data can result in AI models that incorrectly predict outcomes based on artifacts in the data rather than actual clinical results [21]. Therefore, the ethical use of AI in health care must include rigorous validation of the data quality to ensure accurate and reliable outcomes. For example, physicians must balance the efficiency gains offered by AI with the need for clinical judgment and personalized patient care and upholding and maintaining the quality of physician-patient relationships [63].

Teaching the principle of efficiency in the context of AI ethics education should focus on the balance between technology-driven efficiency and patient-centered care. Future physicians need to understand how to leverage AI to optimize health care delivery without compromising quality of care. Therefore, teaching the principle of efficiency highlights the anticipated challenges related to a lack of empathy. It is imperative to ensure that the pursuit of efficiency through AI does not lead to the depersonalization of patient care. Empathy remains a crucial aspect of health care, and AI systems should be used to enhance, rather than replace, the human elements of patient interaction and care.

Common Good Orientation

Common good orientation is a guiding principle of public health ethics, aiming to improve the collective well-being and health of the community or population as a whole [58]. This principle extends the focus of individual patients, emphasizing the interconnectedness between individual and public health. This involves considering the wider impacts of health care interventions and prioritizing actions that promote the health and welfare of the public.

The principle of common good orientation in the context of AI, crucial in guiding the integration of technology into medical practice, calls for a delicate balance between individual patient benefits and the collective well-being of the community. It is essential to recognize how AI in medicine can address or potentially exacerbate health disparities [64]. The ability of AI to process and analyze data can be harnessed to identify and address gaps in health care delivery, offering insights into underserved populations and tailoring interventions to meet their specific needs. Conversely, if not carefully managed, AI could unintentionally increase these disparities by favoring populations with better access to the technology. This duality underscores the need for AI advancements in health care to contribute positively and equitably to public health, promoting fairness in health care access and outcomes. It is important to note that the selective application of AI not only undermines the principle of common good orientation but also risks creating
a perception of elitism in the medical profession. Such a scenario could harm the reputation of the medical field, rendering it as unevenly benefiting certain populations. Furthermore, using AI in medical practice could potentially lead to events where patients are harmed, for example, through biased decision-making or errors made by users. This could potentially lead to a negative perception of AI within the broader population, which in turn may result in a general unwillingness or resistance to adopting AI technologies. This hesitance could directly conflict with the principle of common good orientation, as it hinders the widespread and equitable implementation of AI that could benefit the entire community [25].

Teaching the principle of common good orientation in the context of AI ethics in medical education underscores the importance of developing, implementing, and using AI technologies in ways that serve a wider community not just the individual patient. This includes understanding the potential of AI in managing public health crises such as pandemics. Medical education based on the principle of common good orientation emphasizes aspects of safety, transparency, allocation, and responsibility, which are important to best prepare for potential challenges through AI in medicine and associated ethical considerations.

**Proportionality**

The principle of proportionality in public health ethics necessitates a balanced approach to medical interventions that weighs benefits against risks [57]. Therefore, this principle can be applied to ensure that the measures taken, such as medical interventions, are proportional to the health risks that they aim to mitigate. In medicine, proportionality is important in decision-making, ensuring that the intervention aligns with the expected health outcomes.

In medical practice, the principle of proportionality is important when considering the integration of AI technology to balance benefits against potential risks for individual patients and the broader population. This principle necessitates a careful assessment of the role of AI, particularly in ensuring equitable resource distribution and maintaining public trust [25]. For instance, when using AI for diagnostics, it is necessary to evaluate the accuracy and effectiveness of the technology against risks, such as misdiagnosis or overreliance on AI. This evaluation should consider not only the immediate impact on individual patients but also the broader implications for health care resources and community trust. In the critical area of resource allocation within health care, the use of AI holds substantial promise in enhancing the efficiency and effectiveness of distributing limited medical resources [63]. However, it is essential to guard against the risk of AI systems inadvertently perpetuating existing biases or failing to address the diverse needs of different patient groups. This calls for a transparent, community-engaged approach to the development and deployment of AI in health care, ensuring that AI recommendations do not unfairly disadvantage any patient group [24]. By adhering to the principle of proportionality, health care providers can better navigate the ethical complexities of using AI, ensuring that its application is not only technologically sound but also ethically responsible, both at the individual patient level and in the wider context of public health.

The principle of proportionality can be helpful for future physicians to comprehend the anticipated challenges of AI in medicine, particularly regarding the aspects of allocation. This principle also addresses other anticipated challenges such as transparency and explainability to understand how decisions are made and whether the overall population is considered, ensuring that recommendations are reasonable.

**Discussion**

**Overview**

The integration of AI in medicine necessitates a nuanced approach to ethics education that addresses the unique challenges and opportunities introduced by this technology. By exploring public health and medical ethics principles, medical AI ethics offers a comprehensive framework for guiding future physicians in this complex landscape. The proposed teaching of medical AI ethics in medical education emphasizes the importance of ethical principles rather than focusing solely on anticipated challenges, aiming to foster a deeper understanding of potential ethical considerations and enable adaptation in the light of rapid technological advancements.

Given the dynamic nature of AI and the associated rapid technological advancements, for example, as demonstrated by AI-based chat applications such as ChatGPT, ethical considerations need to be continually adapted [65]. The need for timely adaptation challenges traditional ethics education in medicine, which may not account for the current use of AI in medicine. Traditional ethics education primarily focuses on the 4 principles of medical ethics as formulated by Beauchamp and Childress [41]. While these principles can provide valuable guidance in the age of AI in medicine and are therefore foundational to the proposed medical AI ethics education, adaptation is needed to reflect the complexities and challenges introduced by the implementation and use of AI in medicine and medical practice.

The high level of intersectionality and interdisciplinarity inherited by the implementation and use of AI in medicine highlights the importance of a principle-based approach rather than solely focusing on anticipated challenges. While the proposed ethical principles also show a high level of interconnectivity, the chosen educational approach aims to encourage a more nuanced understanding, not limited to specific anticipated challenges but rather to enable future physicians to adapt to the changing landscape associated with the use of AI in medicine, facilitating the consideration of multiple ethical dimensions simultaneously. In addition to the proposed principles, medical education should incorporate practical case studies and simulations to reflect real-world scenarios. For example, applying AI to patient triage during health emergencies such as the COVID-19 pandemic can offer practical contexts for students. This approach would not only enhance their understanding of ethical principles but also prepare them for decision-making in complex, real-life medical situations influenced by AI. It is important for future physicians to
understand the balance between the potential benefits of AI and the ethical implications of its use, particularly in scenarios in which biased algorithms could lead to unequal treatment of diverse patient groups. Therefore, a comprehensive curriculum that includes both theoretical knowledge and practical applications is essential to cultivate ethically informed medical professionals.

An in-depth and interdisciplinary understanding of ethics is important in the dynamic field of medical AI. This importance is underscored by the fact that the integration of AI into medical education may not always keep pace with rapid advancements in medical practice. A focus on ethical principles rather than solely on specific challenges of AI use in medicine aims to prepare medical students for various scenarios in the medical context. This approach maintains relevance even if the AI applications used in education are not representative of the latest state-of-the-art developments in medical AI. The principle-based approach to AI ethics offers broader applicability and reduces dependence on the most recent AI technologies, potentially benefiting medical schools with limited financial resources. In addition, AI products for teaching, often sourced from third parties and guided by cost considerations, may pose unique challenges such as the risk of bias or rapid obsolescence [66,67]. This necessitates awareness, among medical students, of the potential ethical issues associated with these tools. By emphasizing a principle-based approach to AI ethics, educators can equip students with the necessary understanding to navigate the evolving landscape of AI in medicine, fostering adaptability and ethical sensitivity in future medical professionals. This adaptability is crucial to ensure that future physicians are prepared for the ethical dilemmas they may encounter in a rapidly evolving AI landscape.

In the applicability of the principle-based approach to AI ethics, the paramount importance of AI-based chat applications such as ChatGPT must be assumed [68]. As ChatGPT demonstrated extensive medical knowledge, as exemplified by its ability to pass the written part of the United States Medical Licensing Exam, AI-based chat applications offer new opportunities for medical education and medical students, such as in simulated patient interactions and case study analysis [69,70]. However, as ChatGPT was not explicitly developed for use in the medical context and, for example, does not adhere to stringent medical device regulations, it raises new ethical challenges. This becomes particularly evident, as AI-based chat applications can hallucinate and might not provide correct medical information due to improper “prompting” [70]. The limitations of ChatGPT, such as inaccurate or misleading medical information, necessitate an awareness of not only the technical limitations but also the associated ethical considerations. This reinforces the importance of a principle-based approach to AI ethics in medical education, emphasizing the importance of critically reflecting on and evaluating any use of AI in medicine. Awareness of potential ethical considerations regarding AI-based chat applications also extends from the provision of medical knowledge to a broader medical context, such as scientific research [71]. For example, if AI-based chat applications such as ChatGPT are used for medical research, medical education should facilitate an understanding of how this could impact research integrity or potentially interfere with the existing ethical standards [71]. Medical education should prepare students to navigate through these complexities, ensuring the ethical integration of AI in practice and research.

Although the integration of public health ethics principles as part of medical AI ethics offers a comprehensive approach for teaching AI ethics in the medical setting, it is important to recognize that the field of public health ethics is still evolving [72]. Unlike the well-established principles of medical ethics proposed by Beauchamp and Childress [34], public health ethics principles such as efficiency, common good orientation, and proportionality are not universally agreed upon or applied consistently across different contexts. This lack of standardization presents a challenge for formulating a universally applicable ethical framework for AI in medicine. Furthermore, the interdisciplinary nature of public health ethics, encompassing the aspects of sociology, economics, and political science, adds to the complexity of integrating these principles into medical AI ethics education. This complexity requires careful consideration during curriculum development to ensure that these principles are taught in a manner that is both relevant and applicable to medical students. Moreover, the rapidly changing landscape of AI technology necessitates a dynamic approach to ethics education in which principles and guidelines are continuously revisited and updated. This need for adaptability may challenge the traditional formats of medical education, calling for innovative pedagogical approaches to ensure that future physicians are adequately prepared for the ethical complexities of AI-integrated medical practice.

Limitations

This study and the proposed theoretical foundation to medical AI ethics is subject to several limitations that need to be considered. Continuous evolution in the field of AI presents substantial challenges for the development of static ethical guidelines and frameworks for medical education. The dynamic nature of AI technology underscores the need for an adaptable and responsive ethical framework in medical education, particularly in the context of public health ethics, where principles are still developing and gaining consensus. Given that new advancements, for example, as exemplified by AI-based chat applications such as ChatGPT, cannot be foreseen and that the capabilities of AI and AI-based applications in medicine are anticipated to expand, continuous updates of existing educational frameworks and content are required.

Furthermore, the applicability and relevance of ethical principles as a part of medical AI ethics education may vary across cultural and health care settings. Different regions may have varying access to AI technologies, and cultural values may influence the perceptions of integrating and using AI in the medical setting. This variability could impact the universality of the proposed ethical framework and limit the applicability of teaching medical AI ethics as a part of medical education.

Moreover, integrating new teaching content into medical curricula is challenging due to the need for time-intensive accreditation processes and extensive teaching content. The integration of new teaching content such as medical AI ethics education requires careful planning to ensure that future
physicians are adequately prepared and not overwhelmed by information. In addition, limited access to instructors knowledgeable in ethics, medicine, and AI may pose a challenge to implementing the proposed teaching of medical AI ethics, as these experts may not be available in most institutions.

Conclusions
This study highlights the imperative need for medical AI ethics education and the integration of a comprehensive set of ethical principles into medical education to prepare physicians for the ethical challenges posed by AI in medicine. As the advancement of AI technologies in medicine is expected to increase, it is essential for medical ethics education to adapt and evolve accordingly to keep pace with these developments. Educational institutions should take proactive steps to update their curricula, ensuring that future medical professionals are not only aware of the ethical dimensions of AI in medicine but also equipped to make informed ethical decisions in their practice. The principles discussed, drawn from both traditional medical and public health ethics, provide a multidimensional framework for understanding and navigating the ethical landscape associated with the use of AI in medicine.

Given the rapid advancements in the field of AI, it is essential that these ethical guidelines be regularly revisited and updated to remain relevant in the context of medical education. The proposed dynamic approach, with an emphasis on ethical principles, aims to ensure that medical professionals not only are equipped to use AI in ways that enhance patient care but also uphold the highest ethical standards. Future research is needed to develop problem-based and competency-oriented learning objectives and educational content for medical AI ethics and implementation and validation.

Conflicts of Interest
None declared.

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**Abbreviations**

AI: artificial intelligence  
CDSS: clinical decision support system  
ML: machine learning  
NLP: natural language processing  
SDM: shared decision-making

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Abstract

Despite the increasing relevance of statistics in health sciences, teaching styles in higher education are remarkably similar across disciplines: lectures covering the theory and methods, followed by application and computer exercises in given data sets. This often leads to challenges for students in comprehending fundamental statistical concepts essential for medical research. To address these challenges, we propose an engaging learning approach—DICE (design, interpret, compute, estimate)—aimed at enhancing the learning experience of statistics in public health and epidemiology. In introducing DICE, we guide readers through a practical example. Students will work in small groups to plan, generate, analyze, interpret, and communicate their own scientific investigation with simulations. With a focus on fundamental statistical concepts such as sampling variability, error probabilities, and the construction of statistical models, DICE offers a promising approach to learning how to combine substantive medical knowledge and statistical concepts. The materials in this paper, including the computer code, can be readily used as a hands-on tool for both teachers and students.

KEYWORDS
learning statistics; Monte Carlo simulation; simulation-based learning; survival analysis; Weibull

Introduction

The correct use and application of statistics plays a fundamental role in the health sciences, in turn providing objective and quantitative evidence to support decision-making in public health [1]. Despite the increasing relevance of statistics in health research, it is often taught in isolation, usually through standard lectures covering the theory and methods followed by computer exercises with given data sets. This can lead to a disconnect between statistical and epidemiological methods such as study design, as well as insufficient awareness of important statistical concepts such as sampling variability [2]. Therefore, teaching methods that deliver statistical concepts in conjunction with epidemiology for students in the health sciences are crucial for educational development [3].

Simulation-based learning has previously been proposed as a tool to support engaging learning [4] and has been shown to be an effective learning method to develop critical thinking and reflective skills [5-7]. In the context of public health and epidemiology, 2 articles in particular highlight Monte Carlo simulations [8] (hereafter simulations) as a method to illustrate, learn, and understand statistical and epidemiological concepts. First, Rudolph et al [3] demonstrate how to use simulations to teach and learn nondifferential misclassification and understand the concept of the $P$ value. Second, Fox et al [9] illustrate how to design simple simulations from directed acyclic graphs and use them to explain epidemiological concepts. Both papers provide helpful resources for students to familiarize themselves with the basics of setting up a simulation.

However, despite a broad acceptance of simulations as a helpful tool to learn statistical and epidemiological concepts [5], in our experience, they are rarely implemented as the main teaching and learning method for students in health sciences. Rather than using simulations to learn a stand-alone element of statistics,
we propose a learning method that uses simulations to explore and understand the major steps involved in conducting a scientific investigation. In expanding upon the current foundations of simulation-based learning in health sciences, we introduce DICE (design, interpret, compute, estimate), an engaging, problem- and simulation-based learning method. The overall aim is to promote statistical reasoning in the health sciences by combining medical and statistical knowledge in designing epidemiological studies. The purpose of this viewpoint paper is therefore to describe the concept of DICE and discuss its potential strengths and limitations in learning statistics in the health sciences. The statements expressed in this paper are based on the experiences and opinions of the authors.

The remaining part is structured as follows: we will first describe the proposed method—DICE—and explain the intended learning objectives and outcomes. We will then illustrate the use of DICE with an example of a time-to-event outcome. Finally, we will discuss some potential strengths and limitations of applying the method in a classroom setting.

The DICE Approach

DICE is an engaging learning method that enables students to use simple simulations to design, analyze, and interpret a realistic epidemiological study (note that the acronym DICE represents the learning steps involved, but not in order). The use of DICE as a learning tool combines problem-oriented learning [10,11] with simulations [12]. A detailed description of Monte Carlo methods can be found elsewhere [13]. While there are numerous ways to simulate artificial data, we focus on the approach presented by Fox et al [9] due to its simplicity to implement in statistical software and its easy-to-follow translation from a causal framework. In brief, simulations enable us to study a mechanism empirically by sampling from a statistical model that governs the mechanism. Data are then sampled from a predefined probability distribution (eg, Bernoulli, normal, or Weibull) that defines the mechanism, commonly referred to as the inverse transformation sampling method [14]. Further, the data are analyzed with an appropriate statistical model (preferably the same model that generated the data). These steps can be repeated a large number of times to empirically observe the variability of the sampling process [13].

Steps and Learning Objectives

DICE includes 6 major steps that cover the major stages of a scientific investigation. Figure 1 visualizes the chronological order of these steps and highlights the approximate amount of time that one step requires. The second step—designing an investigation including power and sample size calculations with simulations—is further divided into 3 parts, which can be repeated to calibrate the power and sample size of a study before moving on to step 3.
The key learning objectives and outcomes of DICE, as highlighted in Figure 2, target experiential learning [15] and active learning styles [16] according to Bloom’s taxonomy of educational objectives, including applying recently learned concepts and theories, making informed judgements and evaluations, and generating new knowledge [17]. DICE is a flexible method that accommodates different learning styles that have been shown to play an important role in medical education [18]. As such, each student can work according to their strengths (e.g., taking a leading role in the group to cover a specific aspect of the design of a simulated study, like computer coding or result interpretation). Due to the heterogeneity in the working groups, it can be expected that students will use their own learning styles and strengths to learn from other students with different skills [18].
Figure 2. The main learning objectives and outcomes across the steps of DICE (design, interpret, compute, estimate). The steps of DICE include (1) identifying the health problem, (2) designing an investigation including power and sample size calculations with simulations, (3) generating a unique sample of data, (4) analyzing the sample according to the plan, (5) interpreting the findings carefully, and (6) writing a short abstract to be presented in class.

A Guide Through an Example

Each step is now practically explained with an example. The following example is inspired by 2 recent epidemiological studies [19,20]. All information and data are simulated and only serve educational purposes. The computer code in Stata (StataCorp) and R (R Core Team) can be readily used to replicate the example (the code is provided in Multimedia Appendix 1).

Step 1: Identifying the Health Problem

During the first step of DICE, students should think about a particular problem, population, and area that they would like to investigate. This can be somewhat time-consuming and requires a decision about the nature of the research question (i.e., causal, descriptive, or predictive) [21]. As we focus on simulating data according to a causal framework explained by Fox et al [9], the research questions are intended to answer a causal question. Other forms of research questions can, of course, be incorporated and simulated; however, they are not the focus of this example. In our example, the aim is to examine the effect of physical activity on the 10-year mortality rate in a large cohort of older people.

Step 2: Designing an Investigation Including Power and Sample Size Calculations With Simulations

The second step addresses the overall design of the study, including the assessment methods for the specified variables. The step is further divided into three specific parts: (1) students should reflect on the appropriate study design (e.g., experimental or observational), (2) put forward the possible mechanisms (confounding, interaction, etc) underlying all the random variables involved in the study, and (3) discuss plausible values for all of the parameters. These are discussed in more detail below.

Part 1: Choosing an Appropriate Study Design

Designing an investigation that includes power and sample size calculations with simulations requires careful consideration of available literature and substantive knowledge about the underlying health problem. We recommend allocating sufficient time for this step of planning a realistic simulation study.

In our example, we design a large, observational cohort study with a confounding effect by age. Information on physical activity (3.5 hours per week of moderate to vigorous physical activity [MVPA] vs less), together with age (≥80 years vs <80 years), is assessed at baseline in a short questionnaire. The mortality rate in a cohort of older people is likely to increase over time due to aging, among both physically active and inactive populations. Assuming a baseline mortality rate in the
younger and physically inactive population of 7 deaths per 1000 person-years, we determined that 5000 individuals (about 1005 deaths during 10-year follow-up) would provide a statistical power of about 86% to detect at least a 20% lower mortality rate (age-adjusted hazard ratio 0.8) in the physically active population relative to the inactive population. A 2-sided Wald-type test for the age-adjusted hazard ratio conferred by physical activity equal to 1 with a type II error of 5% is conducted based on a multivariable Weibull survival model including physical activity and age as covariates.

Figure 3 shows the sampling distribution of the age-adjusted hazard ratio comparing physically active versus inactive individuals under the null and alternative hypotheses.

Figure 3. Simulated sample distribution of the age-adjusted mortality hazard ratio comparing active versus inactive individuals under the null and alternative hypotheses (hazard ratio 0.8). The simulated statistical power was obtained by counting the number of studies that correctly rejected the null hypothesis with a 2-sided Wald-type test at a significance level of 5% based on a multivariable Weibull survival model. The number of simulations is 10,000, the sample size of each study is 5000, and the average number of deaths within each study is 1005.

Part 2: Mechanisms Underlying the Random Variables
Parameters and their distributions can be inspired by previous studies, textbooks, or substantive knowledge from group members. For example, if the exposure is defined as systolic blood pressure (mmHg), students can assume an approximately symmetric and bell-shaped distribution with a given mean and SD and derive the parameter from a normal distribution function. For this study, we need the following variables: (1) z, an indicator variable for the older population (1 “>80” vs 0 “≤80 years”); (2) x, an indicator variable for the physically active population (1 “>3.5 h/w of MVPA” vs 0 “≤3.5 h/w MVPA”); and (3) t, the time from baseline to death (in years) or the end of follow-up (10 years), whichever came first.

Part 3: Define the Values for the Parameters
During this step, students should write a few lines of code or a function capable of generating data according to the desired study and mechanism. Simulations can be used to calibrate the sample size and statistical power of the study. To achieve the desired statistical power (eg, 80%), the sample size can be changed accordingly during this step. This requires some time, and we recommend students try to adapt certain values for the parameters or underlying mechanisms from the previous step (Figure 1). This process is commonly referred to as the data generating mechanism (DGM). We understand DGM as the mechanism underlying the causal structure, including the uncertainty governing the observed data. The simulated power of the statistical test to detect an effect is simply given by the sum of studies that reject the null hypothesis of no effect divided by the total number of simulated studies.

In our example, the first variable to be generated is baseline age (about 60% are older than 80 years of age), which is a confounding variable in the relationship between physical activity and mortality:

For the exposure model, the second variable to be generated is baseline physical activity as a function of age. People aged ≤80 years have a probability of being physically active of 50%, whereas the odds of being physically active among older people are 1/3 (67% lower odds) relative to younger people:
Step 4: Analyzing the Sample of Data

The outcome model is specified according to the process underlying the data, and it is estimated based on the only sample available. Students estimate the statistical model whose performance was evaluated in the initial step of the study design. In our example, we estimate a multivariable Weibull regression model including physical activity and age as covariates.

Step 5: Interpreting the Findings

Students carefully interpret the estimated model and write about the inferential results. In our example, during the 10-year follow-up period, a total of 974 people died out of 5000. Compared with inactive people, the age-adjusted hazard ratio for active people was 11% lower (hazard ratio=0.89; 95% CI 0.78-1.03). A Wald-type 2-sided test indicates some compatibility between this sample of data and the hypothesis of a null age-adjusted mortality hazard ratio for physical activity (z=−1.52; P=.13). This unique sample of data is an example of type II error (failing to reject the null hypothesis, which is indeed incorrect). Nonetheless, the magnitude and direction of the hazard ratio indicate a beneficial effect of physical activity on the 10-year mortality rate. This provides an example of correctly differentiating statistical and scientific inference.

Step 6: Writing an Abstract

Each group of students should then write a structured scientific abstract (200-250 words) summarizing all the previous steps suitable for an epidemiological conference. The findings and interpretation are then presented in class. Each group of students briefly presents their findings and reasoning behind the study design. Teachers and peers have the possibility of asking questions. The presentations of each group should not exceed 10 minutes per group.

What Have we Learned?

Based on our experiences teaching with DICE and to conclude the steps of DICE shown in the practical example, we hope the key learning lessons for students will include the following: First, students should realize that the most challenging and time-consuming step is the design of the study and identifying a plausible distribution of the random variables involved, the mechanisms underlying the data, and all the parameters included. Second, students should understand that error probabilities (type I, type II, and power) in conducting a test of a hypothesis can be easily evaluated by replicating the study many times under similar conditions (Figure 3) using a simulation. Third, students should appreciate the fundamental distinction between the analysis of a single study and the analysis of a collection of estimates obtained from its replication (Figure 4). Fourth, students should understand that the ability of a study to find a relevant exposure or intervention effect (statistical power) can be achieved only with respect to one parameter of interest. Fifth, students should learn that the correct use of statistics plays a key role in all stages of a scientific investigation.

Step 3: Generating a Unique Sample of Data

Once the study has been designed with sufficient statistical power to detect the relevant effect, the next step is to draw one unique sample. Students will analyze and present only this sample in class. The uniqueness and reproducibility of the simulated data are guaranteed by setting a numerical sequence, called a seed, before obtaining realizations of the random variables. This is important for the exact replication of the study. Every group of students is asked to use a common seed in generating the analytical sample of data so that all groups replicate the study under the same conditions. Each group will have a different research question and an underlying health problem with varying parameters. The reason for choosing a seed in the beginning is to highlight the uniqueness of a single study generated under a known DGM. The easiest choice is to specify the seed according to the date of the DICE activity. In our example, we use the seed 20230413 (based on the year, month, and date: “YYYYMMDD”). However, for specific tasks such as power calculations or simulating a distribution of effects, the seed must be deleted to ensure variability in the simulations.
Strengths and Limitations of DICE
We proposed an engaging learning method, DICE, to stimulate experimental, active, and enjoyable learning of statistical concepts, fostering key scientific skills in designing and conducting experiments. While the main strengths of this approach lie in its interactivity and group-based nature, we acknowledge several limitations.

First, the proposed simulation method is practically limited to only a few numbers of parameters that can be included in the design of a study. Each additional variable increases the complexity of the DGM exponentially. Thus, this approach is best suited for illustrative, simplified examples of realistic health problems. More sophisticated data derived from multivariate distributions would exceed the simplicity of the method but can, of course, be considered for more advanced classes.

Second, implementing DICE is resource-intensive and should not be done in a short time frame (eg, less than 1 hour). Although this is not a direct limitation of the method, it might be a limitation of its implementation in a classroom.

Third, the effectiveness of DICE in conveying statistical concepts in epidemiology has not been formally evaluated yet. This paper is a description and discussion of the method as implemented in class at a medical university. A formal evaluation of its effectiveness in learning statistics is being devised.

Implementing DICE in the Classroom
Based on the experiences of the authors in using DICE, we summarize the following points for its implementation in the classroom for graduate students in medical sciences, including public health and epidemiology.

First, to implement DICE in a classroom, we recommend a classroom size of approximately 20-40 students, with small groups of 3-5 students from heterogeneous scientific backgrounds. Each group should consist of students who have different strengths and learning styles. We experienced that this could improve interaction between students and increase the joy of learning statistics.

Second, throughout the group work, students are encouraged to discuss and reflect upon the study design, practice the generation and simulation of data under a certain mechanism, and communicate their findings and interpretation of the study. We experienced that some students require more support to understand and use the provided computer code, particularly in settings with fewer students experienced in coding. It can help to go through an example of a simulated study with Stata or R code in front of the class.

Third, DICE can be implemented within a full day of teaching or over several days. For a 1-day implementation, the morning can be used for students to frame their research question and develop the study using simulations (steps 1-3). The afternoon can then be reserved for steps 4-6, ending with the presentation of the abstracts. It is important to keep in mind that the first 2 steps require most of the time (Figure 1). Students should not be rushed through these steps and should be provided with sufficient guidance and support to find an adequate research question, study design, and set up the simulations. Alternatively, DICE can be implemented over several days. An introduction to DICE is given in class, and students can work over several
days in their respective groups. The final day can be used for presenting and discussing the studies and outcomes of each group.

**Conclusion**

This paper introduces an engaging simulation-based method, DICE, to learn statistics in the health sciences. We argue that DICE can boost statistical reasoning and bridge the gap between substantive knowledge and statistics for all major steps of a scientific investigation. Students can learn fundamental statistical and epidemiological concepts with simulations and combine learning of technical aspects such as coding with theoretical concepts such as error probabilities. The materials in this paper can be readily used by teachers and students.

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**Data Availability**

All data generated or analyzed during this study are included in this published article and its supplementary information files.

**Authors’ Contributions**

NO supervised the project. RT wrote the original draft of the manuscript. Both authors contributed equally to the conceptualization, methodology, and software. The authors approved of the final version of the manuscript.

**Conflicts of Interest**

None declared.

**Multimedia Appendix 1**

Computer code in Stata and R to replicate the example used in the paper.

[DOCX File, 19 KB - mededu_v10i1e52679_app1.docx ]

**References**


Abbreviations

DGM: data generating mechanism
DICE: design, interpret, compute, estimate

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Sharing Digital Health Educational Resources in a One-Stop Shop Portal: Tutorial on the Catalog and Index of Digital Health Teaching Resources (CIDHR) Semantic Search Engine

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Abstract

Background: Access to reliable and accurate digital health web-based resources is crucial. However, the lack of dedicated search engines for non-English languages, such as French, is a significant obstacle in this field. Thus, we developed and implemented a multilingual, multiterminology semantic search engine called Catalog and Index of Digital Health Teaching Resources (CIDHR). CIDHR is freely accessible to everyone, with a focus on French-speaking resources. CIDHR has been initiated to provide validated, high-quality content tailored to the specific needs of each user profile, be it students or professionals.

Objective: This study’s primary aim in developing and implementing the CIDHR is to improve knowledge sharing and spreading in digital health and health informatics and expand the health-related educational community, primarily French speaking but also in other languages. We intend to support the continuous development of initial (ie, bachelor level), advanced (ie, master and doctoral levels), and continuing training (ie, professionals and postgraduate levels) in digital health for health and social work fields. The main objective is to describe the development and implementation of CIDHR. The hypothesis guiding this research is that controlled vocabularies dedicated to medical informatics and digital health, such as the Medical Informatics Multilingual Ontology (MIMO) and the concepts structuring the French National Referential on Digital Health (FNRDH), to index digital health teaching and learning resources, are effectively increasing the availability and accessibility of these resources to medical students and other health care professionals.

Methods: First, resource identification is processed by medical librarians from websites and scientific sources preselected and validated by domain experts and surveyed every week. Then, based on MIMO and FNRDH, the educational resources are indexed for each related knowledge domain. The same resources are also tagged with relevant academic and professional experience levels. Afterward, the indexed resources are shared with the digital health teaching and learning community. The last step consists of assessing CIDHR by obtaining informal feedback from users.

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**Results:** Resource identification and evaluation processes were executed by a dedicated team of medical librarians, aiming to collect and curate an extensive collection of digital health teaching and learning resources. The resources that successfully passed the evaluation process were promptly included in CIDHR. These resources were diligently indexed (with MIMO and FNRDH) and tagged for the study field and degree level. By October 2023, a total of 371 indexed resources were available on a dedicated portal.

**Conclusions:** CIDHR is a multilingual digital health education semantic search engine and platform that aims to increase the accessibility of educational resources to the broader health care–related community. It focuses on making resources “findable,” “accessible,” “interoperable,” and “reusable” by using a one-stop shop portal approach. CIDHR has and will have an essential role in increasing digital health literacy.

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**KEYWORDS**
digital health; medical informatics; medical education; search engine; knowledge management; semantic web; language; teaching; vocabulary; controlled; students; educational personnel; French; curriculum

**Introduction**

**Background**

Medicine, health care, and wellness will become increasingly digitized. Thus, digital technologies are more than ever taking a pivotal position in clinical practice, making it crucial to educate future professionals to efficiently grasp digital health and health informatics [1,2]. The World Health Organization views digital health as “a broad umbrella term encompassing eHealth, mHealth, as well as emerging areas, such as the use of advanced computing sciences in big data, genomics, and artificial intelligence.” The World Health Organization affirmed that to strengthen health systems using digital health technologies, finding ways to build capacity and creating a digitally capable health workforce should be key objectives [3,4].

The integration of digital technologies has brought about significant changes in the realm of health professions education. Our research identified various digital education–related inquiries, culminating in a comprehensive and diverse research agenda. We proposed a conceptual framework to assist educators and researchers in developing, designing, and studying digital education. However, we acknowledge the need for further data from lower- and middle-income countries [5].

In 2022, the Delegation of Digital Health of the French Ministry of Health and the French National Research Agency published an open call for projects to support the development of digital health teaching and learning technologies, in French, and dedicated to the community of French health–related professions education institutions educating health-related professionals [6]. These include medicine; dental medicine; pharmacy; midwifery; nursing; physiotherapy; ergotherapy; and, more broadly, any related field such as social work, health administration, and biomedical engineering. By 2027, this heterogeneous community, which includes postgraduates and continuous learners, will reach 210,000 members trained simultaneously in France.

Thus, the association of the departments of digital health (DDHs) of the University of Rouen Normandy (URN) and Côte d’Azur University (CAU) is developing and implementing the SaNuRN (Santé Numérique Rouen Nice) [7], a 5-year project started in September 2022 and granted with €3,951,200 (US $4,163,775) for a total cost of €6,891,923 (US $7,262,708), in the context of the said open call (grant #ANR_22-CMAS-0014) having an overall budget of €71 million (US $77.6 million) dedicated by the government to digital health education.

From an educational perspective, SaNuRN is currently based on existing pedagogical resources developed by the DDHs of URN and CAU. In addition, a large part of these resources follows the concepts structuring the French National Referential on Digital Health (FNRDH) [8] that provides French higher education institutions educating health-related professionals with a guideline to support teaching in digital health. Thus, students and lecturers from URN, CAU, and other higher education institutions and professionals have free and unrestricted access to the Catalog and Index of Digital Health Teaching Resources (CIDHR) as a platform providing structured and validated information contributing to the body of knowledge necessary to master the field [9].

For example, since 1993, the URN DDH has been developing CISMef (Catalogue et Index des Sites Médicaux en langue Française; in English, Catalog and Index of Medical Sites in French Language), a catalog of French-speaking health resources currently containing 128,689 inputs, including 9409 teaching resources. Moreover, since 1999, with the foundation of the French Medical Virtual University [10], all these teaching resources have been freely available in open access [11,12].

Dealing with teaching material in digital health for academic purposes is challenging because of the availability of many resources. However, the French-speaking material is globally limited compared with the one available in English. Therefore, we are developing the CIDHR [9].

In contrast to other educational platforms that mainly cater to English speakers and require payment, such as the Healthcare Leadership Academy [13], various platforms supported by the UK National Health Service [14], or the IMD Health cloud-based platform [15], CIDHR plays an important role in freely engaging French-speaking students and the health care practitioners community in digital health teaching and learning.

One of the primary reasons for emphasizing the need for a French-speaking knowledge catalog in the digital health domain, such as CIDHR, is to bridge the language gap. Although English...
is a dominant language in scientific literature and teaching platforms, it excludes a substantial portion of the global population, particularly those more comfortable with other languages and, more particularly, French in this specific case. Thus, this language barrier can hinder the dissemination of critical information and knowledge transfer in digital health education and the development of a dedicated platform in French (which can comprise resources in other languages) [16-19].

From an informatics perspective, SaNuRN is based on semantic technologies. Since 2000, the DDH of URN has been developing and maintaining a semantic search engine (Doc’CISMeF) that was developed using primarily the Medical Subject Headings (MeSH) thesaurus [20] to manage the CISMeF resources. Starting in 2010, a multiterminology and multilingual approach is being continuously developed and used to allow any CISMeF resource to be indexed by more than 1 health terminology and by more than 1 language, although the MeSH thesaurus remains the pivotal terminology and, for CISMeF, the French and the English are the 2 pivotal languages [21,22].

As a natural evolution with the goal to share as much as possible the open access resources, and within the SaNuRN framework, starting in 2022, we have been developing and implementing a multilingual multiterminology semantic search engine CIDHR. We focus on continuously expanding CIDHR to fit the goal of the SaNuRN project and facilitating the daily teaching and learning practice in medical education by offering easy-to-use indexation and retrieval processes of any educational resource in digital health mainly toward not only French speakers but also toward others; the portal is available among other languages in English, German, Spanish, Greek, Croatian, Chinese (Mandarin), and Finish (Figure 1 [9]).

Figure 1. The Catalog and Index of Digital Health Teaching Resources (CIDHR) portal in French.

Aim, Objective, and Hypothesis
Our main aim in developing and implementing CIDHR, as a multilingual multiterminology semantic search engine, is to enhance knowledge sharing and spreading in digital health and health informatics and to expand the health-related educational community, primarily French speaking but also in other languages [23]. In particular, we aim to support the continuous development of initial (ie, bachelor level), advanced (ie, master and doctoral levels), and continuing training (ie, professionals and postgraduate levels) in digital health for health and social work fields.

Our main objective is to describe the development and implementation of the semantic search engine CIDHR in SaNuRN as a way to foster digital health education and continuous training in France. The hypothesis that guided this research is that controlled vocabularies dedicated to medical informatics and digital health, such as the Medical Informatics Multilingual Ontology (MIMO) [24,25] and the concepts structuring the FNRDH [8], to index digital health teaching and learning resources, are effectively increasing the availability and accessibility of these resources to medical students and other health care professionals.

Methods
Highlights
CIDHR is a part of the SaNuRN project. To better understand how we are developing and implementing CIDHR as a catalog of indexed digital health resources, we present the methodological steps in this process in the next lines. First, resource identification is processed by medical librarians; then, based on controlled vocabularies (an ontology and a competency referential organized as a taxonomy), the teaching and learning resources are indexed for each related knowledge domain. In the third step, the same resources are tagged with relevant academic and professional experience levels. The fourth step consists of sharing the indexed resources with the digital health teaching and learning community (with some focus on the French-speaking community). The last step consists of assessing CIDHR by obtaining informal feedback from users.

Resources Identification
To identify new or updated digital health teaching and learning resources, a group of 3 librarians from URN DDH is working on a continuous information watch, according to an internally developed and validated process comprising the steps and actions.

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Thus, the librarians search proprietarily on a predefined list of academic websites of Schools of Health Sciences (eg, Medicine, Dental Medicine, Pharmacy, Nursing, Rehabilitation), National Agencies (eg, the French Ministry of Health [26]; the French National Authority for Health—La Haute Autorité de Santé [27]; the French national agency for medicines and health products safety—Agence Nationale de sécurité du médicament; and the French Agency for Food, Environmental and Occupational Health & Safety—Agence Nationale de Sécurité Sanitaire de l’Alimentation, de l’Environnement et du Travail); and other organizations involved in digital health education such as universities in France and around the world. They are also using search engine alerts, allowing reception of emails with potentially interesting content detected by their algorithms.

Moreover, the librarians monitor social media platforms, such as X (formerly known as Twitter), LinkedIn, or Facebook, by following and screening digital health–related accounts and groups sharing potentially relevant educational supports in digital health and health care informatics. The same search is performed by reading newsletters from professional organizations and academic institutions.

Furthermore, direct contacts with librarians and professional networks in digital health, particularly in the educational field, are used to obtain early updates about new and updated resources before their publishing over the web.

Resource identification also comprises the users’ engagement with CIDHR as a platform, which can share their comments with the whole team (not only the librarians) and suggest additional resources.

Therefore, by using a variety of identification approaches, the librarians involved in CIDHR can propose to the digital health experts of the SaNuRN project a wide range of digital health educational resources to integrate. It is critical to remember that the resources identified are multilingual (although mostly in French because of the SaNuRN grant requirements).

Librarians evaluate each potential resource against the following three criteria:

1. Is the resource a digital health or health informatics education–related one? The resource should be designed to teach users or to support their teaching (depending on whether the user is a student or a lecturer).
2. Is the resource accurate and up-to-date? The resource should be based on current research and best practices.
3. Is the resource accessible? The resource should be available to many users, including those with disabilities.

If a resource meets all 3 criteria, the resource is added to the SaNuRN or CIDHR repository for tagging and indexing. If a potential resource fails the evaluation, it is excluded, at least temporarily, until the librarians recheck the resource and its positive compliance with the evaluation criteria.

Resources Indexation

For indexing the identified educational resources, CIDHR uses 2 knowledge organization systems (KOSs).

The first is the MIMO, which comprised 3645 concepts in 33 languages as of September 2023 [23-25]. An ontology formally represents a set of concepts within a domain and the relationships between these concepts.

The second KOS was the FNRDH created in 2021. Specifically, FNRDH describes 29 different competencies and 70 different abilities. FNRDH has a 3-level hierarchy. The first relies on 5 main competencies (health data, communication in health, digital tools in health, telehealth, and cybersecurity). The second level relies on 25 subcompetencies (eg, characterizing and managing nominative data, applying [European] regulation [in particular General Data Protection Regulation]), and the last level describes 70 different abilities (eg, understanding the life cycle of the digital health data) [8].

As a side note, MIMO and FNRDH are freely available through the Health Terminology/Ontology Portal [28], also developed by URN DDH over the past 20 years [29,30]. These 2 KOSs are used at an automated stage wherein the resources are preindexed based on keyword identification and then through a librarian indexation validation stage or manual indexation if the automated process is invalid.

Moreover, CIDHR is built around 2 sets of metadata (SoM): the Learning Object Metadata (LOM) set [31] and the Dublin Core Metadata Terms (DCMI-MT) set [32]. LOM is a standard for describing digital learning resources. It provides a set of metadata elements that can be used to describe the characteristics of a learning resource such as its title, description, educational objectives, and technical requirements. DCMI-MT is a simple metadata schema that can describe various digital resources. It provides a set of 15 core metadata elements, including title, creator, and subject. Both SoM are transparent for the final user and allow efficient management of the overall available data related to a selected education resource for being included in CIDHR. These SoM are autocompleted when metadata are available with a resource (ie, a website) and are then validated by a medical librarian. If the automated process fails, the librarian handles this task.

Using 2 KOSs and 2 SoM allows a flexible and comprehensive organization of CIDHR. First, the combination of the KOSs, MIMO as an ontology, and FNRDH as a referential provides a structured way to describe the concepts and skills covered by the teaching resources. Second, the SoM provide a way to describe the characteristics of the teaching and learning resources themselves. Combining KOSs and SoM makes it easy for users to find the appropriate educational resources.

For example, a user (eg, a medical student) interested in learning about the use of artificial intelligence in digital health can use CIDHR to find learning resources that are indexed with the following MIMO concepts: “artificial intelligence,” “digital health,” “machine learning,” and “data mining”; or the same user can find resources indexed with the following FNRDH skill: “use of artificial intelligence in digital health.” Accordingly, CIDHR provides a list of relevant educational resources.
Using KOSs and metadata sets is a common practice in digital learning to organize and represent digital learning resources in a flexible, comprehensive, and user-friendly manner.

**Resources Tagging and Integration to the Curricula**

Resource indexation is a critical stage of the CIDHR knowledge management process and a pivotal component of the overall SaNuRN project. However, the main aim is to use CIDHR as a support for digital health learning and teaching in integrating the medical and health-related undergraduate, postgraduate, and life continuing education curriculum. It is also important to suggest the right resources to the specific end user (ie, student according to his degree and field of study and lecturer according to his students and his field of teaching). Thus, LOM and its instantiation in France, known as SupLomFr [33], and DCMI-MT were previously used in CISMeF that we have introduced above [11].

Thus, the 2 leading metadata are of utmost importance to help health-related students and lecturers find the right educational resources at the right time.

The first metadata is the “field of study” (ie, initial long-path education [>5 years]: medicine [Doctor of Medicine], dental surgery [Doctor of Dental Surgery], pharmacy [PharmD], and midwifery [State Diploma of Midwifery]; initial short-path education [until 5 years]: nursing [registered nurse], physiotherapy [State Diploma of Physiotherapist], and occupational therapy [State Diploma of Occupational Therapist]; and social work [State Diploma of Social Worker]).

The second metadata is the “degree level” (bachelor, master, doctorate, or residency in medicine, dental surgery, and pharmacy). It is important to point out that the graduates of an initial short-path education can continue their education in their fields at the postgraduate levels (master and doctorate degrees and lifelong continuing education).

Therefore, for any query performed on CIDHR, the end user may select and save these 2 metadata, “field of study” and “degree level” (eg, “Nursing” AND “Master Degree”; “Medicine” AND “Residency”). The so-called “training matrix” is generated to provide each combination of learners with a set of resources relevant to their profile. This set of educational resources is defined by consensus by the SaNuRN pedagogical team to be the most exhaustive. The “training matrix” is periodically updated according to the introduction of new resources or updates.

Moreover, any kind of teaching resource is cataloged in CIDHR, thanks to an extensive resources type hierarchy created for CISMeF based on a conceptual extension of the MeSH publication type [20,34]. This resource-type hierarchy has been used fruitfully for more than 20 years by users (health students, academics, and professionals) of the CISMeF platform searching for clinical-focused resources.

The following teaching resources are cataloged by tagging each one based on the following resource-type hierarchy (Figure 2 [28,35,36]): a “classical” teaching resource supporting a face-to-face course delivered with a series of slides (resource type: teaching material); evaluation of knowledge, such as multiple-choice question; and evaluation of competence, such as Objective Structured Clinical Examination or Script Concordance Test. These last 2 innovative approaches used as competency evaluation tools have been proposed for the nursing curriculum [37]; their use will be extended to other fields in CIDHR.

These combinations of the metadata tags “field of study” and “degree level” with the “resource type” tag as filters allow delivery to the user more or fewer indexed resources relevant to the knowledge fields submitted in the query to CIDHR depending on the filters selection submitted with the query.
User Experience Assessment

To assess the reception of CIDHR among users, we conducted an informal assessment including the following steps. First, a group of users consisting of both students (health students in their first year: 10/150, 6.7%) and the 5 teaching staff of digital health (JG, AB, PS, RL, and SJD) from diverse educational backgrounds and institutions was recruited. Then, immediately after the first set of lessons, the student participants were given access to CIDHR and encouraged to explore its features, search for digital health resources, and interact with the platform over a few days. Afterward, each user involved was invited to share, during a short interview, their feedback about their (1) perception of CIDHR’s user-friendliness and “easily navigable” capabilities; (2) comments on content quality comprehensiveness and the ongoing expansion; and (3) perception of CIDHR as a one-stop shop for freely and unrestricted accessible, primarily available digital health resources in their academic (ie, learning, teaching, and research) and professional activities. The last component of the feedback collection consisted of obtaining suggestions from the assessment participants.

Ethical Considerations

This research is dispensed of the ethical committee's approval, the User Feedback for Continuous Improvement being a normal educational practice and classroom management method.
conducted in educational settings. Specifically, as non-interventional research dealing with practical habits analysis the Rouen University Hospital ethical committee does not ask for submitting such kind of research to the ethical committee. Moreover, the whole project SaNuRN that comprises CIDHR has been approved as a whole by the Delegation of Digital Health of the French Ministry of Health and the French National Research Agency [38].

**Results**

**Resource Discovery and Indexation in CIDHR**

The outcomes of the CIDHR resource identification and evaluation processes were executed by a dedicated team of 3 librarians from the URN—Rouen University Hospital DDH, aiming to collect and curate an extensive collection of digital health teaching and learning resources. Our identification strategies yielded a diverse and expansive pool of digital health educational resources through diligent exploratory searching of academic websites and platforms (eg, a systematic review of French universities’ digital health departments and several French national agencies such as *Agence Nationale de sécurité du médicament* and *La Haute Autorité de Santé*) [26,27]. We successfully identified a continuously updating substantial number of resources catering to various aspects of digital health education. The use of search engine alerts (eg, Google Alerts [39] and PubMed alerts [40]), social media monitoring (eg, LinkedIn [41]), newsletters, and professional network notifications (of posts in groups of interests) also contributed significantly to the resource identification process.

In the last year, we identified approximately 500 valuable resources. It is noteworthy that the identified resources reflect a multilingual character (in particular, English). However, to align with the SaNuRN grant requirements, a substantial proportion (>90%) of the resources is in French. However, we ensured a representation of diverse languages to accommodate a wide-ranging audience interested in digital health education. In addition, we supported the ongoing internationalization and French-drafted teaching and self-learning introduced in the French higher education curricula.

**Resources Evaluation**

The “resource evaluation process” disclosed in the *Methods* section together with its 3 fundamental criteria ensures that each resource included up to now has been evaluated for relevance, “accuracy and currency,” and accessibility.

The relevance was scrutinized to ascertain its suitability for teaching and learning digital health education to serve the needs of both students and lecturers. As a result, a significant portion of the identified resources clearly aligned with digital health education objectives (323/503, 64.2%). The 35.8% (180/503) of resources that were excluded were in the scope of digital health, but they did not sufficiently focus on real teaching resources.

Furthermore, each one of the remaining resources was subjected to a rigorous assessment of “accuracy and currency” to ensure its alignment with up-to-date research findings and adherence to best practices within the digital health field. The evaluation step revealed that some resources did not meet these accuracy and currency criteria and were rejected (approximately 36%).

The “accessibility” of the educational supports is a critical aspect emphasized in CIDHR resource evaluation to include in the catalog materials that can effectively be used by a broad range of the digital health educational community, including individuals with disabilities. This evaluation highlighted the commitment of many resources to accessibility.

If a potential resource does meet any one of these criteria, it does not move to inclusion in CIDHR and remains in a secondary list of resources to be periodically re-evaluated for future inclusion.

Resources that successfully passed all 3 evaluation criteria were promptly included in CIDHR. These resources are diligently indexed and tagged as described in the *Methods* section.

**Tailored Learning Paths: Metadata, Training Matrix, and Resource Cataloging in CIDRH**

The semantic search engine of CIDHR based on MIMO and FNRDH allows user-friendly access to previously indexed and tagged resources. At the end of September 2023, CIDHR comprised 371 available resources in the digital health field relevant to students and teaching staff from the first academic year of academic studies to lifelong continuing education. The French grant required that 80% of the effort should focus on the bachelor “degree level.” Therefore, approximately all the 371 resources included in CIDHR are focusing on bachelor’s students.

CIDHR is constantly expanding, with plans to incorporate increasingly as much as possible digital health teaching resources from the French health–related studies curricula over the next few years [6].

**Figure 3** shows an example of the results for the query “dossiers médicaux électroniques” (in English, “electronic health records” or EHRs).
Figure 3. Example of results to the query “dossiers médicaux électroniques” (in English, “electronic health records” or EHRs). CIDHR: Catalog and Index of Digital Health Teaching Resources; CISMeF: Catalogue et Index des Sites Médicaux en langue Française (Catalog and Index of Medical Sites in French Language).

Figure 4 shows an example of a digital health educational resource, as a bibliography card, indexed using MIMO and FNRDH, which is an example of CIDHR’s capabilities. A CIDHR bibliographic card comprises the following metadata: (1) the resource title, (2) the resource publisher or author, (3) the country of the source, (4) the year of publication, (5) the type of resource, (6) an abstract presenting the resource, and (7) a list of the terms and concepts used to index the resource with regard to controlled vocabularies and referential such as MIMO and FNRDH (Figure 4).

Figure 4. Example of an indexed resource in Catalog and Index of Digital Health Teaching Resources (CIDHR) comprising the following metadata: resource title, resource published and author, country, year of publication, type of document, an abstract, and a list of the terms and concepts used for indexation (here with both Medical Informatics Multilingual Ontology [MIMO] and French National Referential on Digital Health [FNRDH]).

The resource is written in French and focuses on EHRs, a concept defined in both MIMO (ie, “dossiers médicaux électroniques”) and FNRDH (ie, “Interagir de manière adaptée entre professionnels, avec l’usager, les aidants et accompagnants et avec les institutions et administrations,” in English, “Interact in an appropriate manner between professionals, with the healthcare customer, caregivers and companions and with institutions and administrations”); and “Utiliser les outils et services socles adaptés et identifier leur articulation avec d’autres dossiers partagés,” in English, “Use the appropriate basic tools and services and identify their connection with other shared files”). It educates the learners on the fundamentals and the importance of the EHRs, making it an invaluable resource for anyone looking to enhance their digital health knowledge. To facilitate the indexing process with FNRDH, which presents considerable complexity for medical librarians, the SaNuRN pedagogical team has established manual associations between MIMO and FNRDH.
MIMO and FNRDH concepts. For instance, this involves manually linking the MIMO concept with the FNRDH competency. It is essential to clarify that this mapping relation does not constitute a strict “exact match”; instead, it means that when a librarian indexes a teaching resource using a MIMO concept (eg, “electronic medical records”) associated with an FNRDH ability (eg, “Interact appropriately between professionals, with the healthcare customer, caregivers and companions and with institutions and administrations”), the educational resource is also indexed with this corresponding FNRDH competency.

Nevertheless, certain cases require manual indexing with FNRDH by medical librarians, primarily because of the absence of the MIMO concepts for specific capacities, still not defined and implemented in MIMO, such as the “lifecycle of health data.” Thus, to minimize the dependency on manual FNRDH indexing, the SaNuRN pedagogical team is actively developing MIMO concepts and establishing mappings between MIMO and FNRDH concepts, including those pertaining to the lifecycle of health data.

In addition, as a part of CIDHR capacities, the end-user process for any query to deliver an organized list of educational resources is considered. The first item on the list must be studied first, followed by the second item, and so on. This organized list is manually created for each FNRDH competency; in other words, we create a breadcrumb navigation for teaching and learning resources linked to each FNRDH competency. Currently, this organized list is familiar to all the students in all municipalities, but also Arabic, Spanish and Portuguese (native language resources. These materials are designed to cater to all aspects of digital health education needs, catering to lecturers, students, and professionals alike.

Table 1. Summary of the feedback collected during the Catalog and Index of Digital Health Teaching Resources user experience informal assessment.

<table>
<thead>
<tr>
<th>Feedback category</th>
<th>Students</th>
<th>Lecturers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Usability</td>
<td>User-friendliness and “easily navigable” capabilities</td>
<td>User-friendly and “simple to understand”</td>
</tr>
<tr>
<td>Content quality</td>
<td>Valuable, “easy to understand”</td>
<td>Valuable, comprehensiveness</td>
</tr>
<tr>
<td>One-stop shop potential</td>
<td>Free resources, easy to access, on various relevant content</td>
<td>Real one-stop shop freely and unrestricted accessible, especially available digital health resources in their academic (ie, learning, teaching, and research) and professional activities</td>
</tr>
<tr>
<td>Participants suggestions for</td>
<td>More than French-only resources, in particular English, but also Arabic, Spanish and Portuguese (native language of the students)</td>
<td>More metadata on bibliographic card; more than French-only resources, in particular English</td>
</tr>
<tr>
<td>improvements</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Discussion**

**Overview**

The integration of digital technologies in health care and medical education is becoming increasingly vital. This study introduces CIDHR as part of the SaNuRN project to enhance digital health education in France. CIDHR is a comprehensive digital platform that indexes and organizes educational resources related to digital health, catering to students and health care professionals. This discussion explores the strengths and limitations of CIDHR, potential future perspectives, and the impact on digital health education.

**Strengths and Limitations**

CIDHR is the heart of a digital health educational platform that provides an extensive array of inclusive and accessible teaching and learning resources to a diverse global audience in the health care professional education landscape. CIDHR has a large and continuously expanding collection of up-to-date and relevant digital health resources that serves as a one-stop shop related to all aspects of digital health education needs, catering to lecturers, students, and professionals alike.

CIDHR is committed to providing comprehensive support to French-speaking individuals seeking digital health education. To ensure that language barriers do not impede access to educational resources, CIDHR has indexed a wide range of materials in multiple languages, in addition to its French language resources. These materials are designed to cater to the fields of study. In the future, this organized list will be, when relevant, adapted to fit with the requirements of each field of study (eg, medicine, nursing), degree level (eg, bachelor, residency), and targeted level competencies or skills (eg, beginner, intermediate, and advanced).

**User Feedback for Continuous Improvement**

To assess CIDHR’s usability and acceptance among users, we collected informal feedback from a select group comprising both first-year health students (10/15, 67%) and teaching staff (5/15, 33%). Their feedback universally reflected a positive sentiment, characterizing the platform as remarkably user-friendly and easily navigable. Moreover, they lauded the platform’s existing resource collection, founded on rigorous content quality control, and appreciated its ongoing expansion. Notably, users articulated their assessment, highlighting CIDHR’s comprehensiveness, precision, and user-friendliness. Nonetheless, their constructive suggestions included the need for augmenting multilingual resources and offering more comprehensive resource information, particularly with respect to metadata. In the users’ collective perception, CIDHR was deemed a one-stop destination for discovering high-quality digital health resources. An additional commendable attribute was the platform’s unrestricted accessibility, which rendered it a valuable asset for all users.

Moreover, additional suggestions related to the need for more multilingual resources and comprehensive metadata were noted (eg, field of study, resource language, and resource scoring; Table 1).
diverse linguistic needs and are available to all individuals seeking to enhance their digital health knowledge. With CIDHR’s vast collection of indexed educational resources, individuals can access high-quality information and support regardless of their native or daily spoken language.

To improve resource indexing and search precision, CIDHR uses controlled vocabularies such as MIMO and FNDRH, which enable users to locate relevant educational materials that align with their specific digital health skills and competencies with ease. Moreover, CIDHR prioritizes resource accessibility, making its platform suitable for a broad audience, including individuals with disabilities [42,43]. Thus, CIDHR, being based on a multilingual semantic search engine, would enhance accessibility and inclusivity. By looking at all (even mainly French speakers currently) health care professionals, researchers, and students, CIDHR allows them to have access to a broader range of educational resources, fostering a more inclusive learning environment. This inclusivity aligns with the principles of health equity and diversity in medical education [44]. Furthermore, the CIDHR platform’s user-friendly interface and straightforward navigation enable users to connect with relevant educational resources quickly and efficiently.

By looking at these advantages and the SaNuRN aim to facilitate digital health educational resources, the current corpus, including 371 elements, will be expanded by continuing the collection and evaluation process, in parallel with cooperation with as many possible faculties and schools of health (ie, 31 medical schools in France). We expect approximately 700 CIDHR resources by mid-2024.

However, some limitations have been identified. First, although CIDHR supports mainly French resources, it would benefit from expanding its multilingual and international support to make it more accessible to a global audience of the digital health education community. Second, it is necessary to expand CIDHR resource collection to incorporate more digital health resources from diverse sources allowing providing them to the educational community and industry insights. Third, although SaNuRN plans to provide personalized learning paths to users, via CIDHR, it is crucial to ensure that these paths are effective and tailored to the individual needs of each user, which requires further research and development [45,46]. Fourth, integrating CIDHR with the learning management systems used by educational institutions would streamline access to digital health resources for students and educators. However, it is crucial to ensure that the integration is smooth and that CIDHR is easy to use within these systems. Finally, developing a feedback and rating system for resources would be helpful in enabling users to identify the most valuable and reliable materials within the platform. However, it is vital to design the system carefully to ensure that it is fair and unbiased. Moreover, it is important to note that CIDHR is under development, and there may be some bugs or glitches in the system. In addition, some features may not be fully implemented.

**Future Perspectives**

Handling the current limitations of CIDHR opens a wide range of perspectives.

To improve the accessibility and user-friendliness of CIDHR, the SaNuRN team will look at different paths. First, expanding multilingual support to cater to a wider global audience (over the French-speaking community) by indexing (based on MIMO as a multilingual ontology dedicated to digital health) more resources in more languages MIMO on the platform. In addition, CIDHR enrichment will benefit from the SaNuRN team’s international partnerships and collaborations to expand CIDHR resource collection and promote knowledge exchange to enrich the user experience [23,47]. Moreover, an additional enhancement is planned to provide personalized learning paths to users based on their profiles, such as their field of study, degree level, CIDHR personal and similar user use, to enable tailored educational experiences and effectiveness. Furthermore, CIDHR will be integrated with the learning management systems used by educational institutions to streamline access to digital health resources for students and educators (eg, Moodle [48]). Finally, CIDHR will benefit from the development of a feedback and rating system for resources not only to help users identify the most valuable and reliable materials within the platform but also to allow the SaNuRN team project to get feedback on the resource collection, indexing, and tagging processes from mass users’ practice. All these measures will augment CIDHR utility and enrich the user experience.

**Conclusions**

CIDHR represents a significant advancement in digital health education, offering a diverse, accessible, and validated resource collection. Although it has strengths in its multilingual approach, controlled vocabularies, and user-friendliness, addressing resource evaluation challenges and enhancing resource information are areas for continuous improvement. The future perspectives for CIDHR include further expansion, collaboration, personalized learning, integration, and user feedback mechanisms, all aimed at enriching the digital health education experience for students and health care professionals.

To the best of our knowledge, no prior published research has described a multilingual semantic search engine to query a digital health educational repository to be used by any health-related field student and lecturer. This is also because of the uniqueness of the development of the Health Terminology/Ontology Portal and MIMO by the members of the SaNuRN team. These projects have no equivalent to date.

The hypothesis that guided this part of the SaNuRN research and that we have validated is that controlled vocabularies and knowledge and skills referential dedicated to medical informatics and digital health, such as MIMO [22,23] and FNDRH [24], to index related educational resources, are effectively increasing the availability and accessibility of these resources to the health care–related community. This approach is possible as MIMO and CIDHR search engine are multilingual.

A European project called the HosmartAI (Hospital Smart development based on AI) project deals with the digital transformation of the European health care sector to make the European health care system more strong, efficient, sustainable, and resilient. CIDHR can play an important role in acquisition of literacy in digital health for professionals [49]. The European
Federation for Medical Informatics is taking part in different projects such as HosmartAI and as a collaboration and cooperation-oriented scientific and academic international organization, it can help disseminate information about CIDHR to promote its use by an increasing number of members of the digital health educational community worldwide.

However, the need to develop and improve digital health competencies for medical learners and broadly for health-related students and professionals is an established objective worldwide [45,50,51]. As a fact, prior studies evaluating digital health competencies among German medical students have shown a significant improvement after a digital health teaching course was introduced in their curriculum, although most students found that digital health is not sufficiently taught in undergraduate medical education, while it may influence everyday work of physicians [52].

Thus, CIDHR will have an important role on the educational grounds to improve digital health literacy of students and lecturers and to increase their engagement with these ubiquitous ways of delivering and receiving health care [46,53]. CIDHR is a fair and findability, accessibility, interoperability, and reusability principles–focused platform looking at making “findable” educational resources by using a one-stop-shop portal approach, “accessible” by integrating these resources available overtime and by anyone (ie, including people with disabilities), “interoperable” by making these resources readable in the most common formats (PDF files and video and audio support on browser-embedded readers, such as YouTube), and finally “reusable” by providing resources freely distributed and under open access licensing [54-56].

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Data Availability

The data sets generated during or analyzed during this study are available from the corresponding author upon reasonable request.

Authors’ Contributions

JG was involved in conceptualization, methodology, software, validation, formal analysis, and investigation and prepared the original draft and reviewed and edited the manuscript. AB contributed to methodology, validation, formal analysis, investigation, and reviewing and editing the draft and acquired funding (HosmartAI [Hospital Smart development based on AI]). F Dufour was involved in validation and reviewed and edited the draft. F Disson performed the software analysis. BD was involved in methodology and software analysis. HC was involved in project administration. RL was involved in conceptualization, methodology, and reviewing and editing the draft. MF reviewed and edited the draft and supervised the study. PS was involved in conceptualization, methodology, formal analysis, and resources; reviewed and edited the draft; supervised the study; and acquired funding (SaNuRN [Santé Numérique Rouen Nice]). SJD was involved in conceptualization, methodology, validation, formal analysis, and resources; prepared the original draft and reviewed and edited the manuscript; supervised the study; participated in project administration; and acquired funding (SaNuRN).

Conflicts of Interest

None declared.

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Abbreviations

CAU: Côte d’Azur University
CIDHR: Catalog and Index of Digital Health Teaching Resources
CISMeF: Catalogue et Index des Sites Médicaux en langue Française (Catalog and Index of Medical Sites in French Language)
DCMI-MT: Dublin Core Metadata Terms
DDH: department of digital health
EHR: electronic health record
FNRDH: French National Referential on Digital Health
HosmartAI: Hospital Smart development based on AI
KOS: knowledge organization system
LOM: Learning Object Metadata
MeSH: Medical Subject Headings
MIMO: Medical Informatics Multilingual Ontology
SaNuRN: Santé Numérique Rouen Nice
SoM: sets of metadata
URN: University of Rouen Normandy

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Unpacking the Experiences of Health Care Professionals About the Web-Based Building Resilience At Work Program During the COVID-19 Pandemic: Framework Analysis

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Abstract

Background: The COVID-19 pandemic has resulted in a greater workload in the health care system. Therefore, health care professionals (HCPs) continue to experience high levels of stress, resulting in mental health disorders. From a preventive perspective, building resilience has been associated with reduced stress and mental health disorders and promotes HCPs’ intent to stay. Despite the benefits of resilience training, few studies provided an in-depth understanding of the contextual factors, implementation, and mechanisms of impact that influences the sustainability of resilience programs. Therefore, examining target users’ experiences of the resilience program is important. This will provide meaningful information to refine and improve future resilience programs.

Objective: This qualitative study aims to explore HCPs’ experiences of participating in the web-based Building Resilience At Work (BRAW) program. In particular, this study aims to explore the contextual and implementational factors that would influence participants’ interaction and outcome from the program.

Methods: A descriptive qualitative approach using individual semistructured Zoom interviews was conducted with participants of the web-based resilience program. A framework analysis was conducted, and it is guided by the process evaluation framework.

Results: A total of 33 HCPs participated in this qualitative study. Three themes depicting participants’ experiences, interactions, and impacts from the BRAW program were elucidated from the framework analysis: learning from web-based tools, interacting with the BRAW program, and promoting participants’ workforce readiness.

Conclusions: Findings show that a web-based asynchronous and self-paced resilience program is an acceptable and feasible approach for HCPs. The program also led to encouraging findings on participants’ resilience, intent to stay, and employability. However, continued refinements in the components of the web-based resilience program should be carried out to ensure the sustainability of this intervention.

Trial Registration: ClinicalTrials.gov NCT05130879; https://clinicaltrials.gov/ct2/show/NCT05130879

(JMIR Med Educ 2024;10:e49551) doi:10.2196/49551

KEYWORDS
resilience; intent to stay; employability; health care professionals; process evaluation; framework analysis; framework; resilience; stress; mental health disorder; prevention; training; qualitative study; web-based tool; tool; sustainability
**Introduction**

**Background**

The emergence of the COVID-19 pandemic has led to extensive changes in the health care landscape. Globally, the repeated waves of COVID-19 infections have led to health care professionals (HCPs) grappling with occupational health hazards and overstretched assignments [1,2]. These constant stressors have led to HCPs experiencing a surge in symptoms of burnout, insomnia, and mental health distress [3-5]. Accordingly, the intensification of physical and mental exhaustion has led to a considerable increase in the turnover of HCPs [6]. With a smaller health care workforce, health care administrators need to prioritize and concentrate their efforts on enforcing supportive measures to ensure that HCPs continue to be inoculated against stress and mental health disorders. Thus, reducing workplace-related stress may have encouraging effects on HCPs’ intent to stay [7,8].

Contemporarily, more persuasive evidence has alluded to the importance of noncognitive skills as protective factors against mental health distress [9,10]. An emerging interest among noncognitive skills is the development of an individual’s resilience. Resilience is the ability to overcome adversities [11,12]. Theoretically, resilience can be understood from various perspectives, as a trait (e.g., personality), process (e.g., interaction with protective factors), or outcome (e.g., becoming resilient). More importantly, building an individual’s resilience has positive effects on their mental well-being [13,14].

Figure 1. Process evaluation framework.

First, contextual factors are unique situational factors that influence how the intervention may be delivered or have affected the participants [25]. These contextual factors may have eventual implications on the implementation and mechanisms of impact. Second, the implementation process is the identification of factors that may influence the delivery of the intervention [25]. This may include the collection of data that reflects intervention fidelity [26]. Third, mechanisms of impact describe participants’ responses to and interaction with the intervention. In addition, mechanisms of impact identify any potential mediators, pathways, or consequences as a result of their participation in the intervention [25]. Thus, conducting process evaluations of interventions may be worthy in providing recommendations for improvements and supporting the eventual implementation of the program. Although prior qualitative evaluations of resilience programs [22,27,28] have made valuable contributions toward an in-depth understanding of participants’ experiences, its findings may not be transferrable because of several factors, such as population, cultural differences, and type of resilience program. For these reasons, conducting a study to encapsulate the experiences of the participants of the Building Resilience At Work (BRAW) program is important.

**Objectives**

This qualitative study explores HCPs’ experiences of participating in the BRAW program. Guided by the process evaluation framework [25], this study also aims to examine the contextual and implementation factors that affected participants’ experiences and identify the outcomes that arose from their participation in the BRAW program.
Methods

Ethical Considerations
This study was approved by the National University of Singapore Institutional Review Board (NUS-IRB-2021-703). This study's procedures were followed in accordance with the Declaration of Helsinki. Eligible participants were recruited from August 2021 to December 2022. Participants were provided with a participation information sheet, and they were allowed to withdraw without penalty. After obtaining informed consent, participants were invited to participate in a web-based semistructured audio- and video-recorded interview via Zoom (Zoom Video Communications). The interview transcripts were de-identified and coded using pseudonyms. Participants were given 20 Singapore Dollars for completing the study.

Research Design
This qualitative study is part of a randomized controlled study conducted in Singapore (ClinicalTrials.gov NCT05130879). A process evaluation approach [25] comprising semistructured individual digital interviews was undertaken to explore participants' experiences of using the web-based BRAW program. This study is reported based on the COREQ (Consolidated Criteria for Reporting Qualitative Research) [29] (Multimedia Appendix 1).

Setting and Participants
This study was conducted from April 2021 to December 2022 in Singapore, a multiethnic and multicultural city-state. Based on the national census [30], there are approximately 70,178 registered HCPs, and most of them are nurses (61.27%). Participants were eligible to participate in this qualitative study if they were practicing as an HCP in Singapore, could comprehend the English language, had access to a device that could connect to the internet, and completed the web-based BRAW program. A total of 33 participants who completed the web-based BRAW program were purposively sampled to participate in this qualitative study.

Web-Based BRAW Program
The web-based BRAW program is a 6-session weekly web-based program hosted via Microsoft Teams (Microsoft Corp). The resilience program was developed based on a systematic review [13] and evidence-based therapies, such as cognitive behavioral therapy [31], acceptance and commitment therapy [32], and problem-solving model [33]. The BRAW program comprised 6 different topics, namely, happiness and positivity, cognitive restructuring, behavioral activation, emotion regulation, positive work climate, and problem-solving (Table 1). It also comprised several elements, short videos, quizzes, and homework (Figure 2). A web-based forum was also provided for participants to interact with each other and provide social support.

Figure 2. Elements of the web-based BRAW program. BRAW: Building Resilience At Work.
Table 1. Overview of the Building Resilience At Work program.

<table>
<thead>
<tr>
<th>Week</th>
<th>Topic</th>
<th>Contents</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Happiness and positivity</td>
<td>• Understanding strengths and resilience</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Fostering positive attitude</td>
</tr>
<tr>
<td>2</td>
<td>Cognitive restructuring</td>
<td>• Identifying dysfunctional automatic thoughts</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Using cognitive behavioral techniques to modify dysfunctional thoughts</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Formulating rational responses to automatic thoughts</td>
</tr>
<tr>
<td>3</td>
<td>Behavioral activation</td>
<td>• Initiating and using behavioral activation techniques</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Building healthy interpersonal relationships and peer support</td>
</tr>
<tr>
<td>4</td>
<td>Emotion regulation</td>
<td>• Regulating emotions</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Preventing and managing conflict</td>
</tr>
<tr>
<td>5</td>
<td>Positive work climate</td>
<td>• Forging a supportive work environment</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Developing supportive collegial relationships</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Promoting coworker support</td>
</tr>
<tr>
<td>6</td>
<td>Problem-solving</td>
<td>• Solving work-life problems using a framework</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Importance of work-life balance</td>
</tr>
</tbody>
</table>

Data Collection
The digital interviews were scheduled at a time convenient for the participants. Participants were reminded to ensure that their cameras and microphones were working prior to the interviews. All interviews were conducted by a female researcher (ZQGL) who received formal training in qualitative research. The interviewer was supported by 2 doctoral-prepared researchers (WHDA and YL) who are experienced in qualitative research. During the digital interview, the interviewer started by building rapport with the participants and sharing the aims and processes of this study. In addition, sociodemographic characteristics including age, sex, ethnicity, and occupation were collected. Afterward, the interview was conducted according to the semistructured guide. The guide was developed based on the process evaluation framework [25] and comprised open-ended questions. Then, the initial guide was circulated to the research team and refined. Subsequently, the interview guide was piloted among 5 participants and was further revised for clarity. The final interview guide can be found in Textbox 1. The mean duration of the interviews was 35.48 (SD 7.83; range 20-54) minutes. Data saturation was achieved at the 31st participant, and 2 additional interviews were conducted to confirm saturation [34].
Textbox 1. Semistructured interview guide.

<table>
<thead>
<tr>
<th>Questions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. What was your experience when completing the Building Resilience At Work (BRAW) training program?</td>
</tr>
<tr>
<td>2. What were the issues with the platforms for the training sessions that you have encountered?</td>
</tr>
<tr>
<td>3. How did you feel about the duration of each training video?</td>
</tr>
<tr>
<td>4. How did you feel about the quizzes?</td>
</tr>
<tr>
<td>5. How did you feel about the homework?</td>
</tr>
<tr>
<td>6. How did you feel about the forum?</td>
</tr>
<tr>
<td>7. How did you feel about the entire duration of the 6-week BRAW training program?</td>
</tr>
<tr>
<td>8. What were the aspects of the intervention (eg, homework, quizzes, and forum) that you particularly liked or disliked?</td>
</tr>
<tr>
<td>9. Were there any sessions that stood out?</td>
</tr>
<tr>
<td>10. How did you feel about the contents?</td>
</tr>
<tr>
<td>11. Could you tell me your overall experience with applying the strategies learned from the BRAW intervention at work?</td>
</tr>
<tr>
<td>12. How was your experience of applying the strategies at work?</td>
</tr>
<tr>
<td>13. Did you encounter any problems or frustrations when trying to apply the strategies at work?</td>
</tr>
<tr>
<td>14. Has the BRAW training program influenced your resilience at work?</td>
</tr>
<tr>
<td>15. Has the BRAW training program influenced your enthusiasm and dedication at work?</td>
</tr>
<tr>
<td>16. Has the BRAW training program influenced your intention to leave?</td>
</tr>
<tr>
<td>17. Has the BRAW training program influenced your ability to gain and maintain employment?</td>
</tr>
<tr>
<td>18. Has the BRAW training program influenced your work performance?</td>
</tr>
<tr>
<td>19. Are there any other strategies that would help you to manage stress and build resilience that we have not mentioned in the BRAW intervention?</td>
</tr>
<tr>
<td>20. Do you have anything else to add that we have not covered in this interview?</td>
</tr>
<tr>
<td>21. Finally, are you okay for me to contact you for some follow-up questions?</td>
</tr>
</tbody>
</table>

Data Analysis

The video-recorded interviews were transcribed verbatim by 1 researcher (ZQGL) and verified for accuracy by another researcher (WHDA). The transcripts were imported and analyzed using NVivo (version 12; Lumivero). Transcripts were returned to the participants for their comments. A deductive framework analysis method [35] was then undertaken as it provides a systematic approach to analyzing qualitative data [36]. In addition, the use of a matrix structure provides a visually straightforward recognition of patterns in the data that can be useful in identifying similarities or differences between participants’ narratives [36]. In line with the research questions, a framework analysis approach is suitable, as this study was guided by the process evaluation framework and sought to examine participants’ experiences of the BRAW program. Particularly, it identifies the contextual and implementation factors that affected their participation and the outcomes of participation.

A 5-step framework analysis approach [35,37] was independently performed by 2 researchers (WHDA and YL). First, the researchers familiarized themselves with the data by reading the transcripts accompanied by listening to the interviews. Second, the transcripts were coded based on the process evaluation framework [25]. After completing the coding for the first 5 transcripts, both researchers compared their codes and developed a standardized code book. Following discussions among the researchers, the eventual code book comprised 11 different categories.

Third, after completing the coding for all transcripts, a total of 347 codes were brought together and discussed among the researchers. The similarities and differences that arose during the coding process were deliberated. Cohen κ was used to calculate the interrater agreement for the coding, and good agreement was found (κ=0.79). Consequently, the codes were organized and indexed based on the process evaluation framework. Fourth, the codes were further reduced by summarizing the key information for the indexed data in each category. Finally, the identified codes were mapped using a coding tree (Table S1 Multimedia Appendix 2) and interpreted using visual and narrative forms. Finally, 3 themes and 7 subthemes were derived from the framework analysis. The themes and subthemes were provided to a select group of participants who were willing to provide feedback on the findings.

Rigor

The principles of credibility, transferability, dependability, and conformability were used to demonstrate rigor [38]. First, a reflexivity journal was maintained by all members of the research team to improve their self-awareness and reduce any potential personal influences on the data. Second, the data
analyses were conducted by 2 independent researchers (WHDA and YL). Third, participants were invited to review their transcripts to clarify the context of the statements and ensure that the final themes and subthemes were representative of their experiences [39]. Subsequently, an audit trail detailing the recruitment, data collection, and analysis process was conducted to ensure ease of replication, transparency, and dependability [38]. Finally, a thick description of the context and the intervention was provided, this facilitates the transferability of the findings of this study [38].

**Results**

**Overview**

A total of 33 HCPs participated in this qualitative study. The sociodemographic variables are presented in Table 2. Most of the participants were between the ages of 31-40 years (n=11, 34%), female (n=24, 73%), ethnic Chinese (n=25, 76%), and nurses (n=15, 46%). The findings from the framework analysis unveiled 3 themes and 7 subthemes that depicted participants’ experiences, interactions, and impacts from the BRAW program. The 3 themes were learning from web-based tools, interacting with the BRAW program, and promoting participants’ workforce readiness (Figure 3).

Table 2. Participants sociodemographic characteristics (N=33).

<table>
<thead>
<tr>
<th>Variables</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age group (years), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>21-25</td>
<td>5 (15)</td>
</tr>
<tr>
<td>26-30</td>
<td>9 (27)</td>
</tr>
<tr>
<td>31-40</td>
<td>11 (34)</td>
</tr>
<tr>
<td>41-50</td>
<td>6 (18)</td>
</tr>
<tr>
<td>51-60</td>
<td>2 (6)</td>
</tr>
<tr>
<td><strong>Sex, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>9 (27)</td>
</tr>
<tr>
<td>Female</td>
<td>24 (73)</td>
</tr>
<tr>
<td><strong>Ethnicity, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Chinese</td>
<td>25 (76)</td>
</tr>
<tr>
<td>Malay</td>
<td>7 (21)</td>
</tr>
<tr>
<td>Indian</td>
<td>1 (3)</td>
</tr>
<tr>
<td><strong>Profession, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Allied health worker</td>
<td>12 (36)</td>
</tr>
<tr>
<td>Clinical administrator</td>
<td>1 (3)</td>
</tr>
<tr>
<td>Clinical researcher</td>
<td>4 (12)</td>
</tr>
<tr>
<td>Nurse (registered and enrolled)</td>
<td>15 (46)</td>
</tr>
<tr>
<td>Physician</td>
<td>1 (3)</td>
</tr>
<tr>
<td><strong>Duration of interviews (minutes)</strong></td>
<td></td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>35.48 (7.83)</td>
</tr>
<tr>
<td>Range</td>
<td>20-54</td>
</tr>
</tbody>
</table>
Theme 1: Learning From Web-Based Tools

Overview

The first theme depicts the BRAW implementation process. It particularly describes how participants learned through web-based tools via Microsoft Teams. This is elaborated in 2 subthemes, namely, engaging with web materials and internalizing the resilience process.

Engaging With Web Materials

The BRAW program provided various web materials, ranging from short videos to quizzes and homework. The short videos were developed using animations, graphics, and subtitles, which appealed to the participants and supported their engagement with the web materials:

The use of graphics was quite good, the animations and all, so like, it kept me wanting to finish watching, not like stop halfway. Yeah...the pace was also good, and like, just nice, not too much information overload.

[Participant 24, female, Chinese, nurse]

However, some participants were encumbered by the number of tasks (eg, weekly quizzes and homework). For instance, the weekly homework was described to be a “chore,” and this can be a disincentivizing factor in completing the program. As an alternative, a participant proposed that renaming the weekly tasks could be a strategy to overcome the inertia:

Because “homework” it sounds like “tsk,” erm, like a chore to be done, you know, but “reflection” is like, you reflect on what you-you-you need to do. So, sounds more forgiving.

[Participant 26, female, Malay, nurse]

Internalizing the Resilience Process

Despite the conflicting work commitments and activities in the BRAW program that participants had to undergo, they credited the quizzes and homework as factors that supported the internalization of the learning process. Particularly, reviewing the questions found in the quizzes and homework facilitated an internalization process:

Just by plain reading the question, it may set you thinking, you see. You don’t know what’s happening or your subconscious, you’re already motivated right, you learn some new content. And that homework may actually be building synapses, you know, trying at the backend that you don’t know about.

[Participant 10, male, Malay, physician]

However, not all participants were well-versed in the contents of the BRAW program. Several participants highlighted difficulties in appreciating the theoretical aspects of the program:

When it gets a little bit more “science-y,” like the brain and then they tell you, I don’t know all the words, I don’t remember, but like the brain and then, certain kinds of thoughts and all that. Then, those kinds of stuff, no, like I haven’t heard of that before.

[Participant 15, female, Indian, clinical researcher]

Notwithstanding, these groups of participants, particularly those who did not receive formal training in health sciences, verbalized how they used the quizzes as an avenue to understand the various technical terms that they were not familiar with:

Especially some of the terms, erm, maybe a bit technical? I’m not that acquainted. So, it [referring to the quizzes] allows me to clarify, review and...
understand and get it correct. [Participant 8, female, Chinese, clinical administrator]

Theme 2: Interacting With the BRAW Program

Overview
The second theme describes the BRAW program’s mechanism of impact and the relevant contextual factors that influenced it. This theme expressed how participants responded and interacted with the BRAW program and is highlighted in 2 subthemes, namely, appreciating the asynchronous self-paced program and relating to the applicability of the contents.

Appreciating the Asynchronous Self-Paced Program
Due to the higher workload brought upon by the COVID-19 pandemic and the resumption of usual clinical duties, participants had to contend with numerous conflicting priorities. Hence, they appreciated how the BRAW program was designed as an asynchronous self-paced program. This allowed them to learn at their own pace and time:

Healthcare workers are busy, so they don’t have to find a specific day and time to attend an intervention, whether be it online or on-site, face-to-face or whatever, so having something that you can access on your own time and target is good. [Participant 4, female, Chinese, clinical researcher]

However, despite the self-paced nature of the program, participants struggled with finding suitable time outside their personal commitments and rest to engage in the program. This was more prominent among HCPs who are on shift work duties:

We are really packed and rushed at work, and there’s a lot of multitasking. It’s like very draining at work. I think the shifts also, so you do rotating shifts. So, it’s quite tiring after work to find time. [Participant 5, female, Chinese, nurse]

Nevertheless, some participants felt that introducing more web-based synchronous elements through videoconferencing tools may be able to better support their learning:

These sessions were to be interactive whereby we can do it via Zoom, to share every participant’s experience, it would be even better. [Participant 28, female, Chinese, nurse]

Relating to the Applicability of the Contents
The BRAW program was conducted at the peak of the COVID-19 pandemic in Singapore. Due to the stressors inflicted by the additional workload, participants felt that the program was delivered at an opportunistic time to support their psychological well-being:

I think you kind of met me at the right time and I feel that I need to self-improve. [Participant 3, male, Chinese, nurse]

In particular, participants appreciated how the contents were relatable to their concerns and felt that they were able to translate their newly acquired theoretical knowledge to an actual situation:

I really appreciate the teamwork and emotional regulation, like the ones I could really practice, putting time for myself, things like that. [Participant 6, male, Chinese, nurse]

Theme 3: Promoting Participants’ Workforce Readiness

Overview
The final theme describes how the BRAW program has influenced participants’ readiness to maintain in the workforce. Through participants’ narratives, the BRAW program has a profound impact on their resilience, intent to stay, and employability. This theme is further elaborated in 3 subthemes, namely, drawing resilience in times of adversity, promoting intent to stay in health care, and becoming future-ready.

Drawing Resilience in Times of Adversity
The BRAW program instilled numerous positive aspects in participants. As participants translated their newly acquired knowledge into practice, they demonstrated resiliency by overcoming the challenges and difficulties experienced in the workplace:

Yup, especially when dealing with negative emotions and how to bounce back up again. [Participant 1, male, Chinese, nurse]

When asked about the extent of the improvements, the majority of the participants felt noticeable improvements. For instance, they observed an evident increase in their ability to overcome situations:

In the past...I take quite a while to recover...Then, nowadays, it’s a bit better, even though I think about it, I can move on from it. And I can have a more positive mindset about it. So, I don’t blame myself for something that happened, or I don’t dwell on the thing that happened. Instead, I focused on the future, like if it happens again, what can I do. [Participant 13, female, Chinese, audiologist]

Promoting Intent to Stay in Health Care
Participants also felt that the BRAW program supported their resilience to remain steadfast in the health care sector. This was an interesting viewpoint expressed by most participants because it proposes that the improvement of psychological well-being has increased their intent to stay in their current role:

This course [referring to the BRAW program] actually helps me dispel away negative thoughts, put things in perspective, and reframe my mind away so that I can still go through the job. [Participant 14, female, Malay, medical technician]

However, most of the participants also felt that resilience training alone may not be sufficient to influence their intent to stay. Instead, one’s intent to stay may be influenced by a larger environmental factor such as management-related reasons:

The management did not do anything, so I feel that I should just quit this organization because they don’t take care of us. [Participant 25, male, Malay, nurse]
**Becoming Future-Ready**

The majority of the participants felt that resilience is a form of a positive attribute. When asked if being resilient is an important factor in securing employment, participants felt that resiliency was a personal competency and may have indirect impacts on getting one employed:

> I won’t say, it’s directly, okay, this [referring to the BRAW program] will help you get the job, but it’s more of like okay, it helps you work on yourself as a person. So, that indirectly translates to being a more employable person. [Participant 13, female, Chinese, audiologist]

Nevertheless, participants perceived that the contents of the BRAW program could help shape an individual’s emotional quotient. This may translate to the development of one’s leadership skills:

> It [referring to the BRAW program] shapes a person who has a lot of EQ and understanding...So, I think it does make, if you can master these techniques very well, I do believe that it can make you a better leader. [Participant 12, male, Chinese, respiratory therapist]

**Discussion**

**Principal Findings**

This qualitative study aimed to explore HCPs’ experiences of participating in the web-based BRAW program during the COVID-19 pandemic. Based on the framework analysis, participants alluded to the importance of the various web-based elements that supported their internalization of the resilience processes. Particularly, the asynchronous and self-paced nature and applicable materials supported participants’ continued engagement with the BRAW program. Finally, after attending the BRAW program, participants became resilient, had greater intent to stay, and were future-ready.

With regard to the web-based elements, the availability of different web-based learning tools has supported participants’ learning. This finding was consistent with prior research that evaluated web-based resilience programs [22,40]. Several key characteristics of web-based learning stood out. First, participants alluded to the importance of short attention-requiring materials such as videos, which was similarly reported in other studies [40,41]. Second, participants credited the availability of quizzes and homework that supplemented their learning. Homework and quizzes can augment the learning process by allowing individuals to apply their newly acquired knowledge [42,43]. Despite the benefits, several participants were overwhelmed by the number of tasks (eg, videos, quizzes, homework, and forum). A unique finding from this study was regarding the nomenclature of the tasks. Particularly, participants mentioned that the term “homework” can be considered a chore and may not be preferred in this form of program. This could be due to participants’ experiences with homework during their schooling years, where numerous negative emotions were associated with that term [44,45].

With regard to the contents, participants credited how the relatability and applicability of the BRAW contents were facilitators for completion. This is an important aspect, as several studies have echoed the importance of providing contextually relevant materials for participants [41,46], and this will facilitate participants’ understanding and transferability of their newly acquired skills. Furthermore, participants appreciated the resilience strategies and applied them in the workplace. For example, the provision of easily replicable strategies such as the application of the problem-solving algorithm was helpful for the participants [27,47].

With regard to the features, the web-based BRAW program was designed as asynchronous and self-paced training for several reasons, such as wider outreach and the presence of the COVID-19 pandemic. The use of a web-based approach was verbalized as an enabler for HCPs to complete the program, which was consistent with other studies [22,48]. In addition, a web-based approach provided HCPs with an opportunity to learn during the COVID-19 pandemic when induced social distancing measures were required. More importantly, the nature of the BRAW program promoted participants’ autonomy and allowed them to gain control over their schedules. This could stimulate personalized learning, which resulted in positive effects on one’s learning outcomes [49,50]. However, despite this, most of the participants also experienced conflicting priorities and were unable to timely participate in the web-based BRAW program. Considering that participation in programs of such nature is of lower priority than their formal work-related commitments, this may have led to their reduced participation [22,27].

Through participants’ narratives, this study also unveiled the positive effects of the web-based BRAW program on their resilience, intent to stay, and employability. From a resilience perspective, the program provided participants with skills ranging from personal (eg, cognitive restructuring), relational (eg, teamwork), and environmental (eg, workplace environment) that promoted their resilience. Based on the resilience theory [11], the introduction of such resilience protective factors can promote resilience. Interestingly, participants’ resilience could also be influenced by the recognition of their resilient potential. Several studies have suggested how the introduction of resilience programs has led to participants becoming aware of their internal strengths and how this influences their resilience [22,51].

Moreover, the web-based BRAW program introduced techniques to enhance cognitive restructuring, positivity, and happiness, and this could be a plausible explanation for improving participants’ intent to stay. Despite the dynamic and stressful health care environment, these techniques potentially supported participants’ positive reframing of a seemingly negative situation [15,31]. Furthermore, it can have positive direct or mediating effects on one’s intent to stay by improving one’s optimism and positivity [52,53]. However, participants also surfaced that macro-organization factors such as hospital administration are factors that may negatively affect their intent to stay [54,55].

While not directly explored in other qualitative evaluations of resilience programs, this study found that the web-based BRAW program has encouraging effects on participants’ employability and future readiness. This could be attributed to the introduction of various noncognitive skills such as problem-solving and...
emotion regulation. More literature has highlighted the pivotal role of noncognitive skills on employment outcomes [56,57].

Based on the findings from this qualitative study, several implications for future resilience programs are outlined. First, HCPs continue to experience mental exhaustion and distress due to the immense workload caused by the COVID-19 waves, and the delivery of a web-based program targeting mental well-being is practical and should be implemented. Second, from a feature perspective, an asynchronous and self-paced program is an acceptable and feasible approach. However, to reduce any potential conflicting work commitments, participants should be provided with protected time to complete these programs. Third, web-based learning should be supplemented by various engagement tools, and it will be helpful to redesignate homework as self-help exercises or tasks to reduce the negative connotation associated with homework. Next, from a content perspective, contextualized personal, relational, and environmental resilience materials should be introduced. Thus, conducting a needs analysis would be necessary to ensure that the resilience program remains acceptable to the target population. In addition, there should be an introduction of technical terms for participants who may not be familiar with the materials. Finally, as resilience programs focus on building an individual’s strengths, it will be important that health care administrators consider building supportive workplace environments to complement resilience programs.

**Limitations**

This study has several limitations, and results need to be interpreted with caution. First, this qualitative study explored participants’ experiences of 1 web-based resilience program, and its findings may not be transferable to other settings. Despite this, our findings may provide insight on the design of future psychosocial web-based interventions. Second, most of them were female and ethnic Chinese participants, thereby resulting in an underrepresentation of other sex and ethnic groups. Nevertheless, a rigorous purposive sampling approach was undertaken to ensure that there is a good representation of individuals across various age groups and professions. Finally, this study was limited to a 1-time point and may not be able to encapsulate the long-term effects of the BRAW program on the participants.

**Conclusions**

This study presented a qualitative evaluation of a web-based BRAW program using framework analysis. Although there were several highlighted facilitators and barriers, the findings show that an asynchronous, self-paced resilience program can be a useful tool in supporting the well-being of HCPs during the COVID-19 pandemic. However, it will be important to ensure that contextually relevant materials, supported by other appropriate web-based engagement tools, such as quizzes and practical exercises are provided to promote learning in a web-based environment. Further work is needed to explore how macro-organization factors can be embedded in resilience programs to promote HCPs’ resilience and well-being.

**Conflicts of Interest**

None declared.

Multimedia Appendix 1

COREQ (Consolidated Criteria for Reporting Qualitative Research) checklist.

[DOXC File, 25 KB - mededu_v10i1e49551_app1.docx ]

Multimedia Appendix 2

Table S1. Coding tree.

[DOXC File, 18 KB - mededu_v10i1e49551_app2.docx ]

**References**


Abbreviations

BRAW: Building Resilience At Work
COREQ: Consolidated Criteria for Reporting Qualitative Research
HCP: health care professional

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Occupational Therapy Students’ Evidence-Based Practice Skills as Reported in a Mobile App: Cross-Sectional Study

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Abstract

Background: Evidence-based practice (EBP) is an important aspect of the health care education curriculum. EBP involves following the 5 EBP steps: ask, assess, appraise, apply, and audit. These 5 steps reflect the suggested core competencies covered in teaching and learning programs to support future health care professionals applying EBP. When implementing EBP teaching, assessing outcomes by documenting the student’s performance and skills is relevant. This can be done using mobile devices.

Objective: The aim of this study was to assess occupational therapy students’ EBP skills as reported in a mobile app.

Methods: We applied a cross-sectional design. Descriptive statistics were used to present frequencies, percentages, means, and ranges of data regarding EBP skills found in the EBPsteps app. Associations between students’ ability to formulate the Population, Intervention, Comparison, and Outcome/Population, Interest, and Context (PICO/PICo) elements and identifying relevant research evidence were analyzed with the chi-square test.

Results: Of 4 cohorts with 150 students, 119 (79.3%) students used the app and produced 240 critically appraised topics (CATs) in the app. The EBP steps “ask,” “assess,” and “appraise” were often correctly performed. The clinical question was formulated correctly in 53.3% (128/240) of the CATs, and students identified research evidence in 81.2% (195/240) of the CATs. Critical appraisal checklists were used in 81.2% (195/240) of the CATs, and most of these checklists were assessed as relevant for the type of research evidence identified (165/195, 84.6%). The least frequently correctly reported steps were “apply” and “audit.” In 39.6% (95/240) of the CATs, it was reported that research evidence was applied. Only 61% (58/95) of these CATs described how the research was applied to clinical practice. Evaluation of practice changes was reported in 38.8% (93/240) of the CATs. However, details about practice changes were lacking in all these CATs. A positive association was found between correctly reporting the “population” and “interventions/interest” elements of the PICO/PICo and identifying relevant research evidence (P<.001).

Conclusions: We assessed the students’ EBP skills based on how they documented following the EBP steps in the EBPsteps app, and our results showed variations in how well the students mastered the steps. “Apply” and “audit” were the most difficult EBP steps for the students to perform, and this finding has implications and gives directions for further development of the app and educational instruction in EBP. The EBPsteps app is a new and relevant app for students to learn and practice EBP, and it can be used to assess students’ EBP skills objectively.

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KEYWORDS

active learning strategies; application; cross-sectional study; development; education; higher education; interactive; mobile application; mobile app; occupational therapy students; occupational therapy; students; usability; use
Introduction

Evidence-based practice (EBP) involves using the best available evidence from relevant research and integrating it with clinical expertise, patient values, and circumstances to make clinical decisions for individual patients [1]. When applying EBP, it is recommended to follow the five EBP steps: (1) identifying information needs and formulating answerable questions (ask), (2) finding the best available evidence to answer clinical questions (assess), (3) critically appraising the evidence (appraise), (4) applying the results in clinical practice (apply), and (5) evaluating performance (audit) [1,2]. These 5 steps reflect the suggested core competencies covered in teaching and learning programs to support future health care professionals applying EBP, including developing EBP knowledge and skills [3].

EBP skills can be understood as applying EBP knowledge by performing EBP steps, ideally in a clinical setting [4]. The literature indicates that EBP knowledge and skills improve when EBP teaching and learning are multifaceted, interactive, clinically integrated, and incorporate assessment [5]. When implementing EBP teaching, it is relevant to document and assess the individual student’s performance [3,5,6]. As it is recommended to follow all 5 EBP steps when teaching and learning EBP [1,2], measuring the performance of all 5 steps is relevant when evaluating EBP learning. However, few evaluation instruments measure all 5 EBP steps [5-9], and most instruments are self-reported questionnaires [6,7]. The use of self-reported questionnaires may contribute to biased results due to recall bias or social desirability responses [9,10]. Objectively measuring EBP learning could result in a true reflection of the situation, and thus, it is recommended to develop objective tools for EBP learning assessment [6,7,11]. To objectively document the performance of the EBP steps, Shaneyfelt et al [6] emphasized using online documentation. Online documentation is feasible through mobile apps, and innovative new methods to evaluate EBP teaching can now be explored [12]. Most students own a smartphone, which makes mobile learning and information sharing possible [13,14]. Thus, mobile apps can potentially be used for documenting and assessing students’ EBP performance. The aim of this study was to assess occupational therapy (OT) students’ EBP skills as reported in a mobile app.

Methods

Design

This study used a cross-sectional design. The reporting of this study followed the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) checklist (Multimedia Appendix 1) [15].

Mobile App

A mobile web app called the EBPsteps app was developed at the Western Norway University of Applied Sciences (HVL) to support health and social care students’ EBP learning [16]. An updated version of this web app is now freely available as a native app [17]. Experiences with using the EBPsteps app for learning EBP have previously been explored [16]. The app provides an opportunity for students to document the 5 EBP steps. A description of the content of the EBPsteps app is presented in Textbox 1.

Textbox 1. The EBPsteps app content.

- **Ask**
  - Reflect on information needs
  - Formulate the clinical question
  - Identify the type of clinical question (drop-down menu)
  - Identify the Population, Intervention, Comparison, and Outcome/Population, Interest, and Context (PICO/PICo) elements

- **Assess**
  - Report information source used to identify research evidence
  - Report links to research evidence identified

- **Appraise**
  - Choose a relevant critical appraisal checklist
  - Complete the critical appraisal using the integrated checklist

- **Apply**
  - Report how research evidence was applied in practice (drop-down menu)

- **Audit**
  - Report if changes in practice were completed and evaluated
  - Describe changes if changes were implemented
  - Evaluate the EBP process (ask, assess, appraise, apply, and audit)
By documenting the EBP process in the app, students produced critically appraised topics (CATs). A CAT can be explained as a summary of research evidence on a clinical question [18]. The CATs completed in the EBPsteps app included information on all EBP steps, and the CATs could be sent through email and shared as a PDF document. The CATs produced in the app were stored on the HVL research server and were accessible to the researchers in this project.

**Participants**

A total of 4 cohorts of fifth-semester OT students from different academic years (from 2018 to 2021) at HVL were eligible for inclusion if they used the EBPsteps app.

**Setting**

In Norway, OT education is a 3-year bachelor’s degree of 6 semesters (180 European Credit Transfer System [ECTS]). According to the Norwegian national curriculum, all health and social care students must be able to acquire new knowledge and make professional assessments, decisions, and actions in line with EBP [19]. At the time of this study, EBP was well integrated into the OT bachelor’s degree program at HVL [20].

Textbox 2 provides an overview of the total number of standalone EBP sessions (n=27) that OT students in this study received by their fifth semester (year 3). This amount of EBP teaching hours is a high number [21]. In addition, EBP was integrated into other learning activities, such as problem-based learning (PBL) group activities, written assignments, and exams.

Using the EBPsteps app was part of the EBP teaching. Students were introduced to the app at the start of the fifth semester. The students watched a video presentation of how to use the app and explored using the app while being supervised by a teacher. During the fifth semester, the students were encouraged to use the EBPsteps app on campus (4 weeks) and during clinical placements (11 weeks). While on campus, students had to use either the EBPsteps app or a Microsoft Word document to complete a mandatory EBP assignment that involved producing a CAT on a clinical topic. Similarly, at the end of the semester, an appendix to the home exam was to use either the EBPsteps app or a Word document to produce a CAT.

**Data Collection**

CATs produced by students during the fifth semester were exported from students’ user accounts in the EBPsteps app to Microsoft Excel [22] at the end of the semester. The Norwegian data, anonymized by authors, are freely available through HVL Open [23] and include our assessment. To objectively assess students’ EBP skills based on how they documented the EBP process in the app, we developed a scoring plan for each EBP step in the CATs (Multimedia Appendix 2). The different steps of the CATs were assessed as correct or incorrect, which were the outcomes investigated in this study. Two researchers independently scored each CAT, and disagreements were resolved through discussion. An overview of the scoring plan is presented in Textbox 3.
Ask
- Was it reflected on the information needs?
- Which clinical question was formulated (eg, prevalence, cause, diagnostics, effect of measures, prognosis, or experiences and attitudes)?
- Which clinical question was identified (drop-down menu)?
- Was there an agreement between the formulated clinical question and the type of question identified from the drop-down menu?
- Was the “population” of the Population, Intervention, Comparison, and Outcome/Population, Interest, and Context (PICO/PICo) correctly reported?
- Was the “intervention/interest” of the PICO/PICo correctly reported?
- Was the “comparison” of the PICO/PICo correctly reported?
- Was the “outcome/context” of the PICO/PICo correctly reported?

Assess
- Which information sources were used (BMJ Best Practice, Cochrane Library, PubMed, etc)?
- Was a link to research evidence reported?
- Was there an agreement between the information source used and the identified research evidence?

Appraise
- Was there an agreement between the identified research evidence and the chosen critical appraisal checklist used?
- Were the questions in the checklist completed?

Apply
- Was the application of the research evidence reported (drop-down menu)?
- If reported applied, was this described?

Audit
- Were changes in practice evaluated?
- Was the EBP process evaluated?

Analysis
Descriptive statistics were used to summarize the assessment of students’ EBP skills based on the completed CATs, including frequencies and percentages for categorical variables and mean and range for continuous variables. Associations between correctly reporting the Population, Intervention, Comparison, and Outcome/Population, Interest, and Context (PICO/PICo) elements and finding research evidence were analyzed with the chi-square test with adjustment for repeated measurements [24]. The significance level was set at 5%. Statistical analyses were performed with SPSS Statistics (version 28.0; IBM Corp) [25] and R (R Foundation for Statistical Computing) [26].

Ethical Considerations
The Norwegian Agency for Shared Services in Education and Research approved the study (project 50425). The students were informed, both orally and in writing, about the purpose of this study and that the data would be treated confidentially. The students agreed to participate in the study and signed a consent form when they created a profile and used the EBPsteps app. The students did not receive any compensation for participating. Students could choose to use the app or a Word document to complete assignments where it was required to produce CATs. The data were securely stored on the research server at HVL.

Results

Participants
Among 4 cohorts with OT students, 79.3% (119/150) of students used the EBPsteps app during their fifth semester. The students who used the app produced 240 CATs. In the first cohort (2018), 41 of 47 students produced 73 CATs; in the second cohort (2019), 25 of 30 students produced 53 CATs; in the third cohort (2020), 21 of 33 students produced 43 CATs; and in the fourth cohort (2021), 32 of 40 students produced 71 CATs. The mean number of CATs produced per student was 2, with a range from 1 to 7.

Step 1: Ask
A need for more knowledge on a clinical problem was reported in 94.6% (227/240) CATs. In 80% (192/240) of the CATs, the type of clinical question was identified using a drop-down menu. A clinical question was formulated in 53.3% (128/240) of the CATs. The “effect of therapy” was the most prevalent clinical question reported (100/240, 41.7%) (Table 1).
All PICO/PICo elements were reported correctly in 10.4% (25/240) of the CATs. Assessing the different PICO/PICo elements separately, the “population” and “intervention/interest” elements were more often correctly reported (187/240, 77.9% and 189/240, 78.8%) than the “comparison” and “outcome/context” elements (44/240, 18.3% and 103/240, 42.9%). This applied to all question types, including when the question had been formulated as a background question (Table 1). In CATs without a clinical question identified, most PICO/PICo elements were incorrectly reported.

Table 1. Correctly reported Population, Intervention, Comparison, and Outcome/Population, Interest, and Context (PICO/PICo) elements by type of question in 240 critically appraised topics.

<table>
<thead>
<tr>
<th>Question Type</th>
<th>Population, n (%)</th>
<th>Intervention/Interest, n (%)</th>
<th>Comparison, n (%)</th>
<th>Outcome/context, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effect of therapy (n=100)</td>
<td>90 (90)</td>
<td>96 (96)</td>
<td>30 (30)</td>
<td>53 (53)</td>
</tr>
<tr>
<td>Qualitative (n=27)</td>
<td>25 (93)</td>
<td>25 (93)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Background (n=64)</td>
<td>55 (86)</td>
<td>52 (81)</td>
<td>11 (17)</td>
<td>32 (50)</td>
</tr>
<tr>
<td>Other (n=1) or missing (n=48)</td>
<td>17 (35)</td>
<td>16 (33)</td>
<td>3 (6)</td>
<td>5 (10)</td>
</tr>
</tbody>
</table>

*Not relevant.*

**Step 2: Assess**

In 240 of the CATs, the information source most frequently reported was the Cochrane Library (65/240, 27.1%), followed by CINAHL (43/240, 17.9%), PubMed (36/240, 15%), and Epistemonikos (17/240, 7.1%). In 12.9% (31/240) of the CATs, no information source was reported. Research evidence was identified and linked to in 81.3% (195/240) of the CATs, and the most common type of research evidence identified was systematic reviews (n=85), randomized controlled trials (RCTs; n=51), and qualitative research (n=44).

We observed a positive association between correctly reporting “population” and “intervention/interest” elements of the PICO/PICo and identifying research evidence. Among those correctly reporting the population element, 92.1% (221/240) identified research evidence, compared to 52.1% (125/240) among those that did not report the population element (*P*<.001). Similar findings were observed for the intervention/interest element.

**Step 3: Appraise**

A checklist was used in 81.3% (195/240) of the CATs. Of these, the correct checklist was used in 84.6% (165/195) of the CATs; that is, there was agreement between the type of checklist and the research evidence identified (Table 2). In 98.2% (162/165) of the CATs with a correct checklist, more than 75% of the checklist questions had been answered. Effect estimates from identified research evidence were documented in 27% (21/77) of the checklists for systematic reviews and 36% (15/42) of the checklists for RCTs.

Table 2. Type of research evidence identified and agreement with choice of checklist.

<table>
<thead>
<tr>
<th>Type of research evidence</th>
<th>The agreement between research evidence and checklist, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Systematic reviews (n=85)</td>
<td>77 (89)</td>
</tr>
<tr>
<td>Randomized controlled trials (n=51)</td>
<td>42 (82)</td>
</tr>
<tr>
<td>Qualitative research (n=44)</td>
<td>42 (95)</td>
</tr>
<tr>
<td>Guidelines (n=4)</td>
<td>2 (50)</td>
</tr>
<tr>
<td>Observational studies* (n=11)</td>
<td>2 (18)</td>
</tr>
<tr>
<td>The total number of research evidence identified (n=195)</td>
<td>165 (84.6)</td>
</tr>
</tbody>
</table>

*Included the following study designs: prevalence (n=1), diagnostic (n=1), cohort (n=3), case-control (n=1), and cross-section (n=5).

**Step 4: Apply**

In 39.6% (95/240) of the CATs, it was reported that research evidence was applied in clinical practice. How the research was applied was described sufficiently in only 61% (58/95) of these CATs.

The most common shared decision-making approach reported from a drop-down menu was “identifying preferences” (78/240, 32.5%) and “exploring possibilities” (78/240, 32.5%). Other shared decision-making approaches reported were “presenting choices” (48/240, 20%) and “recommendations” (46/240, 19.2%), “discussing potential” (45/240, 18.8%), “deciding follow-up” (28/240, 11.7%), and “checking recommendations” (24/240, 10%).

**Step 5: Audit**

Evaluation of practice changes was reported in 38.6% (93/240) of the CATs. However, details of practice changes were lacking in all these CATs. In 46% (43/93) of the CATs that reported evaluation, it was reported, “did not change practice,” and in 54% (50/93) of these CATs, it was reported that it was “not relevant to change practice.” The EBP process was reported as evaluated in 54.6% (131/240) of the CATs.
Discussion

Principal Findings
This study assessed OT students’ EBP skills as reported in the EBPsteps mobile app. We found that students were most often able to perform the EBP steps of “ask,” “assess,” and “appraise” correctly. A positive association was found between formulating the PICO/PICO elements and identifying research evidence. Applying the evidence and evaluating practice change were the least frequently correctly reported steps of the EBP process.

Comparison to Previous Work
Using data from the EBPsteps app, where students had documented how they followed the EBP process for their clinical question, enabled us to collect objective data on students’ EBP skills. Instruments that objectively measure EBP skills are recommended for acquiring a true reflection of the situation [6,7,11], as opposed to more frequently used self-report assessment tools [6,7]. Although objective assessment is advised, it can be time-consuming to complete and assess [4]. Consequently, self-reported questionnaires are often chosen because of their practicality of administration [9]. Developing an easy-to-administer scoring plan for the EBPsteps app has therefore been important. Against this background, the EBPsteps app can be a valuable contribution to objectively assessing EBP skills related to all 5 steps of the EBP process.

Ask and Assess
We found a positive association between correctly reporting population and intervention/interest elements of the PICO/PICO and finding research evidence, indicating that completing the PICO/PICO supports students’ ability to retrieve relevant research evidence. These findings align with previous research reporting that a clearly defined question supports students’ ability to retrieve relevant information [27,28]. Furthermore, structuring the question using the PICO/PICO format makes it easier to decide on search terms [2].

Appraise
The appropriate critical appraisal checklist was chosen in 68.8% (165/240) of the CATs in this study. Nevertheless, few effect estimates were reported in checklists for RCTs and systematic reviews. This might suggest that the students had difficulties interpreting the statistical results. Lack of confidence in interpreting statistical results has previously been reported among health and social care students [29,30]. Acquiring an understanding of effect estimates is necessary when applying EBP [3], and spending more time teaching the understanding of research results to support the students learning and interpretation of research results is recommended [31].

Apply and Audit
Only about half of the students in this study reported that they applied the research evidence they found, indicating that they struggled using EBP skills beyond the classroom setting, which also correlates with previous research [32,33]. Lehane et al [34] suggest that structural incorporation of EBP during clinical placement, for instance, through easy access to research, EBP mentors, or regular journal clubs, may support the students in applying research evidence. In addition, incorporating assessment of EBP into clinical placement has been shown to influence EBP behavior [5]. In this study, EBP assignments were mandatory in class but not during clinical placement, which may explain why students in this study struggled with the steps of applying and evaluating practice. Providing a mandatory EBP assignment during the clinical placement may support the students in applying EBP and thus also mastering the 2 last steps of the EBP process.

An alternative explanation for why students struggled with the steps of applying and evaluating practice could be that they experienced fatigue or other difficulties using the app. To explore whether other issues influenced students’ skills, we could have further tested the usability of the app. When developing mobile apps for teaching and learning, usability testing is important [35]. Other research methods are necessary to investigate why the 2 last steps of the EBP process were less frequently completed. Future research should include cognitive interview studies (eg, think-aloud methods) and other pilot studies in different populations to evaluate the comprehensivenes and comprehensibility of the app.

Future Directions
Knowledge of which EBP steps students find most challenging has implications and gives directions for further development of the EBPsteps app and educational instruction in EBP. For example, providing a more comprehensive explanation of how to interpret statistical results in the app could be beneficial. In addition, spending more time teaching statistics and how to read the results seems necessary to improve students’ EBP performance.

A better alignment between what is taught during classes on campus and what students do at placements could also perhaps better facilitate EBP behavior among students. A mandatory assignment where research evidence must be found and discussed with the clinical instructors may help the students apply and evaluate the use of research evidence during clinical placement.

Currently, the EBPsteps app is available only in Norwegian. In the future, we aim to provide user interface translations for several languages [16]. However, we will need to modify options in the app according to the free access resources available in the different countries (eg, databases, guidelines, and e-learning resources). Efforts will be made to find the best solution and to accommodate needs in low- and middle-income countries.

Methodological Considerations
The main limitation of this study was that we included students from only one profession and from the same educational institution, and thus the generalizability of the results to other institutions and to other health and social care students is reduced. However, the sample consisted of 4 student cohorts from different academic years (from 2018 to 2021; n=119), including 240 CATs. Accordingly, we believe the results from this study can be recognizable and relevant across other populations.
A strength of this study was that the EBPsteps app allowed us to objectively measure the performance of the EBP process using an app that includes all 5 EBP steps. It is recommended that educators select instruments that objectively measure EBP performance [11]. Shaneyfelt et al [6] emphasized the use of online documentation of the EBP steps as a promising approach.

Another strength was that 2 researchers assessed the CATs independently based on a scoring plan, and disagreement was solved through discussion. However, the EBPsteps app and the scoring plan are not validated for assessing EBP, and measurement properties should be examined in future studies.

Conclusions

We assessed the students’ EBP skills based on how they documented following the EBP steps in the EBPsteps app, and our results showed variations in how well the students mastered the steps. “Apply” and “audit” were the most difficult EBP steps for the students to perform, and this finding has implications and gives directions for further development of the app and educational instruction in EBP. The EBPsteps app is a new and relevant app for students to learn EBP and can be valuable for assessing EBP skills objectively.

Acknowledgments

The authors would like to thank Johannes Mario Ringheim at Medialab, HVL, for the programming and technical development of the EBPsteps app and data extraction from the EBPsteps app for this study. In addition, the authors would like to thank all the students who participated in the study and used the EBPsteps app.

Data Availability

The Norwegian data, anonymized by the authors, are publicly and freely available through HVL Open [23].

Authors' Contributions

SGJ and NRO conceptualized this study. NRO was responsible for the funding of the study, and the initial analysis of the results and the project administration were performed by SGJ and NRO. The formal analysis was conducted by SGJ and BE. SGJ, BE, LL, DC, and NRO decided on the methodology. SGJ, BE, and NRO provided resources. Validation was done by SGJ, BE, and NRO, and visualization by SGJ and NRO. The writing of the original draft was done by SGJ, and review and editing were done by SGJ, BE, LL, DC, and NRO.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) checklist.

Multimedia Appendix 2

The scoring plan of EBPsteps.

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Abbreviations

CAT: critically appraised topic
EBP: evidence-based practice
ECTS: European Credit Transfer System
HVL: Western Norway University of Applied Sciences
OT: occupational therapy
PBL: problem-based learning
PICO/PICo: Population, Intervention, Comparison, and Outcome/Population, Interest, and Context
RCT: randomized controlled trial
STROBE: Strengthening the Reporting of Observational Studies in Epidemiology

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Telehealth Education in Allied Health Care and Nursing: Web-Based Cross-Sectional Survey of Students’ Perceived Knowledge, Skills, Attitudes, and Experience

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Abstract

Background: The COVID-19 pandemic has highlighted the growing relevance of telehealth in health care. Assessing health care and nursing students’ telehealth competencies is crucial for its successful integration into education and practice.

Objective: We aimed to assess students’ perceived telehealth knowledge, skills, attitudes, and experiences. In addition, we aimed to examine students’ preferences for telehealth content and teaching methods within their curricula.

Methods: We conducted a cross-sectional web-based study in May 2022. A project-specific questionnaire, developed and refined through iterative feedback and face-validity testing, addressed topics such as demographics, personal perceptions, and professional experience with telehealth and solicited input on potential telehealth course content. Statistical analyses were conducted on surveys with at least a 50% completion rate, including descriptive statistics of categorical variables, graphical representation of results, and Kruskal Wallis tests for central tendencies in subgroup analyses.

Results: A total of 261 students from 7 bachelor’s and 4 master’s health care and nursing programs participated in the study. Most students expressed interest in telehealth (180/261, 69% very or rather interested) and recognized its importance in their education (215/261, 82.4% very or rather important). However, most participants reported limited knowledge of telehealth applications concerning their profession (only 7/261, 2.7% stated profound knowledge) and limited active telehealth experience with various telehealth applications (between 18/261, 6.9% and 63/261, 24.1%). Statistically significant differences were found...
between study programs regarding telehealth interest ($P=0.005$), knowledge ($P<0.001$), perceived importance in education ($P<0.001$), and perceived relevance after the pandemic ($P=0.004$). Practical training with devices, software, and apps and telehealth case examples with various patient groups were perceived as most important for integration in future curricula. Most students preferred both interdisciplinary and program-specific courses.

**Conclusions:** This study emphasizes the need to integrate telehealth into health care education curricula, as students state positive telehealth attitudes but seem to be not adequately prepared for its implementation. To optimally prepare future health professionals for the increasing role of telehealth in practice, this study can be considered when designing telehealth curricula.

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**KEYWORDS**
telehealth; health care education; student perspectives; curriculum; interdisciplinary education

**Introduction**

**Background**

Telehealth has become increasingly important in recent years, particularly considering technological and societal developments. Telehealth is the use of information and communications technologies to deliver health services where there is a physical separation between care providers or recipients over both long and short distances [1]. It has the potential to help overcome barriers to accessing care, particularly in remote or underserved areas [2], and can be particularly beneficial for patients with chronic diseases [3] to improve long-term adherence [4], as well as addressing shortages in the health care workforce [5]. Owing to the COVID-19 pandemic, the integration of telehealth into the services of health care providers was further increased to prevent further infections and to serve patients in isolation [6-10].

However, the growing use has further highlighted the need for telehealth education for health care providers [11-16]. To successfully and sustainably implement telehealth and subsequently reap the benefits, it is necessary to integrate telehealth into the curricula of future health care providers [5]. A lack of knowledge and experience, as well as a lack of appropriate telehealth training, have been identified as major barriers to telehealth implementation among health care providers [17]. Conversely, telehealth education and training can increase the willingness to adopt telehealth, the perceived readiness, and confidence [5,13,18-20].

Providing telehealth services not only requires a basic understanding of telehealth and its applications but also an assortment of competencies spanning from theoretical knowledge to practical skills, closely mirroring the concepts of Miller pyramid of clinical competence [21] or its adapted version, the Miller prism [22]. As they outline, there are different levels of competence, such as knowledge, skills, and attitudes. In terms of telehealth competencies, knowledge involves the basic understanding of telehealth, its tools, and its applications. This also includes knowledge on how to ensure privacy and confidentiality [11,23-27]. The second competence level skills refers to the know-how. In telehealth, it requires health care professionals to organize and apply their knowledge to conduct physical assessments via telehealth, make perceptive observation-based examinations, and communicate effectively in a nontraditional clinical setting [5,10,11,15,16,19,23,24,26-29]. In the performance or show level, professionals demonstrate their ability to select, implement, and use appropriate telehealth tools in a simulated or controlled environment. This is where technological skills become crucial [11,23-27]. Finally, at the action or does level, health care professionals are expected to perform these skills in real-life situations, providing high-quality and safe telehealth services, and effectively incorporating ethical considerations into their practice [23-25]. Attitude is considered a vital component, along with knowledge, skills, and performance, that contributes to actual work competency. It refers to the behavioral and emotional aspects that influence how knowledge and skills are applied in practice [30]. Attitude can encompass elements such as motivation, ethical considerations, professionalism, and openness to learning, which seem to be important in the telehealth context.

In accordance with the principles of competency-based frameworks, curricula of health care study programs need to be adapted to qualify health care professionals at all levels of competency, increasing the probability that telehealth is effectively implemented in daily practice [11]. Two reviews [26,31] conducted in 2021 highlighted significant shortcomings in the training and curricula in allied health and nursing. They showed that there was a lack of consistency and absence of a systematic approach in integrating telehealth into these curricula [26,31]. Thus, it is crucial to design telehealth curricula with competency-based frameworks in mind to meet the diverse needs of students and ensure they are equipped with the necessary knowledge, performance skills, and attitude to effectively use telehealth technologies in their future health care practices. An increasing number of standards and guidelines are becoming available to guide the development of individual telehealth courses. They focus on various aspects such as administrative [32,33], ethical [32,34], clinical [32], technical [32,35], or soft skills [36]. However, they often do not address the specialized needs of allied health professionals [37]. Therefore, identifying the specific interests and learning needs of students can help educators to plan their teaching methods and provide tailored curricula or courses in individual study programs. This can further help to promote student engagement and motivation, ensure that the education is relevant and meaningful to their future professional practice, and ultimately improve learning outcomes.
Aim
The primary objective of this study was to assess the perceived telehealth knowledge, skills, attitude, and experience among health care professionals and nursing students to understand students’ current self-assessed telehealth competencies and identify their learning needs. Our secondary objective was to evaluate students’ preferences for telehealth content and teaching methods withing their respective curricula. This dual focus is intended to provide a rounded perspective of the students’ perceived readiness for telehealth practice and to inform effective educational strategies.

Methods

Study Design
We conducted an anonymous cross-sectional web-based survey among the total population of selected health care profession students at FH Campus Wien (University of Applied Sciences). Reporting followed the Checklist for Reporting Results of Internet E-Surveys (CHERRIES) [38].

Sample Characteristics
Given the exploratory nature of this study, the sample size was not predetermined but was derived from the number of students enrolled in the targeted health care and nursing programs who were available and consented to participate during the survey period. At the time of the survey’s release, 2273 students in the following selected academic health care professions were actively studying at the “FH Campus Wien” (University of Applied Sciences, Vienna, Austria) and were thus eligible to participate: BSc dietetics (DIE), BSc occupational therapy (OT), BSc health care and nursing (NUR), BSc midwifery (MID), BSc speech and language therapy (SLT), BSc orthoptics (ORT), BSc physiotherapy (PT), MSc health assisting engineering (HAE), MSc advanced nursing counseling (ANC), MSc advanced nursing education (ANE), and MSc advanced nursing practice (ANP). Participants who answered <50% of the questions were excluded.

Survey Administration
Students of all semesters were contacted directly with an email invitation. The survey was not listed publicly, no advertisement or incentive offers were put in place, and survey participation was voluntary. The survey was created using the web-based platform LimeSurvey (version 5.3.12 [39]), and it was open for participation between May 2 and May 30, 2022. An invitation email was sent on May 2, 2022. As a measure to improve the response rate, a first reminder was sent on May 9, 2022, and a second reminder was sent on May 25, 2022. Data were stored in a password-secured folder to which only selected study team members had access. Cookies were used to prevent users from accessing the survey twice, and IP addresses were not stored. No other measures to identify multiple entries were used. To ensure anonymous participation no registration process was put in place.

Ethical Considerations
Anonymous surveys currently do not require a formal review by a research ethics committee under Austrian research governance, in which the Declaration of Helsinki defines applicability to research on identifiable human data [40]. Exemption from ethical review has been formally confirmed by the Ethics Committee of the FH Campus Wien University of Applied Sciences (waiver no. W02/24). The survey followed ethical research practices (ie, voluntary participation; reassurance of anonymity, data protection, and confidentiality; advance information on purpose and content; provision of contact details of the research team; and full disclosure of involved organizations). This information was summarized on the first page of the web-based survey. Anonymous electronic consent to voluntary participation was required to begin the survey, but no signatures were obtained. All data processing procedures have been discussed in detail with the data protection officer of FH Campus Wien (University of Applied Sciences, Vienna). All data obtained in this survey will be stored for 10 years in compliance with national research legislation and the funding body.

Data Collection Methods
We used a newly developed, project-specific questionnaire (Multimedia Appendices 1 and 2). Feedback from project members on topics, constructs, and scales was iteratively incorporated into a first complete survey draft. Subsequent face-validity testing for usability and technical functionality was performed by 3 persons, not involved in the project, requiring minor usability and wording revisions. The survey consisted of 5 pages with 20 questions, of which 16 questions were mandatory: 6 demographical questions (including a question on the self-assessed information and communications technology competence to further describe the technology skills of the sample), 5 questions about personal perceptions of telehealth, 1 question on professional experience with telehealth, and 4 questions on potential content for telehealth courses or curriculum. The 4 optional questions were included to facilitate additional input or clarification.

Eligibility criteria were queried at the beginning of the survey: “Do you study at FH Campus Wien?” and “Which study program do you attend?” Respondents who clicked the survey link but were not eligible were taken directly to the end of the survey. Telehealth interest and perceived importance of telehealth in education were rated on a 4-point Likert scale (1=not interested/important, 2=less interested/important, 3=rather interested/important, and 4=very interested/important), and perceived relevance of telehealth after the pandemic was also rated on a 4-point Likert scale (1=for sure not, 2=rather not, 3=probably, and 4=for sure). Telehealth knowledge was rated by selecting 1 of 5 statements (1=I have never heard of telehealth, 2=I know the term but not more about it, 3=I know telehealth in medical services but not so much about it in my own profession, 4=I know some telehealth applications in my own profession, and 5=I know a lot of telehealth applications in my own profession). Experience with telehealth was rated among the options “performed,” “observed,” and “neither nor” for given examples. The perceived relevance of types of telehealth for the profession was assessed with multiple selections of given examples. Participants rated their interest in telehealth content on a 4-point Likert scale (1=for sure, 2=rather yes, 3=rather not, and 4=for sure) for given
examples. The preferred setting for learning about telehealth was assessed using single choice selection. The option “Don’t know” was implemented, where applicable. Items were not randomized and were always presented in the same order to maintain the survey structure.

**Statistical Analysis**

Questionnaires with a completion rate of at least 50% were analyzed. Predefined subgroup analysis to compare for study programs, age, gender, and study year was undertaken. Descriptive statistics of categorical variables were reported as absolute and relative frequencies, and ordinal variables were reported with median. Histograms, heat maps, and boxplots were deployed for graphical illustration of the results. Boxplots display the first and third quartiles as a rectangular box, with whiskers extending from the box to indicate the minimum and maximum values, except for outliers. The median is depicted by a horizontal line. Outliers are represented by individual dots, whereas the mean is denoted using an “x” symbol. Stacked bar charts represent the frequencies of positive (right to 0) and negative responses (left to 0) for categorical variables with higher values in the middle. Kruskal Wallis tests were conducted to test for central tendencies in the subgroup analyses. The α value was set at .05, and exact P values were reported. The Bonferroni-adjusted statistical significance was summarized graphically using spider web figures. Pairwise comparisons were not conducted if the alternative hypothesis was rejected by the overall Kruskal Wallis test.

**Results**

**Overview**

A total of 2273 students of the selected academic health care professions were potentially eligible to participate. The link to the web-based survey was accessed by 281 students, of whom 261 (92.9%) completed the questionnaire (ie, answered at least 50% of the questions) and were therefore included in the analysis, resulting in a completion rate of 93%. Overall, 206 students were attending a bachelor’s degree program and 55 students were attending a master’s degree program (Table 1). The demographic characteristics of the survey participants are presented in Table 2.

**Table 1.** Participation across the selected bachelor’s and master’s programs (N=261).

<table>
<thead>
<tr>
<th>Programs</th>
<th>Values, n (%)</th>
<th>Response rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Bachelor’s programs</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dietetics</td>
<td>20 (9.7)</td>
<td>36</td>
</tr>
<tr>
<td>Occupational therapy</td>
<td>24 (11.7)</td>
<td>24</td>
</tr>
<tr>
<td>Nursing</td>
<td>32 (15.5)</td>
<td>2</td>
</tr>
<tr>
<td>Midwifery</td>
<td>35 (17)</td>
<td>31</td>
</tr>
<tr>
<td>Speech and language therapy</td>
<td>25 (12.1)</td>
<td>37</td>
</tr>
<tr>
<td>Orthoptics</td>
<td>23 (11.2)</td>
<td>51</td>
</tr>
<tr>
<td>Physiotherapy</td>
<td>47 (22.8)</td>
<td>13</td>
</tr>
<tr>
<td><strong>Master’s programs</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Advanced nursing counseling</td>
<td>7 (13)</td>
<td>35</td>
</tr>
<tr>
<td>Advanced nursing education</td>
<td>16 (29)</td>
<td>27</td>
</tr>
<tr>
<td>Advanced nursing practice</td>
<td>13 (24)</td>
<td>28</td>
</tr>
<tr>
<td>Health assisting engineering</td>
<td>19 (34)</td>
<td>40</td>
</tr>
</tbody>
</table>
Table 2. Demographic characteristics of survey participants (N=261).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Total, n (%)</th>
<th>Bachelor’s (n=206), n (%)</th>
<th>Master’s (n=55), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Generation Z (years)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;20</td>
<td>33 (12.64)</td>
<td>33 (16.02)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>21-25</td>
<td>124 (47.51)</td>
<td>118 (57.28)</td>
<td>6 (10.9)</td>
</tr>
<tr>
<td><strong>Generation Y (years)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>26-30</td>
<td>48 (18.39)</td>
<td>33 (16.02)</td>
<td>15 (27.27)</td>
</tr>
<tr>
<td>31-35</td>
<td>27 (10.34)</td>
<td>14 (6.8)</td>
<td>13 (23.64)</td>
</tr>
<tr>
<td>36-40</td>
<td>7 (2.68)</td>
<td>4 (1.94)</td>
<td>3 (5.45)</td>
</tr>
<tr>
<td><strong>Generation X, baby boomers (years)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>41-45</td>
<td>13 (4.98)</td>
<td>4 (1.94)</td>
<td>9 (16.36)</td>
</tr>
<tr>
<td>46-50</td>
<td>3 (1.15)</td>
<td>0 (0)</td>
<td>3 (5.45)</td>
</tr>
<tr>
<td>&gt;50</td>
<td>6 (2.3)</td>
<td>0 (0)</td>
<td>6 (10.9)</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Man</td>
<td>228 (87.36)</td>
<td>184 (89.32)</td>
<td>44 (80)</td>
</tr>
<tr>
<td>Woman</td>
<td>30 (11.49)</td>
<td>19 (9.22)</td>
<td>11 (20)</td>
</tr>
<tr>
<td>Nonbinary</td>
<td>3 (1.15)</td>
<td>3 (1.46)</td>
<td>0 (0)</td>
</tr>
<tr>
<td><strong>Semester</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BSc 1-2</td>
<td>103 (39.46)</td>
<td>103 (50)</td>
<td>N/A(^a)</td>
</tr>
<tr>
<td>BSc 3-4</td>
<td>61 (23.37)</td>
<td>61 (29.62)</td>
<td>N/A</td>
</tr>
<tr>
<td>BSc 5-6</td>
<td>42 (16.09)</td>
<td>42 (20.39)</td>
<td>N/A</td>
</tr>
<tr>
<td>MSc 1-2</td>
<td>33 (12.64)</td>
<td>N/A</td>
<td>33 (60)</td>
</tr>
<tr>
<td>MSc 3-4</td>
<td>22 (8.43)</td>
<td>N/A</td>
<td>22 (40)</td>
</tr>
<tr>
<td><strong>Self-assessed ICT(^b) competence(^c)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1=very good</td>
<td>80 (30.65)</td>
<td>65 (31.55)</td>
<td>15 (27.27)</td>
</tr>
<tr>
<td>2=good</td>
<td>129 (49.43)</td>
<td>101 (49.03)</td>
<td>28 (50.91)</td>
</tr>
<tr>
<td>3=medium</td>
<td>50 (19.16)</td>
<td>38 (18.45)</td>
<td>12 (21.82)</td>
</tr>
<tr>
<td>4=sufficient</td>
<td>1 (0.38)</td>
<td>1 (0.49)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>5=not sufficient</td>
<td>1 (0.38)</td>
<td>1 (0.49)</td>
<td>0 (0)</td>
</tr>
</tbody>
</table>

\(^a\)N/A: not applicable.
\(^b\)ICT: information and communications technology.
\(^c\)Corresponding to the Austrian school grading system.

**Subgroup Differences**

A Kruskal Wallis H test (Table 3) showed that there was a statistically significant difference between the study programs in telehealth interest (\(P=.005\)), telehealth knowledge (\(P<.001\)), perceived importance of telehealth in education (\(P<.001\)), and perceived relevance of telehealth after the pandemic (\(P=.004\)). Corresponding box plots are shown in Figures 1-3. There were no significant differences between genders in telehealth interest (\(P=.63\)), telehealth knowledge (\(P=.19\)), perceived importance of telehealth in education (\(P=.73\)), and perceived relevance of telehealth after the pandemic (\(P=.55\)). On the basis of age and generation, there were significant differences in the perceived importance of telehealth education (\(P=.01\)) but no significant differences in telehealth interest (\(P=.14\)), telehealth knowledge (\(P=.19\)), and perceived relevance of telehealth after the pandemic (\(P=.06\)). There was a significant difference between students of different semesters in telehealth knowledge (\(P<.001\)) and perceived relevance of telehealth after the pandemic (\(P=.008\)) but not in telehealth interest (\(P=.09\)) and perceived importance of telehealth in education (\(P=.09\)). Details on pairwise comparisons between the different subgroups are described in Multimedia Appendix 3. For each item, smaller values indicate better (more positive) agreement. In summary, significant pairwise differences were observed mainly for the study programs, specifically when comparing the ratings regarding telehealth knowledge (HAE<ORT, HAE<DIE, HAE<ANE, HAE<MID, HAE<NUR, SLT<MID, SLT<NUR, OT<NUR, OT<PT, PT<MID, and PT<NUR), telehealth importance (HAE<PT, HAE<MID, and SLT<MID), and the postpandemic role of telehealth (ANP<PT, ANP<MID, and
ANP<ORT). For gender, the null hypotheses were rejected by the overall Kruskal Wallis tests for all 4 domains, and thus, no subsequent pairwise comparisons were conducted. For generations, the only significant pairwise comparison was for the role after the pandemic, where Generation Z had more positive ratings than Generation Y. For study progress, the only significant pairwise comparison was for the role after the pandemic, where the first 2 master’s semesters had more positive ratings than the fifth to sixth bachelor’s semesters.

Table 3. Results of the Kruskal Wallis H test for each subgroup test.

<table>
<thead>
<tr>
<th></th>
<th>Telehealth interest</th>
<th>Telehealth knowledge</th>
<th>Telehealth importance in education</th>
<th>Telehealth relevance after pandemic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Kruskal Wallis H</td>
<td>P value</td>
<td>Kruskal Wallis H</td>
<td>P value</td>
</tr>
<tr>
<td></td>
<td>test (df)</td>
<td></td>
<td>test (df)</td>
<td>test (df)</td>
</tr>
<tr>
<td>Study programs</td>
<td>25.3 (10)</td>
<td>.005</td>
<td>70.6 (10)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Genders</td>
<td>0.9 (2)</td>
<td>.63</td>
<td>3.3 (2)</td>
<td>.19</td>
</tr>
<tr>
<td>Age and generation</td>
<td>4.0 (2)</td>
<td>.14</td>
<td>3.3 (2)</td>
<td>.19</td>
</tr>
<tr>
<td>Semester</td>
<td>8.2 (4)</td>
<td>.09</td>
<td>43.1 (4)</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

Figure 1. Box plots of (A) telehealth interest, (B) telehealth knowledge, (C) perceived telehealth importance in education, and (D) perceived telehealth relevance after pandemic for each study program. Higher values represent higher interest, knowledge, importance, and perceived relevance. ANC: advanced nursing counseling; ANE: advanced nursing education; ANP: advanced nursing practice; DIE: dietetics; HAE: health assisting engineering; MID: midwifery; NUR: health care and nursing; ORT: orthoptics; OT: occupational therapy; PT: physiotherapy; SLT: speech and language therapy.
Figure 2. Box plots of (A) telehealth interest, (B) telehealth knowledge, (C) perceived telehealth importance in education, and (D) perceived telehealth relevance after the pandemic, based on semester. Higher values represent higher interest, knowledge, importance, and perceived relevance.

- **BSc 1-2**: Bachelor's students in the first or second semester,
- **BSc 3-4**: Bachelor's students in the third or fourth semester,
- **BSc 5-6**: Bachelor's students in the fifth or sixth semester,
- **MSc 1-2**: Master's students in the first or second semester,
- **MSc 3-4**: Master's students in the third or fourth semester
Figure 3. Box plots of (A) telehealth interest, (B) telehealth knowledge, (C) perceived telehealth importance in education, and (D) perceived telehealth relevance after the pandemic for different generations. Higher values represent higher interest, knowledge, importance, and perceived relevance. Gen Z (Generation Z): up to 25 years; Gen Y (Generation Y): 26–40 years; Gen X, BB (Generation X, baby boomer): ≥41 years.

Telehealth Interest
Overall, 19.5% (51/261) of the students were very interested and 49.4% (129/261) of the students were rather interested in telehealth. Study programs with the highest interest ratings (very or rather interested) were ANC (7/7, 100%), DIE (17/20, 85%), and ANP (11/13, 84%). Moreover, 24.1% (63/261) of students were less interested and 0.4% (1/261) were not interested in telehealth. The study programs with the most uninterested students (rather not or not interested) were PT (17/47, 36%), SLT (8/25, 32%), MID (11/35, 31%), and NUR (10/32, 31%). The percentages by study program are presented in Figure 4.
Figure 4. Students’ interest in telehealth based on the study program. ANC: advanced nursing counseling; ANE: advanced nursing education; ANP: advanced nursing practice; DIE: dietetics; HAE: health assisting engineering; MID: midwifery; NUR: health care and nursing; ORT: orthoptics; OT: occupational therapy; PT: physiotherapy; SLT: speech and language therapy.

Telehealth Knowledge

Only 2.7% (7/261) of the students stated that they have already dealt intensively with telehealth in their own profession and that they knew a lot of applications, 27.2% (71/261) stated that they knew some telehealth applications in their own profession, 20.3% (53/261) stated that they knew telehealth in medical services but not in their own profession, 34.1% (89/261) stated that they knew the term but nothing more about it, and 15.7% (41/261) had never heard of telehealth. The percentages by study program are presented in Figure 5.
Figure 5. Students’ self-assessed knowledge about telehealth based on the study program. ANC: advanced nursing counseling; ANE: advanced nursing education; ANP: advanced nursing practice; DIE: dietetics; HAE: health assisting engineering; MID: midwifery; NUR: health care and nursing; ORT: orthoptics; OT: occupational therapy; PT: physiotherapy; SLT: speech and language therapy.

Overall, 31.4% (82/261) of the students thought telehealth was very important for their education, and 50.9% (133/261) of the students rated it as rather important. The study programs with the highest importance ratings (very or rather important combined) were ANC (7/7, 100%), HAE (19/19, 100%), and OT (22/24, 91%). Moreover, 10% (26/261) of the students thought it was rather not important, and 1.1% (3/261) thought it was not important. The highest percentages of unimportance ratings (not or rather not important) were in MID (8/35, 23%), DIE (3/20, 15%), and ORT (4/23, 13%), PT (3/47, 13%), and ANE (1/13, 13%). The percentages by study program are depicted in Figure 6.

Telehealth Importance in Education

Overall, 31.4% (82/261) of the students thought telehealth was very important for their education, and 50.9% (133/261) of the students rated it as rather important. The study programs with the highest importance ratings (very or rather important combined) were ANC (7/7, 100%), HAE (19/19, 100%), and OT (22/24, 91%). Moreover, 10% (26/261) of the students thought it was rather not important, and 1.1% (3/261) thought it was not important. The highest percentages of unimportance ratings (not or rather not important) were in MID (8/35, 23%), DIE (3/20, 15%), and ORT (4/23, 13%), PT (3/47, 13%), and ANE (1/13, 13%). The percentages by study program are depicted in Figure 6.
Figure 6. Students’ perceived importance of telehealth in education. ANC: advanced nursing counseling; ANE: advanced nursing education; ANP: advanced nursing practice; DIE: dietetics; HAE: health assisting engineering; MID: midwifery; NUR: health care and nursing; ORT: orthoptics; OT: occupational therapy; PT: physiotherapy; SLT: speech and language therapy.

Telehealth Relevance After the Pandemic
Overall, 30.7% (80/261) of the students thought that telehealth will, for sure, be relevant in their profession after the pandemic, and 53.3% (139/261) of the students thought that telehealth would probably be relevant in their profession. The study programs that rated the future relevance of telehealth as highest were HAE (19/19, 100%), DIE (19/20, 95%), and ANE (15/16, 94%). Furthermore, 12.3% (32/261) of the students stated that it will rather not be relevant and 3.4% (9/261) stated that it will for sure not be relevant. The study programs that least anticipated a future relevance of telehealth were MID (11/35, 32%), ORT (6/23, 26%), and PT (7/47, 15%). The percentages by study program are depicted in Figure 7.
Figure 7. Students’ perceived relevance of telehealth after the pandemic. ANC: advanced nursing counseling; ANE: advanced nursing education; ANP: advanced nursing practice; DIE: dietetics; HAE: health assisting engineering; MID: midwifery; NUR: health care and nursing; ORT: orthoptics; OT: occupational therapy; PT: physiotherapy; SLT: speech and language therapy.

### Relevance of Different Forms of Telehealth Provision

The given relevance of different forms of telehealth provision in their own profession was confirmed as follows: video call consultation, 82.8% (216/261); apps for self-management, 75.1% (196/261); information for self-management via video courses or websites, 72.8% (190/261); phone call consultation, 68.2% (178/261); sensor-based monitoring of vital parameters, 46% (120/261); sensor-based monitoring of movement or activity, 39.8% (104/261); video call treatment or therapy, 32.2% (84/261); virtual reality or exergaming at home, 25.3% (66/261); and phone call treatment or therapy, 5.4% (14/261). The details of the study program are shown in Figure 8.

Figure 8. Students’ perception of the relevance of different forms of telehealth concerning their own profession (the percentage of students that believes this telehealth form is relevant in their profession). ANC: advanced nursing counseling; ANE: advanced nursing education; ANP: advanced nursing practice; DIE: dietetics; HAE: health assisting engineering; MID: midwifery; NUR: health care and nursing; ORT: orthoptics; OT: occupational therapy; PT: physiotherapy; SLT: speech and language therapy.

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<tr>
<td>MID</td>
<td>75.1% (196/261)</td>
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<td>NUR</td>
<td>72.8% (190/261)</td>
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<td>OT</td>
<td>68.2% (178/261)</td>
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<td>ORT</td>
<td>46% (120/261)</td>
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<td>PT</td>
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<td>SLT</td>
<td>32.2% (84/261)</td>
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<td>ANC</td>
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| Video call consultation | 83 |
| Self-management apps | 75 |
| Information for self-management via video courses or websites | 73 |
| Phone call consultation | 68 |
| Sensor-based monitoring of vital parameters | 46 |
| Sensor-based monitoring of movement or activity | 40 |
| Videocall treatment/therapy | 32 |
| Virtual reality or exergaming at home | 25 |
| Phonecall treatment/therapy | 5 |

**Bachelor’s programs**

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### Breakdown of Relevance:

- **80-100%**: Video call consultation (82.8%)
- **60-79%**: Self-management apps (75.1%), Information for self-management via video courses or websites (72.8%)
- **40-59%**: Phone call consultation (68.2%), Sensor-based monitoring of vital parameters (46%), Sensor-based monitoring of movement or activity (39.8%)
- **20-39%**: Video call treatment or therapy (32.2%), Virtual reality or exergaming at home (25.3%)
- **0-19%**: Phonecall treatment/therapy (5.4%)
Telehealth Experience

Overall, 45.6% (119/261) of the students already had telehealth experience. Furthermore, 22.2% (58/261) of the students had observed and 10.7% (28/261) of the students had performed phone call–based or video call–based counseling, treatment, or therapy; 17.2% (45/261) of the students had observed and 9.2% (24/261) of the students had performed the implementation of apps for self-management and self-training of monitoring; and 5.7% (15/261) of the students had observed and 1.5% (4/261) of the students had performed the implementation of virtual reality, exergaming, or sensors over the distance. The details of the study program are shown in Figure 9.

Figure 9. Students’ telehealth experience. The circles represent the percentage of students that have observed this form of telehealth, the squares represent the percentage of students that have performed this form of telehealth. ANC: advanced nursing counseling; ANE: advanced nursing education; ANP: advanced nursing practice; DIE: dietetics; HAE: health assisting engineering; MID: midwifery; NUR: health care and nursing; ORT: orthoptics; OT: occupational therapy; PT: physiotherapy; SLT: speech and language therapy.

Table 1. Students’ telehealth experience by study program.

Telehealth Content Within the Curriculum

Students’ preferences for telehealth content within their curriculum from highest to lowest ranking were practical training with devices, software, or apps (median 1), case examples for telehealth with various target groups (median 1), practical tips and exercises for telehealth provision (median 1), introduction of devices, software or apps (median 1.5), legal aspects of telehealth (median 2), data protection aspects of telehealth (median 2), technical skills for the application of devices and software (median 2), development of telehealth content (eg, video exercises or training plans; median 2), knowledge about the critical appraisal of health apps (median 2), practical implementation in field work (median 2), content about usability, user experience, and telehealth acceptance (median 2), knowledge about movement analysis via telehealth (median 2), analytical skills for data interpretation (median 2), scientific evidence on telehealth (median 2), content about gamification and feedback systems (median 2.5), and technical knowledge about principles of devices and software (median 3). Details by the study program are shown in Figure 10.

Overall, 21.8% (55/252) of the students preferred to learn about telehealth with students in their study program, 10% (25/252) preferred interdisciplinary courses, 60.7% (153/252) preferred both of them, 3.2% (8/252) did not want to learn about telehealth at all, and 4.4% (11/252) did not know. Furthermore, 30.6% (77/252) of the students wanted telehealth to be taught within required subjects, 62.3% (157/252) wanted telehealth to be taught within elective subjects, 1.6% (4/252) thought it should not be incorporated into the curriculum, and 5.6% (14/252) did not know. In bachelor’s programs, 10.5% (20/190) of the students preferred the first or second semester, 60.5% (115/190) preferred the third or fourth semester, 26.8% (51/190) preferred the fifth or sixth semester, and 2.1% (4/190) of participants preferred none of them. Overall, 30% (13/44) of the master’s students thought that the first or second semester and 68% (30/44) thought that the third or fourth semester would be most appropriate, and 1 (N=1, 2%) student felt that none was appropriate.
**Discussion**

**Overview**

Our study provides novel insight into the telehealth know ledge, skills, attitudes, and experience of health care and nursing students and its potential integration into health care and nursing education and practice. The results suggest that there is substantial interest in telehealth among health care and nursing students but a lack of knowledge and experience with it. We discovered similarities and differences among various student groups, which will be discussed in detail and with regard to previously proposed telehealth competency frameworks for health care professionals.

**Telehealth Interest**

There was a generally high level of interest in telehealth across all study programs. The study programs with the highest median interest in telehealth were 3 master’s programs (ANC, ANP, and HAE) and 1 bachelor’s program (DIE). Interest in telehealth appears to be higher among master’s students than among bachelor’s students, possibly because of their advanced level of education and experience. Students in master’s programs may have gained more professional working experience, which could have raised their awareness of the potential benefits of telehealth, such as increasing access to care [43], improving patient outcomes [44], and reducing health care costs [45]. Moreover, they might have encountered that telehealth has not yet become a ubiquitous component of the health care system. Furthermore, health care master’s programs often place greater emphasis on leadership and innovation, which could make students more interested in exploring new methods [46]. Students in master’s programs may be more focused on career advancement opportunities and recognize the potential of telehealth to create new roles or expand existing ones in the health care sector. This result also suggests that higher education may play an important role in promoting the adoption and use of telehealth in health care.

However, the students of the bachelor’s programs displayed a substantial level of interest in telehealth, which remained consistent across various semesters and generations. The slight differences in interest between the study programs could be because of differences in their professions and the extent to which telehealth is currently integrated into their practices. For example, dietitians may have a stronger focus on counseling and patient education without manual or physical approaches compared with other professions, such as MID, NUR, PT, and OT. Although these professions also have an important educational role, their physical nature may make in-person consultations more essential for their professions, whereas for DIE, telehealth consultations may be a more practical and effective option. In addition, SLT has a strong focus on communication and telehealth, especially in the form of synchronous videoconferencing, and has been successfully used for several years, for example, in rural and remote areas of countries such as Australia and Canada [47].

The high level of interest in telehealth among health care students shows a positive attitude toward the technology, indicating that many perceive it as a beneficial tool in their future professional practice. However, enthusiasm alone is not

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**Figure 10.** Students’ preferences for telehealth content based on the study program. The circles represent the median of all answers with 1=for sure, 2=rather yes, 3=rather not, or 4=for sure not. ANC: advanced nursing counseling; ANE: advanced nursing education; ANP: advanced nursing practice; DIE: dietetics; HAE: health assisting engineering; MID: midwifery; NUR: health care and nursing; ORT: orthoptics; OT: occupational therapy; PT: physiotherapy; SLT: speech and language therapy.
sufficient for effective telehealth practice; it must be supplemented by the right competencies as well as the ability to demonstrate successful performance in using telehealth tools and services.

**Telehealth Knowledge and Experience**

In general, most students showed some level of familiarity with telehealth, with only a small number of students reporting that they had never heard of it. However, there appears to be a profound lack of specific telehealth knowledge, profession-specific applications, and telehealth experience. Moreover, there were significant differences between the professions in terms of the level of knowledge about telehealth. For example, students from the bachelor’s programs PT, OT, and SLT and the master’s program HAE reported the highest levels of knowledge about telehealth applications in their professions. We can see that in some professions most students had never heard of telehealth or only knew the term but nothing more about it (applies to DIE, MID, NUR, and ANE). While in 3 of the 4 master’s programs all students at least knew the term telehealth, this was not the case for 6 of the 7 bachelor’s programs.

A relatively low percentage of students already had experience with telehealth applications. In Austria, health care professionals have worked mostly in face-to-face settings, but the COVID-19 pandemic had a significant influence on the attitudes toward telehealth service provision and its implementation [9,48]. Nevertheless, the findings of this study suggest that especially bachelor’s students have only rarely come into touch with it. However, increased exposure to telehealth in academic settings and practical experience are important to enhance awareness and adoption of this emerging health care approach [49]. Only 35.4% (86/243) of all students reported direct or indirect experience with phone or video call–based counseling, treatment, or therapy; 29.5% (69/234) had implemented apps for self-management, self-training, or monitoring; and only 8.3% (19/229) had experience with the implementation of virtual reality, exergaming, or sensors over a distance. However, these percentages vary among different health care profession students. The highest percentage of students with experience in phone or video call–based counseling, treatment, or therapy were studying the bachelor’s programs SLT, MID, and DIE and the master’s programs ANE, ANP, and HAE. While master’s students usually already have gained professional experience and thus determine their chosen methods themselves, the experience of bachelor’s students mostly is limited to practical training within the curriculum and placements. Therefore, their experience with telehealth methods highly depends on their implementation by their teachers and supervisors. However, it remains unclear why some professions have had greater exposure to telehealth among their students than others. It is possible that the urgency of certain cases, particularly those related to acute therapy, led to greater adoption of telehealth in some professions. Another explanation could be that some professions, such as MID and DIE, might already have used telephone consultations more often before the pandemic than other professions. Students in the HAE program had the highest percentage of experience in implementing apps for self-management, self-training, or monitoring, and the implementation of virtual reality, exergaming, or sensors over a distance. This is not surprising as this program has a focus on health care technology and students might have an affinity for integrating more complex technologies into their practice.

**Telehealth Attitudes**

Most students in all health care programs expected that telehealth will play an important role in their profession also after the pandemic. This aligns with current research that supports the future relevance of telehealth in health care [5,50-52]. The overall high rates of expectations among health care students regarding the integral role of telehealth in the future of health care emphasizes the need for a stronger integration of telehealth education into health care curricula. Previous surveys in other countries also found a strong belief of students that telehealth services will be strongly integrated in the future [49,52]. Approximately 30% of the participants from MID (11/35) and ORT (6/23) form an exemption and believed that telehealth will not or rather not be relevant in their profession after the pandemic. In ORT, in particular, telehealth practices may not yet be as established as in other health care professions. Similar to other professions, orthoptists heavily rely on hands-on procedures, but they may require even more specialized equipment than others for the assessment and treatment of eye disorders.

Video call consultations seem to be the most widely accepted form of telehealth provision, with a high percentage of students from all study programs agreeing that they have an important role in their profession. Students may recognize the benefits of video integration for observations, capturing interpersonal features, nonverbal cues, and eye contact that may be lost when relying solely on phone calls [51]. Moreover, in recent years, videoconferencing has seen substantial growth across various aspects of daily life, driven by technological advancements, faster internet speeds, and the transition to remote work, particularly during the COVID-19 pandemic [53]. Hence, it is conceivable that students can best envision the use of video calls within the scope of telehealth, as they are familiar with this technology from other contexts.

Self-management apps are also widely accepted, with the exception of MID, which has noticeably lower scores. This is in line with previous research that reported that 58% of the surveyed nonphysicians (including MID) categorically rejected self-monitoring apps in pregnancy [54]. Self-management apps hold potential value for a wide range of contexts and stakeholders, including patients, health care professionals, and caregivers [55] and should therefore be incorporated into education [56]. In addition, the provision of information for self-management via video courses or websites was perceived as relevant by a majority of the students. Moreover, simple phone call consultations were perceived as more relevant compared with treatments or therapy over the phone, which received more skepticism among the surveyed students. This appears to indicate students’ uncertainty regarding the feasibility or effectiveness of implementing specific interventions, techniques, or procedures through virtual means. Sensor-based monitoring of vital parameters is relatively well accepted among students in NUR and those in master’s programs. Compared
with the other students examined, students in NUR likely already had the most frequent experience with monitoring vital parameters in their current roles and constitute a significant portion of patient care. Consequently, students may perceive a direct potential for alleviating their workload in their professional lives through remote monitoring technologies. Virtual reality or exergaming at home is not widely accepted among students, although it is most accepted among students in the OT, PT, and HAE programs. Exergaming interventions have demonstrated effectiveness in enhancing balance, function, physical activity levels, strength, fatigue, emotions, cognition, and pain relief [57]. Consequently, these interventions hold relevance for professionals and students in related fields.

There was a high level of agreement among students in all study programs that telehealth is important for their education. Only a minority of students of MID and ANP programs thought that this was not important. However, curricula for health care professionals have not yet widely incorporated telehealth [26] and are not consistent in their educational approaches [31]. However, health educators have started to recommend or plan to incorporate telehealth into the curriculum [58]. Furthermore, research is being conducted on which telehealth competencies should be implemented in education and with what didactic means [16,31,59-61].

Students expressed a strong desire for practical training that included hands-on experience with telehealth devices, software, and apps; case examples for telehealth with various target groups; and practical tips and exercises for telehealth provision. Previously published telehealth curricula had similarly presented a strong focus on practical experience [61]. As with any new technology or practice, students often benefit from experiential learning and simulation [62]. Therefore, it is reasonable for inexperienced health care students to prioritize practical training with devices, software, or apps; case examples for telehealth with various patient groups; and practical tips and exercises for telehealth provision. This is in line with a prior study reporting that new graduate physiotherapists perceived exposure to and practical skills training for telehealth as essential for their profession [27]. Another study with new graduate speech and language therapists concluded that they should learn to initiate telepractice service delivery through demonstration and role play to reduce initial anxieties [63].

The students’ preference for both interdisciplinary and program-specific courses might be because telehealth is a complex and multidisciplinary field that requires a broad range of knowledge and skills [5,31] but still has profession-specific requirements and applications. Previous research has shown that students benefit from an interprofessional telehealth course [60]. The main reason for preferring electives could be that students want the flexibility to choose courses that align with their specific interests and career goals. Moreover, as mentioned by some students with additional comments, the curricula and timetables are already very intense and dense. Students might fear that the introduction of new content into the curriculum would come at the expense of other relevant study content. On the other hand, the preference for compulsory subjects by 30.6% (77/252) of the students could be because students feel that telehealth is an important topic that should be incorporated into the core curriculum of their program. Most bachelor’s students had a preference for learning about telehealth in the third or fourth semester. Master’s students also showed a slight preference for telehealth content in the second part of their education. This could be because students have already acquired a foundational knowledge of health care by this time and are better equipped to understand the complex nature of telehealth. In contrast, students in their first or second semester may be overwhelmed with this topic and may not have the necessary foundational knowledge to fully comprehend the nuances of telehealth.

Implications for Telehealth Education

Given the observed high interest and mainly positive attitude, but relatively low levels of perceived knowledge, and experience in telehealth, we conclude that it is important to enhance telehealth education for health care and nursing students. The apparent divide between perceived telehealth competence and importance of telehealth underscores the necessity that telehealth education should be integrated into the core curriculum, despite students having a preference for elective courses when directly asked. On the basis of the limited availability of publicly funded, profession-specific master’s programs in Austria [64], we believe that it is important to integrate basic telehealth education at the bachelor’s level to reach as many students as possible. However, this might not be applicable to countries with a different educational structure. Curricula should strategically incorporate the principles of Miller pyramid of clinical competence into telehealth education by emphasizing competency across the levels of knowledge, skills, performance, and action and by providing opportunities to form attitudes, as highlighted by other authors [16,60]. We suggest that there is a need for increased knowledge transfer, practical exposure, and training in the use of telehealth applications, especially in professions with lower levels of knowledge about telehealth, to increase their awareness and understanding of the potential benefits of telehealth, their specific skills, and therefore overall competency in their respective fields. It is further crucial to empower educators with the necessary competencies to effectively teach telehealth and to provide organizational framework conditions to integrate telehealth into the curricula [65].

As the students preferred to learn about case examples and hands-on experience with devices, software, and apps used in telehealth, we suggest that they early on can become more familiar and comfortable with using them. Case examples for telehealth with various target groups can help students understand the diverse needs of different patient populations and learn how to adapt their approach accordingly. Practical tips and exercises for telehealth provision can also help students to develop skills and confidence in their ability to provide telehealth services; improve their overall competency; and understand the ethical, clinical, and legal aspects that arise when using them. Furthermore, courses should expand on the essential knowledge details of legal aspects, data protection, technical skills, critical appraisal, and scientific evidence based on or in combination with practical examples. Even if these aspects did not rank highest in the needs analysis, students confirmed their relevance. Students need to build knowledge about the legal
framework in which they will operate, the importance of protecting patient data and how to maintain data privacy, and the potential risks and liabilities involved. As telehealth relies heavily on technology, students need to have the technical skills to use and troubleshoot various telehealth tools and platforms [66]. Furthermore, students need to be able to apply clinical reasoning in a telehealth context and critically appraise the scientific evidence on telehealth, including its benefits and limitations, to make informed decisions about its use [67].

In terms of content, we conclude that future telehealth curricula should focus on teaching the basics and the application of practical training on consultation over the phone with or without video integration, the integration of self-management apps, and the development or integration of video courses or websites for self-management within all study programs. This focus has been previously suggested for nurse practitioner training [5]. Furthermore, specific courses for therapeutic professions (SLT, OT, and PT) could teach the possibilities of direct therapy approaches through video calls and further exergaming and virtual reality. Sensor-based monitoring of vital parameters, movement, and activity might be more appropriate for NUR, PT, and OT students, within specialization courses for students of other bachelor’s programs that are interested in this topic, and for master’s programs. Guidelines that are specific to each profession and report on implementation, financial, and technical considerations [68] should also be integrated into the development of curricula. For instance, incorporating strategies for executing telehealth practices in fields such as OT [69], musculoskeletal physiotherapy [70], SLT [71], and nursing [72] can be beneficial.

Limitations
This study has several limitations that impact the interpretation of the results. The sample size of 261, representing a small segment of eligible health care students, and the overall low (11%) and variable response rate across programs, may affect the results’ generalizability and comparability and raises the possibility of nonresponse bias, whereby the views of those who did not participate may systematically differ from those who did. This issue poses the risk of over- or underestimation of the true distribution of perceived telehealth competencies in the target population. In addition, the cross-sectional design, capturing attitudes at a single point in time, further limits the findings. The generation distribution differed between bachelor’s and master’s programs, which may confound the perceived importance of telehealth education, knowledge levels, and postpandemic telehealth relevance across generations. Although a large portion (151/206, 73.3%) of students in bachelor’s programs belonged to Generation Z, master’s programs had a higher representation of Generation Y, Generation X, and baby boomers (49/55, 89%). Therefore, the statistical differences in the perceived importance of telehealth education between generations and differences in telehealth knowledge and perceived relevance of telehealth after the pandemic must be interpreted with caution. It should also be noted that health professionals pursuing a master’s degree later in their careers might show more interest in innovation, making these results less generalizable to other health professionals of the same generations. Regarding the statistical analysis, it should be mentioned that multiple comparisons increase the risk of type I errors. Even with the Bonferroni adjustment, which is conservative, there is a tradeoff with statistical power, potentially leading to type II errors [73]. In addition, self-reported measures of telehealth interest and knowledge may be influenced by social desirability bias or inaccurate self-assessment. Furthermore, it was not possible to directly assess student’s telehealth skills and actual performance using a web-based survey. In addition, the study’s context, focused on students from specific health care programs in 1 Austrian university, restricts the applicability of the findings to other institutions or countries. Finally, a limitation of this study is the potential impact of the COVID-19 pandemic on the participants’ attitudes, experiences, and perspectives toward telehealth. The students who participated in this study in May 2022 were probably affected by the pandemic in various ways, including disruptions in their placements and the rapid adoption of telehealth services in health care settings. As a result, their views on telehealth might be influenced by the unique circumstances of the pandemic, which could limit the generalizability of the findings to other periods.

Recommendations for Further Research
Future research should consider several steps to build on this study. First, expanding the study to include a larger, more diverse sample of health care students from different institutions and countries will allow for examining potential variations in knowledge, skills, performance, action, and attitudes in telehealth. In addition, exploring factors that may act as barriers or facilitators to the adoption of telehealth within health care education, such as the interest, skills, and knowledge of educators, technological infrastructure, legal and ethical considerations, or institutional barriers, is crucial. Second, conducting more intervention-based studies that aim at improving telehealth knowledge, competence, and interest among health care students [74,75] will be valuable for investigating the effectiveness of different teaching methods and content that can help identify the most effective strategies for telehealth education. Moreover, conducting longitudinal research would enable tracking changes in students’ attitudes, knowledge, and interest in telehealth over time as they progress through their education, providing a comprehensive understanding of the development and potential factors influencing these perspectives, especially in the time after the COVID-19 pandemic. Assessing the impact of telehealth training on clinical practice is important. Investigating the relationship between telehealth training during health care education and its application in clinical practice, as well as evaluating the impact of telehealth knowledge and competence on patient outcomes and health care delivery, can provide valuable insights. Finally, examining the role of interprofessional collaboration in telehealth education and practice and its impact on students’ attitudes and knowledge regarding telehealth is essential [76]. Evaluating the effectiveness of interdisciplinary courses in fostering collaboration and improving telehealth competence among health care students can contribute to the development of more efficient telehealth education strategies.
Conclusions
Our study findings underscore the need for structured telehealth education within health care curricula to equip students with the necessary competencies for future practice. Students recognize the importance of telehealth in their future profession and feel that they need to be adequately prepared. However, the study also revealed that the level of telehealth experience and knowledge among participating health care students is currently low. Therefore, there is an urgent need to provide comprehensive telehealth education and training to health care students to prepare them for the future demands in their profession. By incorporating telehealth education into health care curricula, institutions can better prepare students for the evolving landscape of health care and promote the successful integration of telehealth into future practice.

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Data Availability
The data sets generated during or analyzed during this study are available from the corresponding author upon reasonable request.

Authors’ Contributions
LR was involved in project administration; LR and LA with the support from all authors conceptualized the study; LR and PP finalized the methodology; LR did data curation; LR and PP were involved in formal analysis and investigation; LR prepared the original draft; all authors reviewed and edited the draft; LR and FW acquired the funding; and SK supervised the study.

Conflicts of Interest
SK is the founder and shareholder of MED.digital. All other authors declare no other conflicts of interest.

Multimedia Appendix 1
Original questionnaire (German version).
[PDF File (Adobe PDF File), 103 KB - mededu_v10i1e51112_app1.pdf]

Multimedia Appendix 2
Translated questionnaire (English version).
[PDF File (Adobe PDF File), 232 KB - mededu_v10i1e51112_app2.pdf]

Multimedia Appendix 3
Pairwise comparisons.
[PDF File (Adobe PDF File), 657 KB - mededu_v10i1e51112_app3.pdf]

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Abbreviations

ANC: advanced nursing counseling
ANE: advanced nursing education
ANP: advanced nursing practice
CROSS: Consensus-Based Checklist for Reporting of Survey Studies
DIE: dietetics
HAE: health assisting engineering
MID: midwifery
NUR: health care and nursing
ORT: orthoptics
OT: occupational therapy
PT: physiotherapy
SLT: speech and language therapy

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Evaluating the Impact of the National Health Service Digital Academy on Participants’ Perceptions of Their Identity as Leaders of Digital Health Change: Mixed Methods Study

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Abstract

Background: The key to the digital leveling-up strategy of the National Health Service is the development of a digitally proficient leadership. The National Health Service Digital Academy (NHSDA) Digital Health Leadership program was designed to support emerging digital leaders to acquire the necessary skills to facilitate transformation. This study examined the influence of the program on professional identity formation as a means of creating a more proficient digital health leadership.

Objective: This study aims to examine the impact of the NHSDA program on participants’ perceptions of themselves as digital health leaders.

Methods: We recruited 41 participants from 2 cohorts of the 2-year NHSDA program in this mixed methods study, all of whom had completed it >6 months before the study. The participants were initially invited to complete a web-based scoping questionnaire. This involved both quantitative and qualitative responses to prompts. Frequencies of responses were aggregated, while free-text comments from the questionnaire were analyzed inductively. The content of the 30 highest-scoring dissertations was also reviewed by 2 independent authors. A total of 14 semistructured interviews were then conducted with a subset of the cohort. These focused on individuals’ perceptions of digital leadership and the influence of the course on the attainment of skills. In total, 3 in-depth focus groups were then conducted with participants to examine shared perceptions of professional identity as digital health leaders. The transcripts from the interviews and focus groups were aligned with a previously published examination of leadership as a framework.

Results: Of the 41 participants, 42% (17/41) were in clinical roles, 34% (14/41) were in program delivery or management roles, 20% (8/41) were in data science roles, and 5% (2/41) were in “other” roles. Interviews and focus groups highlighted that the course influenced 8 domains of professional identity: commitment to the profession, critical thinking, goal orientation, mentoring, perception of the profession, socialization, reflection, and self-efficacy. The dissertation of the practice model, in which candidates undertake digital projects within their organizations supported by faculty, largely impacted metacognitive skill acquisition and goal orientation. However, the program also affected participants’ values and direction within the wider digital health community. According to the questionnaire, after graduation, 59% (24/41) of the participants changed roles in search of more prominence within digital leadership, with 46% (11/24) reporting that the course was a strong determinant of this change.

Conclusions: A digital leadership course aimed at providing attendees with the necessary attributes to guide transformation can have a significant impact on professional identity formation. This can create a sense of belonging to a wider health leadership structure and facilitate the attainment of organizational and national digital targets. This effect is diminished by a lack of locoregional support for professional development.

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KEYWORDS
digital leadership; professional identity; dissertation of practice

Introduction

Background

Delivering the digital transformation of the United Kingdom’s National Health Service (NHS) has been a long-standing aim. In the “What Good Looks Like” framework, by 2025, the NHS aims to have all integrated care systems and associated trusts reach core digital capability [1]. The key to this digital leveling-up strategy is the need to support professional development and training opportunities across integrated care systems [2]. To facilitate system-wide progress, there is a growing need for digitally proficient leadership teams; however, one of the main barriers identified by the NHS Transformation Directorate has been a lack of a “clear steer” for digital decisions [3].

Digital health resources and digital tools that were adopted through necessity during the COVID-19 pandemic have led to a paradigm shift in routine care. The scope of these resources has been significant across health care, including remote patient-clinician consultations and diagnostics [4-6]. However, as the health care service looks to enact facets of the NHS Long Term Plan and scale future sustainable digital change, possessing robust leadership to set this direction is key [7].

The NHS Digital Academy (NHSDA) designed its flagship course to deliver this support to emerging leaders. Each cohort of approximately 100 professionals is selected from applicants who are directly employed by the NHS or social care in England [8]. Digital health leadership is delivered in 2 accredited components. The first, resulting in a Postgraduate Diploma (PGDip) in Digital Health Leadership, uses a blended learning approach to provide a theoretical foundation for topics such as user-centered design [9,10]. This involves web-based teaching on 6 core modules structured around assessment deadlines including the essentials of health systems, implementing change, health information systems, user-centered design, actionable data analytics, and leadership change. Subsequently, students can undertake a 1-year Master of Science (MSc) degree. The MSc degree uses a dissertation of the practice model, where students focus on practicable applications of theory within defined digital transformation projects. This self-directed period of study involves candidates’ leading projects within their own host organizations with periodic deadlines to guide progress and continued access to the support of the teaching faculty. In this manner, the course facilitates a workplace-based learning model geared toward supporting students to use research to solve a real-world problem in their organization. Although the course has been shown to effectively impact the attainment of national digital priorities [11], little is known about the effect on participants’ perceptions of themselves as digital leaders or their professional identity.

Defining professional identity is difficult owing to a lack of standardization of the term. It has been associated with knowledge acquisition, performance of typical tasks, displays of expected behaviors, or shared ethos and value systems [12]. In other contexts, professional identity involves the integration of the personal and professional selves [13]. A scoping review by Cornett et al [14] identified 5 constructs associated with health professional identity, including lived experience (eg, practicing), the world around me (eg, the workplace), belonging (eg, collective identity), me (eg, self in relation to the profession), and learning (eg, acquiring skills). However, the review examined health professional practice and did not specifically examine digital leaders [14]. Understanding what constitutes the identity of a digital health leader is potentially more problematic, given that the field is relatively nascent. Consequently, understanding what knowledge is needed, the tasks or behaviors that are expected of leaders, and what constitutes core values is likely to remain ill-defined until the digital health landscape has evolved. Furthermore, an individual’s perception of their professional role is a dynamic process and can be augmented by one’s context [15]. Determinations regarding the extent to which one feels like a professional can therefore be difficult to ascertain.

Despite these challenges, professional identity formation has been shown to be an increasingly important aspect of learning development. Within clinical settings, professional identity contributes to the delineation of practice boundaries as well as avoiding confusion regarding individuals’ roles within wider teams [16]. With a growing body of clinicians involved in digital leadership, this is particularly important, as studies have demonstrated that doctors can often encounter difficulties when reconciling managerial and clinical responsibilities. Moreover, aspects of professional identity, such as “belongingness,” have been associated with greater workforce retention [17]. Therefore, there is a growing drive to evaluate how courses and educational curricula impact an individual’s identity.

Aim

This mixed methods study aimed to understand the influence of the NHSDA Digital Health Leadership program on participants’ perceptions of themselves as digital health leaders. This will facilitate a greater understanding of the core values associated with digital leadership and provide insights to improve courses globally.

Methods

This study was conducted as a mixed methods study involving a web-based questionnaire, interviews, and focus groups.

Recruitment

Participants in the first 2 cohorts of the NHSDA’s flagship Digital Health Leadership program were recruited for the study. All participants had completed both years of the program and were >6 months from completion to avoid recency bias. This could involve overemphasizing the impact of later teaching in course compared to that which occurred earlier. Studies suggest that a later evaluation can provide a more holistic evaluation [18]. It also provided time for candidates to reflect on future career opportunities. No other exclusion criteria were placed...
upon participants; therefore, a nonprobabilistic sampling method to reach the necessary sample size was used. Eligible participants were contacted through email by a member of the research team (AA) with no direct link to the NHSDA. Both cohorts were impacted by the COVID-19 pandemic, particularly with respect to their dissertation projects that were undertaken during the pandemic.

Scoping Questionnaire
A previously validated web-based scoping questionnaire was used to provide insights and feedback on the course [11]. This questionnaire explored the impact of the course on the development of facets such as “social intelligence,” “interpersonal skills,” and “courage.” It also examined the effect of the course on future goals, asking “Would you consider any of the following additional training options in Digital Health Leadership or a related field within the next 2 years?” This questionnaire was developed to map specifically onto the NHSDA program objectives and encompassed questions including individuals’ perspectives on development and digital leadership. It also sought to ascertain feedback on the aspects of the course that were most influential on participants. A total of 2 authors (RCB and AA) developed the survey questions, whereas a third (AS) independent author was involved to discuss disagreements. The participants were recruited via an email containing an anonymous link. The links were delivered to all eligible individuals separately from the program to avoid selection and response biases based on prior performance in the course.

Semistructured Interviews
Following the survey, anonymous responses were quantitatively (multiple-choice questions) and qualitatively analyzed (free-text sections). Themes derived from the analysis were elicited by 2 authors (RCB and AS). The results from the survey were then used to develop the question guides for interviews and focus groups (Multimedia Appendix 1). A third author (AS) was involved to help resolve disagreements. Interviews were designed to gain a more in-depth understanding of individuals’ perceptions of the values and skills associated with digital health leadership and how the course has influenced these areas. Enrollment to an interview was not dependent on completion of the survey or prior performance. All interviews were conducted web-based via Microsoft Teams (Microsoft Corporation). AA conducted all the semistructured interviews, and AA had no formal role within the NHSDA and no prior interaction with any participants to avoid response biases.

Focus Groups
To ascertain the shared experience of participants and paralleling the collaborative learning approach used by the program, web-based focus groups were also undertaken using the Microsoft Teams platform. In addition, the focus groups examined the participants’ contrasting experiences of the course. A total of 3 focus groups were conducted, with the facilitator (AA) not being affiliated with the NHSDA. Each focus group involved 4 to 5 participants. The invitation to participate in the focus groups was not contingent on the completion of any previous phase of the study. As with the interviews, the focus groups used open-ended prompts to foster responses. In addition, the facilitator encouraged open discussion between participants. Identity involves the development of attributes congruent with the profession, that is, a common set of values about what it means to be a digital health leader [19]. By facilitating focus group discussions regarding how digital leadership is perceived, its underpinning principles, and how one can develop the necessary skills to become a more effective leader, a greater understanding of these shared values was attained.

Analysis
Survey responses were collated through the web-based tool Qualtrics (Qualtrics International Inc). Qualtrics automatically aggregates replies and provides frequencies from the respondents by choice. Given the small number of responses and because the initial survey was used to inform further study phases, no statistical analysis was undertaken. Free-text options were inductively thematically analyzed until data saturation was achieved by an author (AA) and validated by another (RCB). Both qualitative and quantitative responses were used to inform the development of the topic guides following discussion between the authors. Specifically, the authors focused on areas of disagreement or if a particular topic recurred across the responses of different participants.

Audio recordings, obtained with the consent of participants for both interviews and focus groups, were transcribed using the web application Descript (Descript, Inc). The accuracy of the outputs was confirmed by one author (AA), who was present in the interviews and focus groups. Anonymized transcripts were then uploaded to the analysis tool MAXQDA (VERBI GmbH). A deductive thematic analysis was conducted using a technique previously used in similar studies [20]. This involved familiarization with the transcripts by 2 authors (RCB and AA). The transcripts were then coded with the data explored to examine the frequency and relationship of the codes. Similar codes were combined into themes and subthemes, which were aligned with the components of professional identity elicited by Chin et al [19]. This review was selected as a framework on which to base the thematic analysis for 3 reasons: first, because of its comprehensive evaluation of identity with 10 evidence-based facets described; second, the examination of internship or workplace-based learning parallels the educational model of the NHSDA’s second year; and finally, the authors’ examination of how these components map to other contexts can facilitate cross-discipline comparisons was helpful in understanding the participant’s identity across wider teams [21]. Although Chin et al [19] found that only a subset of these components was applicable to higher education internships, this study examined the relevance of all components, as some were more significant in postgraduate studies.

As a means of validation, the anonymized transcripts were reviewed again, and themes were amended until a consensus was attained. All discrepancies in the coding exercise or allocations of themes were discussed until resolution. Themes that were consistently mentioned by different participants, those that aligned with findings from the questionnaire or focus group, and those that were regarded as stronger determinants were considered more impactful influences. A constructivist approach
was used as the basis of this study, which paralleled the active learning undertaken throughout the program. The paradigm focuses on the importance of active learning and its transformation through experience [22,23]. It involves the engagement and reflection of the learner, which can be impacted by context, knowledge, motivation, values, or organizational setting [24]. This is particularly pertinent to identity development, which can be influenced by such intrinsic and extrinsic factors.

High-scoring dissertations across the 2 included cohorts were also evaluated independently by 2 authors (RCB and AA). The authors then mapped the skills exhibited in these manuscripts to the components of professional identity. Students were required to make explicit reference to a particular component for it to be mapped. The authors discussed any disagreements until a consensus was reached.

Ethical Considerations
Approval to conduct this study was provided by the Institutional Review Board at Imperial College London (reference EERP2021-026a). All participants provided explicit written consent to participate in the study and were free to withdraw at any time. No participant received financial remuneration for being involved in the study. All data including transcripts and survey data were kept anonymous, in keeping with the secure data storage policies of Imperial College London.

Results
Overview
A total of 41 eligible participants completed the web-based survey, of which 42% (17/41) were female and 59% (24/41) were male. Most participants were in clinical health care roles (17/41, 42%), whereas 34% (14/41) were in program delivery or management roles; 20% (8/41) were in informatics or data science roles, and 5% (2/41) were in “other” roles. Of those surveyed, 59% (24/41) reported that the NHS Digital Academy course had a strong and direct impact on their working practice, 27% (11/41) reported some impact, and only 2% (1/41) reported no effect. In total, 4 key themes were elicited from the inductive analysis of the free-text sections: transformative impact, valuing collaboration, goal setting, and improving positive perceptions. The selected results are presented in Multimedia Appendix 1.

Semistructured interviews were conducted with 34% (14/41) of participants. The demographics of which paralleled those from the wider cohort, with 43% (3/7) of participants identifying as female and 50% (7/14) working in clinical roles. In total, 3 focus groups were held with more than half of the attendees (7/13, 54%) not involved in the preceding interviews. The data sources including the number of participants used in the study is presented in Figure 1.
Thematic analysis mapped findings from interviews and focus groups to 8 of the 10 components of professional identity highlighted by Chin et al [19]. Internship experience was not measured, as most of the cohort had been in their roles before the NHSDA and could not be considered entering an internship. However, aspects encompassing skill acquisition during dissertations were covered in other domains. The work environment was also not included, as the participants came from disparate fields, precluding comparisons. However, the findings were mapped to the following domains: commitment to the profession, critical thinking, goal orientation, mentoring, perception of the profession, socialization, reflection, and self-efficacy. When undertaking the thematic analysis and mapping of the highest-scoring dissertation to the components from the framework by Chin et al [19], only 4 were found to be applicable. These included critical thinking, goal orientation, mentoring, and reflection. This is likely because the dissertation was more descriptive of a specific transformation project rather than reflective of the attitudes of participants toward digital health leadership as a whole.

Table 1 demonstrates how the course impacted these areas through quotations from the respondents.
Table 1. Key domains\textsuperscript{a,b} of professional identity with quotes from participants on the impact of the course.

<table>
<thead>
<tr>
<th>Domain</th>
<th>Definition</th>
<th>Quote</th>
</tr>
</thead>
</table>
| Commitment to profession     | The physical, mental, and emotional commitment to being a digital leader. Understanding the aims of leadership and demonstrating a willingness to achieve them. | • “People saw what I was learning from the course and my enthusiasm for my career...I was invigorated and it encouraged me to do the best in my career path.” [Interviewee 13]  
• “Having gone through the course, I want to pursue careers in digital in some fashion...it’s shifted the course of my career, I’m aspiring to national level roles.” [Interviewee 7] |
| Critical thinking             | A metacognitive skill to critically evaluate the current standard and elicit new solutions. Involves understanding one’s own role as a digital leader and how one would want it to be. | • “There is a critical language element to it [digital leadership]...you have more critical analysis aspect to your work...it [the National Health Service Digital Academy] has changed the way I approach and think about problems.” [Interviewee 6]  
• “I became more strategic in my approach...it’s broader...it’s about thinking right...we need it think from top to bottom.” [Interviewee 5] |
| Goal orientation              | How one achieves and defines the specific outcomes associated with being a digital leader. Involves having a conducive environment for task mastery and development as a digital leader. | • “My perception has shifted...I see myself as a facilitator of digital transformation...I aim to maintain virtual delivery and my organization is helping me meet that need.” [Interviewee 11]  
• “One of the most valuable things from the digital Academy...it made me understand where to make change, improve processes, how to measure that change and feeding it back...it is the core of our aims.” [Interviewee 1] |
| Mentoring                     | Acting as a mentor and having mentorship.                                    | • “I believe in paying it forward, I’ve brought back what I’ve learnt to building my informatics team.” [Interviewee 7]  
• “I became very invigorated by the community...I spent an afternoon with a module lead in user design... then the head of user design centre in the NHS offered me an opportunity to shadow them.” [Interviewee 13] |
| Perception of the profession  | Ideas about what it is to be a digital leader, the skills required, and its place in wider health care infrastructure. | • “The NHSDA meant I didn’t hold those people on a pedestal...it [digital leadership] is not about having all the technical knowledge, it’s being able to pull together everyone toward the solution.” [Interviewee 11]  
• “It has been transformational...just in the knowledge it has given me...on understanding the role...where it fits into organizational strategy...the scope.” [Interviewee 4] |
| Professional socialization    | A sense of belonging to the wider community and being accepted as part of a group. Includes credentialing and peer networks. | • “It has a level of kudos...there is good recognition that it, the academy skilled them up.” [Interviewee 12]  
• “Now I’ve got a network of probably 100 or more contacts nationally...I would go and talk to them and say you must know someone locally who does this, any chance you could put me in touch?” [Interviewee 8] |
| Reflection                    | Reflecting on knowledge, cognition, professional identity, maturity, and the sense of professionalism within digital leadership. Involves ideas regarding professional development. | • “It’s highlighted the positives and the negatives of my leadership style, my digital knowledge and also where I fit within an organization and nationally. So it’s given me that sort of self-awareness.” [Interviewee 10]  
• “It helped me become better leader. It helped me understand how would I help people in the organization transform and be more innovative.” [Interviewee 2] |
| Self-efficacy                 | Self-belief or belief in one’s own capabilities to perform as a digital leader. Includes impostor syndrome and the impact of external opinions upon one’s own beliefs. | • “When I first went on the digital academy...it felt like we were interlopers...throughout it continued to build my confidence levels and where I fit as a digital leader locally.” [Interviewee 14]  
• “It made me think that I am a leader...I would never have applied for that Royal College job without it.” [Interviewee 3] |

\textsuperscript{a}Work environment not included as relevant components covered in “mentoring,” and participants came from disparate environments. 

\textsuperscript{b}Internship experience was not included. The participants represent the existing digital health leadership whose roles would not include internship. Areas of skill-building are covered within other domains.

**Commitment to the Profession**

The program appeared to influence individuals’ commitment to digital health leadership. In total, 59% (24/41) of the cohort reported changing their roles following the course. Among the participants who changed their roles following the course, 46% (11/24) reported that the program had a strong impact on this decision. Inductive thematic analysis of the survey comment elicited this transformative impact of the course upon candidates’ careers, with several describing “life-changing” or “career-changing” effects. In one focus group, one informatician mentioned that “I do now feel like a leader, and I wasn’t going to stay in that organisation.” This new commitment led them to “find somewhere else that I [they] could be a digital leader.” Others reported that they “were looking at influencing policy, in a way I [they] hadn’t before...because of the course.” This commitment to digital health leadership has led them to apply for chief clinical informatics officer (CCIO) roles. The course
also appeared to reaffirm participants’ motivation for undertaking digital health leadership roles. One CCIO stated:

*The course* hasn’t necessarily given me all the technical skills...but it’s greater than that. It’s given the background of how we’ve got to where we are now and inspired me to change things going forward.

**Critical Thinking**

Critical thinking, which involves understanding a context and deriving new solutions, was found to be fostered predominantly through the MSc dissertation. As presented in Table 2, all but 3 of the 30 highest-ranking dissertation topics across the 2 cohorts involved critical analysis.

Providing a supportive environment for change enabled candidates to put theoretical learning into practice. An interviewee said “I [they] approach things differently, I’m [they are] more strategic, more constructed after the project.” These cognitive skills have continued postgraduation with individuals feeling they have “different tools that were picked up during the academy, which I [they] use day-to-day.”
Table 2. Topics of the highest-scoring dissertations of the 2 cohorts and components of identity that were incorporated.

<table>
<thead>
<tr>
<th>Dissertation topic</th>
<th>Critical thinking</th>
<th>Goal orientation</th>
<th>Mentoring</th>
<th>Reflection</th>
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<td>BYOD policy design and development for NHS Trusts</td>
<td>✓✓</td>
<td>✓</td>
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<td>Board level digital readiness</td>
<td>✓✓</td>
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<tr>
<td>Blueprint for digital excellence in the development of a new hospital</td>
<td>✓✓</td>
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<tr>
<td>Implementing recommendations of Topol review</td>
<td>✓✓</td>
<td>✓</td>
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<tr>
<td>Impact of digital working on patient care</td>
<td>✓✓</td>
<td>✓</td>
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<tr>
<td>Improving performance of a cardiorespiratory outpatient department</td>
<td>✓✓</td>
<td>✓</td>
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<tr>
<td>App to reduce suicide and self-harming and improve safety and clinical outcomes in mental health</td>
<td>✓✓</td>
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<td>✓</td>
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<tr>
<td>Standards and processes for sharing data across platforms and organizations</td>
<td>✓✓</td>
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<tr>
<td>Blueprint for digital first GP</td>
<td>✓✓</td>
<td>✓</td>
<td>✓</td>
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<tr>
<td>Participant preferences for contact and clinical research study enrollment</td>
<td>✓✓</td>
<td>✓</td>
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<tr>
<td>Evaluating impact of digital maturity on effectiveness and efficiency of care in adolescent inpatient mental health units</td>
<td>✓✓</td>
<td>✓</td>
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<tr>
<td>Digital transformation of epilepsy care and monitoring</td>
<td>✓✓</td>
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<tr>
<td>Implementing SNOMED-CT coding into an EHR for clinical decision support, data sharing and medical pathway transformation</td>
<td>✓✓</td>
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<tr>
<td>Direct web-based advice from consultant psychiatrists to GPs</td>
<td>✓✓</td>
<td>✓</td>
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<tr>
<td>Enabling effective and appropriate use of virtual consultations with adolescents in psychiatry specialty settings</td>
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<tr>
<td>An impact analysis of Morse system implementation and mobile device use by health visitors in rural Scotland</td>
<td>✓✓</td>
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<tr>
<td>Optimizing remote access to primary care during COVID-19: a focus on patients with moderate to severe mental health needs</td>
<td>✓✓</td>
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<tr>
<td>Making quite voices louder: addressing health inequalities for people with moderate to severe mental health illness</td>
<td>✓✓</td>
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<td>Digitally enabling primary care beyond the COVID-19 pandemic</td>
<td>✓✓</td>
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<tr>
<td>The impact of digital tools and ways of working on staff burnout and enjoyment of work in psychiatry</td>
<td>✓✓</td>
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<tr>
<td>Optimizing culture of collaboration and learning to tackle health inequalities: a study of digital health Canada</td>
<td>✓✓</td>
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<tr>
<td>Digital delivery: the future of UK diabetes education</td>
<td>✓✓</td>
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<tr>
<td>Impact of the implementation of a critical care information system on patient-facing clinical staff in an intensive care unit during the COVID-19 pandemic</td>
<td>✓✓</td>
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<tr>
<td>The key components of organizational culture for a digital first strategy</td>
<td>✓✓</td>
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<tr>
<td>The relationship between funding and the digital maturity of NHS provider organizations</td>
<td>✓✓</td>
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</tr>
<tr>
<td>Partnership between health care provider organizations and industry in adopting AI into health care practice</td>
<td>✓✓</td>
<td>✓</td>
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<tr>
<td>A framework for effective prioritization of digital transformation projects in recently merged secondary care organizations</td>
<td>✓✓</td>
<td>✓</td>
<td>✓</td>
<td></td>
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<tr>
<td>Best practices for digital inclusion in at risk pediatric populations</td>
<td>✓✓</td>
<td>✓</td>
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</tr>
<tr>
<td>Transformation at pace and scale by EPR sharing among high and low digitally mature hospital systems</td>
<td>✓✓</td>
<td>✓</td>
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</table>

*BYOD: bring your own device.
Goal Orientation

Goal orientation encompasses defining and accomplishing the specific outcomes of digital leadership within the NHS. This may involve achieving national priorities outlined in health policies, such as the NHS Long Term Plan or locoregional transformation targets. As the MSc model was designed to provide a supported environment to undertake these projects, it was unsurprising that all the dissertations evaluated involved an element of goal orientation. These projects varied from digitizing diabetes education platforms and booking processes to projects focusing on the implementation of the recommendations of the Topol review [25]. An interviewee said, “The reason I [they] chose this MSc project was because...it was my day job.” This pragmatic approach helped align the goals of the course with those of digital leaders. Survey comment analysis also elicited “goal setting” as a key theme. Several candidates identified future opportunities for further professional development across a broad range of areas, including policy development, finance, teaching, and strategy.

Mentoring

The influence of the NHSDA on the provision and reception of mentorship was variable. Only 27% (11/41) of the survey respondents felt they acquired mentoring skills; however, 59% (24/41) reported that they were more able to develop capabilities within their teams. Moreover, 50% (15/30) of dissertations reflected the provision of mentoring within participants’ local organizations. Following attendance at the NHSDA, some candidates were encouraged to “develop the professional training development with my [their] own teams,” with a common theme being “paying forward” the knowledge they had acquired. Furthermore, the program provided opportunities for candidates to receive mentorship or “shadowing opportunities.” One candidate who developed an interest in user-centered design “spent a really impactful afternoon with a module lead” and, subsequently, connected with designers from NHS England. This culminated in a career change to a health care–based user experience department. These experiences were significantly influenced by candidates’ work environments, with others noting they were “still alone in the organization...with little guidance from management.”

Perception of the Profession

An informatician reported, “since the course...I see myself [themselves] as a facilitator of digital transformation,” as opposed to their previous notions regarding a more technical role. This was echoed by others who perceived digital leaders as change agents: “not just somebody with the skills...but the ability to make connections to bring about transformation.” For more junior candidates, the course also helped level the hierarchy within the digital ecosystem. Having previously put “digital leaders on a pedestal” and believing that becoming one “was an unachievable target,” following the course, they believed that “it [being a digital leader] is not about having all the technical knowledge but being able to pull everyone together toward a solution.” Conversely, more established digital leaders had constructed their perceptions of digital leadership before the NHSDA, with 1 CCIO explaining, “it [the course] hasn’t changed the way I perceive what I do, it has made me more effective.”

Professional Socialization

Socialization was a key untaught component of the course. In the questionnaire, 46% (19/41) reported that the MSc program influenced their feelings of socialization within digital leadership. Inductive thematic analysis of the survey elicited “valuing collaboration” as a common theme among respondents. Many were reporting that they now found value in a “network of like-minded professionals” and wanted to “understand [their] colleagues better.” Moreover, most respondents highlighted that the program taught them how to maintain effective relationships (29/41, 71%) and inspired a shared purpose among colleagues (30/41, 73%), both facilitating a common sense of belonging. A participant suggests the “main impact of the MSc was this community of leaders who understand transformation...and share knowledge with each other.” This “collaboration is helping me [them] realise they were no different.” This network facilitated wider professional socialization by providing participants with “incredible peer support” as well as “recognition within the wider community” of the NHSDA.

Reflection

Reflection upon practice was a core facet of the dissertation, with candidates actively encouraged to examine their own practice and how it correlates with their perceptions of digital health leadership. Therefore, 80% (24/30) of the dissertations demonstrated evidence of reflective practice. This encouragement to reflect upon practice has led to several candidates reporting the academy “highlighted the positives and the negatives of my [their] leadership style,” fostering a “sort of self-awareness.” Reflection was also associated with candidates refining their perceptions of the nature of digital transformation. One CCIO from cohort 1 notes the NHSDA “makes you reflect on how we embark on this challenge of having to scale digital at pace in the context of the pandemic.”

Self-Efficacy

The development of self-efficacy was found to be a key tenet of the program, with 61% (25/41) of the respondents reporting that the course had positively increased their confidence in their role. One candidate noted that “When I [they] first went on the digital academy there was an element of imposter syndrome,”
being told, “not to think about imposters, you need to think as pioneers.” Others had reflected that the digital academy had given them “the confidence to lead in digital” and “empowerment...to recognize that I [they] have the ability to do anything I [they] put my [their] mind to.” This has led to several candidates being recognized as leaders within the wider digital health ecosystem, but not necessarily in their own organizations. One clinician noted that they “had taken up a few national unpaid roles”; however, another noted that “they [the director] was not interested...did not recognize the training we had.”

Discussion

Principal Findings

This study is one of the first to demonstrate the impact of a focused program on digital health leadership on attendees’ professional identity. The findings demonstrate that the course has a diverse range of impacts including commitment to the profession, critical thinking, goal orientation, mentoring, perception of the profession, socialization, reflection, and self-efficacy. By using a dissertation of the practice model, in which students undertake a supported digital transformation project, participants are provided with an opportunity to develop metacognitive and reflective skills. The effect of this skill development lasts beyond the course, with several participants altering their leadership style and developing more agile and collaborative approaches. Furthermore, the projects enable participants to define and attain digital goals, which may have been more difficult to define, benchmark, and achieve previously. The program reaffirmed attendees’ commitment to being or becoming a digital health leader, leading to more than half of the participants changing their roles after graduation. Among the group of individuals that changed roles, almost half noted that their experience within the NHSDA had a significant impact on this decision. In addition, the program dispelled the imposter syndrome felt by emerging leaders by increasing their confidence and a sense of professional belonging. This was facilitated by the network of alumni, which may help mitigate the organizational isolation felt by some participants.

Professional identity formation has become the focus of a diverse range of fields, including medical education [26]. Among health care professionals, studies have shown that the development of a shared core value set can have substantial benefits, including improving the well-being and resilience of physicians [27]. Professional identity’s influence in other areas is less well documented, but some benefits may be appreciable across a range of disciplines. In a study by Meadows and de Braine [28], industry leaders displayed stronger leadership identities during the COVID-19 pandemic to help overcome challenges such as the implementation of new technologies. Digital health leadership teams who were faced with comparable issues are likely to have also relied on stronger leadership identities during this time. Consequently, there is increasing interest in understanding how educational programs can foster professional identity in their cohorts. Some have suggested that to develop identity requires departing from traditional pedagogy and using greater participatory or sociocultural learning opportunities [29]. The NHSDA program uses a mixed approach, blending didactic learning with collaborative work in the first year and a dissertation of the practice model in the second year. Therefore, a breadth of impact, both intended and unintended, upon the identity of participants as digital health leaders were noted.

A principle focus of the course and the dissertation project is on reflective practice. Therefore, it was not surprising that 80% (24/30) of the projects incorporated these skills. Reflective exercises are an important component of professional identity and can help leaders hone their metacognitive and inductive reasoning skills. Studies have shown that through these processes, learners can also identify their own cognitive biases and avoid errors [30]. Moreover, the dissertation was also noted to foster critical thinking, with several participants reporting that they had become more “strategic.” Critical thinking is a higher-level cognitive skill in which individuals understand phenomena through their interpretation and inference of contributory factors and variables. Critical thinking enables learners to become more agile [31]. Given that the digital health landscape is continuing to evolve in the United Kingdom following the pandemic and the continued challenge of resource allocation, an ability to acclimatize to these newer contexts would appear integral. In fact, when asked directly “What is a digital health leader?” several respondents referred to this adaptability, noting the need for “fearlessness, curiosity, and being comfortable going into unknown territories.”

One of the key unintended consequences of this course has been its impact on professional socialization. Socialization is crucial for emerging learners to learn the values and beliefs necessary to succeed within their roles as well as to form a robust idea of what constitutes a digital health leader. The peer support, or “sphere of networking,” that has developed among participants has facilitated not only knowledge sharing but also a sense of a community of digital health leaders. Several participants refer to a sense of confidence and validation of their identity as they were able to collaborate with recognized digital leaders. This socialization is seen in other areas of health professional development and provides a sense of “belonging,” as well as facilitating transition across clinical roles (eg, clinician to leader) [14]. This may mitigate the varying support that participants receive within their organizations.

On the other hand, few participants reported being mentored, and many participants felt unrecognized within their local institutions. Mentorship is a crucial facet of identity, as it enables the observation, modeling, and imitation of leadership behaviors, as described by the social learning theory [32,33]. Consistent with previous studies, time pressures and competing demands are often barriers to mentoring in health care environments. Moreover, several participants reported a lack of recognition by their local management teams following the course. This lack of external validation as an emerging leader in digital health may have thus contributed to this shortage of mentorship opportunities. However, several, having engaged in the collaborative environment of the NHSDA, participants were more open to facilitating the future training of more junior members of their own teams. In addition, these local barriers may underpin the drive to find different opportunities and explain the high rates
of role switching after graduation. Future work should look to examine these findings as well as how accreditation from courses such as the NHSDA can impact organizational buy-in.

Limitations

However, these findings must be considered within the limitations of the study. Despite using a robust approach, the respondents represent a subsection of the eligible cohorts involved. Moreover, only high-scoring dissertations were evaluated, which may have skewed our findings. However, this decision was made because scores were given based on the comprehensiveness of the write-up not the quality or results of the project. Therefore, they provided a more detailed impression of the elements of professional identity included. These selection effects were mitigated by delivering the questionnaire widely, and not all perspectives could be explored. This may affect the generalizability of the results, but it does provide a strong indication of the breadth of influences of the course. Furthermore, as previously mentioned, there is no set definition of what it is to be a digital health leader. As such, components from other contexts have been used to frame this study, which may mean that certain nuances have been omitted. Although the use of a previous extensive systematic review reduced the likelihood of this, it cannot be considered comprehensive. Furthermore, both cohorts enrolled undertook at least part of their study during the COVID-19 pandemic, in which there was a significant change in the delivery of health care and the need for digital solutions [34]. The influence of these changes on participants’ experience of the course or its impact on their professional identity cannot be ascertained. Future work should examine what constitutes a digital health leader and how this differs from health leadership more generally. This could potentially result in defining a core value set to facilitate the evaluation of digital and clinical leadership courses. This examination would need to consider the technical and nontechnical aspects of digital health leadership, as understanding both facets is essential as digital transformation continues to accelerate.

Conclusions

The increasing demand for clinical management to guide the next stages of transformation efforts requires a digitally adept corps of health leadership professionals. These digital leadership proficiencies must not only encompass technical skillsets but also include the values, judgments, and cultural beliefs about what it is to be a digital leader. The NHSDA and similar courses are likely to impact this identity formation through a broad range of effects, including socialization and professional commitment. However, further work is needed to understand what attributes are needed by a digital health leader so that training courses can be iterated and adapted. Moreover, this categorization will support the recognition of potential digital leaders who can be mentored within their local organizations, and key barriers to this progression can be overcome.

Acknowledgments

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Data Availability

The data that support the findings of this study are available from the authors, but restrictions apply to the availability of these data, which were used under license for this study and thus are not publicly available.

Authors' Contributions

AA, AS, and RCB were all involved in the study design, conduct, and data analysis. AA and RCB drafted the manuscript, with AS involved in editing and reviewing the manuscript submission. AD provided infrastructural support that enabled the study to occur and oversaw study conduct.

Conflicts of Interest

AD is the codirector of the National Health Service Digital Academy and Chair of the Health Security initiative at Flagship Pioneering UK Ltd. RCB is the Principal Teaching Fellow for the Master of Science in Digital Health Leadership and Chair of Master of Science Dissertations across the Institute of Global Health Innovation. Both authors acted independently during the conduct of this study.

Multimedia Appendix 1

Survey results and interview topic guide.
[DOCX File , 46 KB - mededu_v10i1e46740_app1.docx ]

References


Abbreviations

CCIO: chief clinical informatics officer
PGDip: Postgraduate Diploma
MSc: Master of Science
NHS: National Health Service
NHSDA: National Health Service Digital Academy

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Use of Multiple-Choice Items in Summative Examinations: Questionnaire Survey Among German Undergraduate Dental Training Programs

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Abstract

Background: Multiple-choice examinations are frequently used in German dental schools. However, details regarding the used item types and applied scoring methods are lacking.

Objective: This study aims to gain insight into the current use of multiple-choice items (ie, questions) in summative examinations in German undergraduate dental training programs.

Methods: A paper-based 10-item questionnaire regarding the used assessment methods, multiple-choice item types, and applied scoring methods was designed. The pilot-tested questionnaire was mailed to the deans of studies and to the heads of the Department of Operative/Restorative Dentistry at all 30 dental schools in Germany in February 2023. Statistical analysis was performed using the Fisher exact test (P<.05).

Results: The response rate amounted to 90% (27/30 dental schools). All respondent dental schools used multiple-choice examinations for summative assessments. Examinations were delivered electronically by 70% (19/27) of the dental schools. Almost all dental schools used single-choice Type A items (24/27, 89%), which accounted for the largest number of items in approximately half of the dental schools (13/27, 48%). Further item types (eg, conventional multiple-select items, Multiple-True-False, and Pick-N) were only used by fewer dental schools (≤67%, up to 18 out of 27 dental schools). For the multiple-select item types, the applied scoring methods varied considerably (ie, awarding [intermediate] partial credit and requirements for partial credit). Dental schools with the possibility of electronic examinations used multiple-select items slightly more often (14/19, 74% vs 4/8, 50%). However, this difference was statistically not significant (P=.38). Dental schools used items either individually or as key feature problems consisting of a clinical case scenario followed by a number of items focusing on critical treatment steps (15/27, 56%). Not a single school used alternative testing methods (eg, answer-until-correct). A formal item review process was established at about half of the dental schools (15/27, 56%).

Conclusions: Summative assessment methods among German dental schools vary widely. Especially, a large variability regarding the use and scoring of multiple-select multiple-choice items was found.

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KEYWORDS
alternate-choice; assessment; best-answer; dental; dental schools; dental training; education; educational assessment; educational measurement; examination; German; Germany; k of n; Kprim; K'; medical education; medical student; MTF; Multiple-True-False; multiple choice; multiple-select; Pick-N; scoring; scoring system; single choice; single response; test; testing; true/false; true-false; Type A; Type K; Type K'; Type R; Type X; undergraduate; undergraduate curriculum; undergraduate education

Introduction

Summative examinations of theoretical knowledge are an integral part of university degree programs. As they are intended to assess examinees’ ability regarding predefined learning objectives, they should reflect examinees’ true knowledge as closely as possible. To assess examinees objectively and efficiently, multiple-choice examinations were described as early as 1916 [1,2]. To date, these types of examinations have been expanded by further item types, and multiple-choice examinations are frequently used within higher education including but not limited to dental training programs [3-5]. Multiple-choice items (ie, questions) can be subdivided into single-choice items (eg, Type A, Type K, Type R, and alternate-choice) and multiple-select items (eg, Pick-N and Multiple-True-False [Type K']) [6]. While dichotomous scoring (ie, 1 full credit point is awarded if examinees mark the correct...
Besides paper-based examinations, examinations are nowadays frequently delivered electronically. While electronic examinations are well perceived by examinees [10], comprehensive studies regarding their effectiveness are still lacking [11]. However, the use of different examination software (eg, UCAN’s [Umbrella Consortium for Assessment Networks] CAMPUS examination software) might improve the ease of multiple-choice examinations, accelerate the evaluation of examinations and item analysis, and allow for more complex scoring algorithms. Despite the benefits associated with electronic examinations, the availability of hardware and software at the level of individual institutions might limit its use.

In Germany, the revised undergraduate dental curriculum consists of 10 semesters and includes preclinical training (4 semesters), training using simulators or phantom heads (2 semesters), and clinical training (4 semesters). Following the state examinations after each part (ie, after the fourth, sixth, and 10th semester), students receive their license (“Approbation”) to practice dentistry. Besides practical skills, theoretical knowledge is taught within the undergraduate dental curriculum, and students’ ability is often assessed using written multiple-choice examinations. However, such examinations are not standardized among German dental schools. While general recommendations exist for their design and evaluation [12,13], details such as suitable item types and applied scoring methods are often defined in local examination guidelines at the level of individual dental schools. However, these details might impact examinees’ scoring results [5]. To the best of our knowledge, a comprehensive overview regarding the used item types and applied scoring methods at German dental schools does not exist.

Therefore, this study aimed to gain insight into the current use of multiple-choice items in summative examinations in German undergraduate dental training programs. The null hypothesis is that the use of digital examinations does not impact the use of more complex (ie, multiple-select) multiple-choice items.

**Methods**

### Ethical Considerations

The study was designed as a prospective investigation. In preparation for the investigation, the websites of all German dental schools were screened (n=30), and the names of the heads of the Department of Operative/Restorative Dentistry and the deans of studies were noted for later procedures.

The study was performed after approval by the local ethics committee of the University Medical Center Göttingen (approval number 22/1/23). Participation in this study was voluntary, and participants gave their informed consent for the anonymous evaluation of the provided answers by returning the questionnaires. Participants did not receive any incentives or compensation.

### Questionnaire

A paper-based questionnaire, consisting of 10 items about the construction and evaluation of summative examinations, was jointly designed by the authors and pilot-tested in the University Medical Center Göttingen (Multimedia Appendix 1). Both closed and open-ended items were used. The opening questions related to different examination types used for the summative assessment of theoretical knowledge, and whether or not electronic examinations were being used. Additionally, it was asked whether the examination items undergo a formal review process and if so, the participants had the chance to give a brief description of this procedure. The more specific questions related to the types of multiple-choice items used and asked for the relative percentage to which these items were being used. Furthermore, the participants were asked to describe the applied scoring methods for each of the item types used. Finally, participants were provided with a text field open for comments and their contact details (ie, if required for further clarification) and were asked to supply a copy of their local examination guidelines or program regulations.

Following the evaluation of the pilot survey among 5 dentists at the University Medical Center Göttingen, the questionnaire was slightly modified for clarification, printed, and mailed to (1) the heads of the Department of Operative/Restorative Dentistry and to (2) the deans of studies on February 1, 2023. The wording was slightly adjusted for each recipient: (1) “used in your department” versus (2) “permitted at your dental school”. Mailings included a personalized cover letter, an overview illustrating different multiple-choice item types (Figure 1), and a stamped return envelope. The survey was closed after 12 weeks. Nonresponders were reminded once 6 weeks after the initial distribution of the questionnaires.
Figure 1. Exemplary presentation of the most commonly used multiple-choice item types referenced in the questionnaire. Round marking boxes represent 1 answer option to be selected (1 out of x), while square marking boxes imply that multiple answer options or statements (x out of X) can be chosen.

Statistical Analysis

First, data were manually transferred into a digital chart using a piloted spreadsheet containing columns for each item of the questionnaire. This step was independently performed by 2 authors (LR and PK). In case of disagreement, data were repeatedly extracted from the returned questionnaires.

In case of disagreement between the heads of the Department of Operative/Restorative Dentistry and the deans of studies, results were based on the responses from the heads of the Department of Operative/Restorative Dentistry. For further clarification, responses were cross-validated with the supplied or publicly available examination guidelines and program regulations. If required, respondents were contacted for further clarification if they had agreed to do so previously.

Second, statistical analysis was performed using the software SPSS Statistics (Macintosh version 29.0.0.0; IBM Corp). The effect of delivering digital examinations on the use of multiple-select items was assessed using the Fisher exact test. The level of significance was set at .05.
Results

Overview
In total, responses from 27 dental schools were received yielding a response rate of 90% (27/30 dental schools). More specifically, 25 Departments of Operative/Restorative Dentistry and 17 deans of studies replied. All dental schools responded that they use written multiple-choice examinations for the assessment of examinees' theoretical knowledge. Therefore, subsequent results are based on the number of respondent dental schools.

Multiple-Choice Items Used
The most commonly used multiple-choice item types at German dental schools were single-choice Type A or Type A negative items with 3 to 6 answer options (24/27, 89%). Pick-N items (ie, the number of answer options to be selected is known to examinees) were reported to contain between 3 and 26 answer options and were used by 67% (18/27) of dental schools. Type K items were reported to contain between 3 and 6 statements and were used by 52% (14/27) of the dental schools. Multiple-True-False (also known under further names such as Kprim, Type K', or Type X) and conventional multiple-select items (ie, the number of answer options to be selected is unknown to examinees) were reported to contain between 4 and 6 statements or answer options and were both used by 44% (12/27) of the dental schools. The use of further item types is shown in Table 1.

<table>
<thead>
<tr>
<th>Item type</th>
<th>Dental schools, n (%)</th>
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<td>Type A</td>
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</tr>
<tr>
<td>Pick-N</td>
<td>18 (67)</td>
</tr>
<tr>
<td>Type K</td>
<td>14 (52)</td>
</tr>
<tr>
<td>Conventional multiple-select</td>
<td>12 (44)</td>
</tr>
<tr>
<td>Multiple-True-False (Type K')</td>
<td>12 (44)</td>
</tr>
<tr>
<td>Type R</td>
<td>6 (22)</td>
</tr>
<tr>
<td>Alternate-choice</td>
<td>4 (15)</td>
</tr>
</tbody>
</table>

Examination Setting
Key feature problems consisting of a clinical case scenario followed by a number of items focusing on critical treatment steps were used by approximately half of the dental schools (15/27, 56%). Not a single school used alternative testing methods (eg, answer-until-correct). Also, a formal item review process prior to the delivery of the examination was only established at about half of the dental schools (15/27, 56%).

Delivery of Examinations
The percentage of dental schools that deliver examinations electronically amounted to 70% (19/27). However, the software used by the dental schools differed: a dedicated examination software (ie, UCAN’s CAMPUS or tEXAM, Q-Exam [IQUL GmbH]) was used by 8 dental schools, while learning management systems such as Moodle (Moodle Pty Ltd), ILIAS (ILIAS open source e-Learning e.V.), or OpenOLAT (frentix GmbH) were used by 7 dental schools for the purpose of examination delivery. The remaining 4 dental schools did not provide any information regarding the examination software they used.

Dental schools with the possibility of electronic examinations used multiple-select items slightly more often (14/19, 74% vs 4/8, 50%). However, this difference was statistically not significant (P=.38).

Applied Scoring Methods
All dental schools scored single-choice items (ie, Type A, Type A negative, Type K, Type R, and alternate-choice) dichotomously (ie, 1 full credit point is awarded if examinees mark the correct answer option or statements, otherwise no credit is awarded). Scoring of multiple-select items was more heterogeneous and no single scoring method that was commonly used was identified: some dental schools used scoring algorithms resulting in partial (ie, 0.5 credit points) or intermediate partial credit (ie, 1/n partial credit for each correct response) besides dichotomous scoring on multiple-select items. However, scoring methods resulting in negative points (ie, malus points) were not used at any location.

Discussion
Principal Findings
The aim of this study was to gain insight into summative assessment methods that involve the use of multiple-choice items and are used at German dental schools. The purpose of summative assessment is to evaluate examinees’ knowledge at the end of a course by comparing their scores to a predefined standard (ie, cutoff score) [14]. Our results demonstrate that all respondent dental schools use multiple-choice examinations for summative assessment of theoretical knowledge. Besides individual items, approximately half of the dental schools also use key feature problems.

Single-choice Type A items are the most popular item types used at German dental schools. These items are used by almost every respondent dental school and often account for the largest number of items at the respective dental schools. This might be explained by the demand for ease of scoring (ie, dichotomous scoring, no partially correct responses).
Multiple-select item types such as Pick-N or Multiple-True-False are used by fewer dental schools. For these item types, the applied scoring methods vary considerably: Some dental schools award partial or even intermediate partial credit for partially correct responses while others do not. However, the exact cutoff levels and scoring methods for partial credit differed. For example, Partial Scoring 50% (PS\(_{50}\)) was used by some dental schools for Pick-N items: In these cases, 1 full credit point is awarded if all answer options are marked correctly, and 0.5 credit points are awarded if at least half of the true answer options are marked, otherwise no credit is awarded [9,15]. Furthermore, a similar scoring method named Half-point Scoring was used by some dental schools for Multiple-True-False and conventional multiple-select items: 1 full credit point is awarded if all statements or answer options are marked correctly, 0.5 credit points are awarded if the response to 1 statement or answer option is incorrect, otherwise no credit is awarded [8,16].

In addition, some dental schools awarded intermediate partial credit on multiple-select items: In the case of Partial Scoring 1/n (PS\(_{1/n}\)), 1/n partial credit was awarded for each correct response [8,9]. Some dental schools also subtracted 1/n partial credit for each incorrect response (Blasberg-Method) [8,9,17].

As a result, the scoring of multiple-select items at different German dental schools can be considered very heterogeneous. This is not surprising, as a vast number of different scoring methods for multiple-select items have been described in the literature [8,9]. As stated previously, it is not possible to suggest a single versatile scoring method. Different requirements as defined in dental schools’ local examination guidelines (eg, fixed pass-mark and fixed proportion of true answer options) impact the scoring method to be selected. Regarding jurisdictional requirements, scoring methods resulting in negative points (ie, malus points) must not be used in Germany [13]. Consequently, not a single dental school uses scoring methods resulting in malus points. However, almost half of the dental schools do not use a formal item review process. A formal review process is recommended prior to the delivery of the examinations and might further improve the quality and overall validity of the examinations.

In addition, 70% (19/27) of all dental schools stated to deliver examinations electronically. While the electronic delivery of examinations allows for automatic scoring and more complex scoring methods (ie, within the context of multiple-select items), no statistically significant relation between the type of delivery (paper-based vs electronic) and the use of multiple-select item types was found. Therefore, our results fail to reject the null hypothesis. This might be explained by the software used for the delivery and scoring of electronic examinations: it was found that dental schools use learning management systems such as Moodle, ILIAS, or OpenOLAT besides dedicated examination software such as UCAN’s CAMPUS, UCAN’s tEXAM, or Q-Exam for the delivery and scoring of summative assessments.

Interestingly, not a single dental school used alternative testing methods that deviate from the standard setting during examinations (ie, examinees mark the answer options or statements they believe to be correct or true but receive no immediate feedback regarding correctly or incorrectly marked answer options or statements). Within multiple-choice examinations, alternative testing methods such as confidence weighting scoring (ie, examinees are requested to indicate the degree of confidence in their marking) [18], elimination scoring (ie, examinees are instructed to mark the incorrect instead of correct answer options) [19], or answer-until-correct [20,21] have been described in the literature. Within the answer-until-correct method, examinees receive immediate feedback and examinees may correct their marking on previously incorrectly marked items, thereby still receiving partial credit. However, the benefit of such testing methods within the field of dental education is questionable. Dental school examinees are becoming future dentists. While treating patients, dentists are required to make informed choices and dentists might not always have a second chance without potentially harming their patients. In addition, such alternative testing methods benefit from the electronic delivery of examinations and set even higher requirements for the used examination software.

**Strengths and Limitations**

To the best of our knowledge, this is the first study to systematically assess the use and scoring of multiple-choice item types in summative examinations among German dental schools. A number of strengths are present. First, a pretested questionnaire was used. Second, our questionnaire survey study yielded a high response rate of 90% (27/30 dental schools). Third, our results might be considered representative of the current use of multiple-choice items in summative examinations among German dental schools.

Nevertheless, limitations are also present. First, our questionnaire focused on multiple-choice items; therefore, the use of other assessment types (eg, objective structured clinical examinations, oral examinations) remains unknown. Second, the number of dental schools in Germany is limited. Thereby, results from the Fisher exact test might be underpowered despite the high response rate. Furthermore, this study could not control for potential confounders (eg, location, number of students per dental school) due to the overall low number of dental schools. Third, transferability and generalizability to other educational settings might be limited due to different jurisdictional requirements or the overall lower importance of written examinations.

**Future Directions**

New dental licensing regulations (“ Approbationsordnung“) have been in effect since 2021, which restructured the undergraduate dental curriculum in Germany. For the first time, a nationwide written board examination with single-choice items takes place at the end of all undergraduate dental programs (ie, after the 10th semester) [22]. Therefore, multiple-choice examinations in general and especially single-choice Type A items will remain a popular format for summative examinations among German undergraduate dental programs. Ideally,
examinees already become familiar with single-choice Type A items during their studies. Therefore, all dental schools should use single-choice Type A items to adequately prepare their students for the final board examination.

Nevertheless, additional examinations (eg, objective structured clinical or practical examinations) are required to test examinees’ practical skills [3]. Regardless of the used item type, multiple-choice examinations are not suitable to assess the higher levels Miller’s Pyramid of clinical competence (ie, does and shows how) [23].

Conclusion

While students from almost all dental schools can be expected to be familiar with single-choice Type A items, techniques for the summative assessment of theoretical knowledge differ widely among German dental schools. Especially, a large variability regarding the use and scoring of multiple-select multiple-choice items was found. In addition, implementing a formal item review process might further improve the quality and overall validity of the examinations.

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Data Availability

All data generated during or analyzed during this study are included in this published article.

Authors' Contributions

LR, MH, AW, and PK contributed to the study’s conception and designed the questionnaire. LR and PK transferred the data. PK performed statistical analyses. All authors interpreted the data, critically revised the manuscript, and approved the final version of the manuscript.

Conflicts of Interest

PK is an associate editor of JMIR Medical Education at the time of this publication. Other authors have no competing interests to declare.

Multimedia Appendix 1

Authors’ translation of the used questionnaire, which was originally distributed in German.

References


Abbreviations

PS<sub>1/n</sub>: Partial Scoring 1/n
PS<sub>50</sub>: Partial Scoring 50%

UCAN: Umbrella Consortium for Assessment Networks
Development of a Clinical Simulation Video to Evaluate Multiple Domains of Clinical Competence: Cross-Sectional Study

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Abstract

Background: Medical students in Japan undergo a 2-year postgraduate residency program to acquire clinical knowledge and general medical skills. The General Medicine In-Training Examination (GM-ITE) assesses postgraduate residents’ clinical knowledge. A clinical simulation video (CSV) may assess learners’ interpersonal abilities.

Objective: This study aimed to evaluate the relationship between GM-ITE scores and resident physicians’ diagnostic skills by having them watch a CSV and to explore resident physicians’ perceptions of the CSV’s realism, educational value, and impact on their motivation to learn.

Methods: The participants included 56 postgraduate medical residents who took the GM-ITE between January 21 and January 28, 2021; watched the CSV; and then provided a diagnosis. The CSV and GM-ITE scores were compared, and the validity of the simulations was examined using discrimination indices, wherein ≥0.20 indicated high discriminatory power and >0.40 indicated a very good measure of the subject’s qualifications. Additionally, we administered an anonymous questionnaire to ascertain participants’ views on the realism and educational value of the CSV and its impact on their motivation to learn.

Results: Of the 56 participants, 6 (11%) provided the correct diagnosis, and all were from the second postgraduate year. All domains indicated high discriminatory power. The (anonymous) follow-up responses indicated that the CSV format was more suitable than the conventional GM-ITE for assessing clinical competence. The anonymous survey revealed that 12 (52%) participants found the CSV format more suitable than the GM-ITE for assessing clinical competence, 18 (78%) affirmed the realism of the video simulation, and 17 (74%) indicated that the experience increased their motivation to learn.

Conclusions: The findings indicated that CSV modules simulating real-world clinical examinations were successful in assessing examinees’ clinical competence across multiple domains. The study demonstrated that the CSV not only augmented the assessment of diagnostic skills but also positively impacted learners’ motivation, suggesting a multifaceted role for simulation in medical education.
Introduction

Japan’s medical schools follow a 6-year curriculum comprising 4 years of preclinical and 2 years of clinical education, after which they enter a 2-year postgraduate residency program as “postgraduate residents” or simply “residents” [1-3]. This residency enables new doctors to acquire and practice basic clinical knowledge, problem-solving, general medical and communication skills, and a professional attitude. All residents receive supervised training as they rotate through 7 specialties over the 2 years, including internal medicine, surgery, pediatrics, obstetrics and gynecology, psychiatry, emergency medicine, and community medicine. Most residents then enter specialty-based residency training.

In 2011, the nonprofit Japan Institute for Advancement of Medical Education Program (JAMEP) developed the General Medicine In-Training Examination (GM-ITE), an in-training examination for assessing the clinical knowledge of residents, similar to the US Internal Medicine Residency Examination [4]. The purpose of the GM-ITE is to elicit practical feedback on the training programs aimed at identifying improvement areas using an objective and reliable assessment of residents’ clinical knowledge [5].

The traditional assessment of clinical competencies through multiple-choice questions (MCQs), while valuable, may not encompass the full scope of a clinician’s diagnostic process in real-world practice [6]. In clinical settings, physicians must navigate through complex problem-solving and decision-making processes, often divided into domains such as leading or working diagnosis, management and treatment, hypothesis generation, problem representation, diagnostic justification, and information gathering [7]. Video simulation, as an assessment tool, can capture these nuances by providing contextualized real-world scenarios where residents must apply their knowledge dynamically, as they would in actual patient interactions [8].

Designed by a committee of experienced attending physicians organized by the JAMEP, the 2-hour GM-ITE comprises 80 MCQs covering multiple domains [9]. The scores range from 0 to 80, with higher scores indicating better performance and knowledge of internal medicine. The content and validity of each question undergo review by JAMEP’s question-development committee comprising experienced physicians from various fields, an independent peer-review committee, and examination-analysis experts [10]. The GM-ITE is not used as a pass or fail test for training advancement but only as a source of education feedback. The test is strictly voluntary, and approximately one-third of residents take the examination each year (7669 in the 2020 academic year, 6869 in the 2019 academic year, 5593 in the 2017 academic year, and 4568 in the 2016 academic year) [11,12].

An assessment of the validity of the GM-ITE [10] revealed a strong positive correlation between GM-ITE scores and scores on the Professional and Linguistic Assessments Board test, Part 1, designed to assess the depth of medical knowledge and levels of medical and communication skills [13]. In validity testing, the discrimination index (DI) indicates how well the item differentiates between students of high and low aptitude, that is, whether high-aptitude students performed better, worse, or the same as low-aptitude students [14]. Therefore, an item with a high DI is more effective in identifying respondents with adequate knowledge than an item with a low DI. The GM-ITE has indicated better discriminative power than the Professional and Linguistic Assessments Board test, Part 1 examination [10].

The JAMEP based the content of the GM-ITE on the clinical training objectives presented by Japan’s Ministry of Health, Labour and Welfare [13], which requires residents to master skills related to professionalism, physical examination and clinical procedures, and the diagnosis and treatment of common diseases. The GM-ITE shows evidence of generalization by covering 4 categories, including medical interview or professionalism (MP), clinical diagnosis (CD) consisting of symptomatology and clinical reasoning, physical examination or procedure (PP), and disease knowledge (DK). However, the relatively small number of questions in the GM-ITE provides evidence of low generalization.

Given the large number of residents taking the GM-ITE each year, using MCQs seems both expedient and appropriate when considering the viability and sustainability of the GM-ITE. However, a 2-hour test comprising only MCQs may not adequately assess the situational variations affecting clinical performance or competence in multiple domains. Therefore, this study developed a clinical simulation video (CSV) named “innovative examination” for the GM-ITE to assess residents’ clinical competency in a real-world setting using two components: (1) a high-quality CSV showing a medical interview and physical examinations with a patient and family in an emergency room and (2) follow-up questions for the residents to provide their diagnosis and recommendations. The study then evaluated the relationship between the participants’ GM-ITE and CSV innovative examination test scores by comparing their discriminative ability in each assessment domain. Therefore, this study aimed to evaluate the relationship between GM-ITE scores and resident physicians’ diagnostic skills by having them watch a CSV and to explore resident physicians’ perceptions of the CSV’s realism, educational value, and impact on their motivation to learn.
Methods

Study Design
We conducted a multicenter cross-sectional observational study in Japan.

Study Participants
The study extended an invitation to all 8526 resident physicians who took the GM-ITE in the 2021 academic year (January 21-28, 2021) to voluntarily participate in the innovative examination, and 56 residents—23 from postgraduate year (PGY) 2 and 33 from PGY 1—agreed and participated. These individuals were selected from the entire cohort of residents who took the GM-ITE. Owing to the exploratory nature of this study and the extensive distribution of the questionnaire to all eligible resident physicians, no formal sample size calculation or power analysis was performed.

Procedures

Innovative Examination Using High-Quality Patient-Simulated Video
In this study, we wrote a script depicting a simulated clinical interaction. The approximately 5-minute video (“innovative examination”), shot from a resident’s point of view, depicts a newly arrived patient and his family at an emergency room (Multimedia Appendix 1). The resident conducts a medical interview and examination, asking and answering questions, while the camera records the patient’s and family members’ verbal and nonverbal responses. Professional actors coached by the medical supervisors played the roles effectively. A professional television production company shot the video and added effects (eg, heart sounds). In total, 3 of the authors (KS, YN, and SF) and 3 JAMEP medical supervisors oversaw the video production. The study participants watched the video immediately after completing the GM-ITE. Next, they answered the CSV innovative examination questions described below.

Extended Matching Questions
We used extended matching questions that listed the patient’s symptoms to obtain up to 3 pertinent positive findings that contributed to the diagnosis (Q1 and Q2 in Textbox 1).
### Clinical simulation video (CSV) innovative examination questions.

- Q1. Which 3 physical findings would you expect to be positive in this patient? Please choose 3 of the following:
  - Pallor of the eyelid conjunctiva
  - Pupil irregularity
  - Angry external jugular vein
  - Cervical vascular murmur
  - Thyroid gland enlargement
  - “Fixed” splitting of the second heart tone
  - Loud P2
  - Systolic murmur
  - Diastolic murmur
  - Torsion sound at the base of the lung
  - Tender points in the abdomen
  - Fresh blood in stool on rectal examination
  - Barre sign positive
  - Muscle stiffness
  - Loss of tendon reflexes

- Q2. Please state the most likely diagnosis for this patient (free text).

- Q3. Following the SBAR (situation, background, assessment, and recommendation) format, please prepare a patient handoff record for the internal medicine physician in charge of admission.
  - Q3-1. Situation (free text, 100 words maximum)
  - Q3-2. Background (free text, 100 words maximum)
  - Q3-3. Assessment (free text, 100 words maximum)
  - Q3-4. Recommendation (free text, 100 words maximum)

- Q4-1. Do you think the simulated patient-examination video was better suited to assessing your clinical competence than the traditional all-text format?
- Q4-2. Was the video simulation realistic enough for you to assess the patient?
- Q4-3. Did this experience increase your motivation to learn?

### Modified Essay Questions

The third question required brief free-form answers (Q3 in Textbox 1).

### Anonymous Posttest Questionnaire

After the participants completed Q1-Q3, we asked them to answer a fourth question (anonymously) to briefly describe (in writing) their experiences with the CSV innovative examination (Q4 in Textbox 1). Only 23 (41%) of the 56 participants chose to answer Q4.

### Measurements

The GM-ITE uses a methodology similar to the US Internal Medicine Residency Examination [4,15,16]. The 80 questions cover 4 main categories: MP (8 questions), CD (18 questions), PP (18 questions), and DK (36 questions). We examined the validity of the GM-ITE questions using the DI $\phi$ as defined by equation 1 [17]:

$$
\phi = \frac{a - b}{c + d} - 1
$$

where $a$ is the number of correct answers in the top 25th percentile, $b$ is the number of incorrect answers in the top 25th percentile, $c$ is the number of correct answers in the bottom 25th percentile, and $d$ is the number of incorrect answers in the bottom 25th percentile. The range of $\phi$ is $-1 \leq \phi \leq 1$. Questions are considered unreliable if this index is below 0. A DI of $\geq 0.20$ would indicate that the question has high discriminatory power, and a DI of $\geq 0.40$ would indicate that the question is a very good measure of the subject’s qualifications.

### Statistical Analyses

We conducted these analyses using SPSS Statistics for Windows (version 26.0; IBM Corp), following the Strengthening the Reporting of Observational Studies in Epidemiology guidelines. Two authors (KS and SF) independently assessed the answers and then discussed, identified, and agreed on them. We measured the intrarater reliability with the $\kappa$ coefficient (0.8-1.0=almost perfect, 0.6-0.8=substantial, 0.4-0.6=moderate, 0.0-0.4=poor, $\leq 0.00$=no agreement).
and 0.2-0.4=fair) [18]. The Angoff method was used to define the cutoff for the DI calculation [19].

**Ethical Considerations**

This research was conducted in accordance with ethical standards and the principles of the Declaration of Helsinki. The ethics review board of the JAMEP, Tokyo, Japan, approved the study protocol (21-10). All participants read and signed the informed consent document before participating in the study. To ensure confidentiality, all participant data were anonymized prior to analysis. No compensation was provided to the participants for their involvement in this study. Informed consent was obtained from all participants for publication of identifying information in an online open-access publication. In accordance with ethical standards and journal policy, we have obtained explicit informed consent from all actors appearing in the video material associated with this study. The actors have acknowledged and agreed that the video will be published as part of the study’s material.

**Results**

A total of 8526 residents from 642 teaching hospitals in Japan took the GM-ITE in the 2021 academic year. Among these, 56 (23 PGY 2 and 33 PGY 1) residents also agreed to take the CSV innovative examination. The mean GM-ITE score of all 56 participants was 47.8 (SD 8.2). A DI revealed that several items had discrimination indices exceeding 0.2 (Table 1).

A total of 6 (11%) out of 56 participants answered Q2 correctly, and all the correct answers came from PGY 2 residents. The DI for the entire CSV innovative examination portion of the GM-ITE indicated high discriminatory power in all domains.

Figure 1 shows the DI for the MP (8 questions) domain, with 6 innovative questions scoring a DI of ≥0.20, indicating its robustness in differentiating examinee proficiency.

Figure 2 focuses on the CD (18 questions) domain, with 5 innovative questions achieving a DI of ≥0.20, which is indicative of its strong discriminatory capability among examinees.

In Figure 3, the PP (18 questions) domain is analyzed, with 5 innovative questions achieving a DI of ≥0.20, demonstrating its effectiveness in assessing the examinees’ clinical skillset.

Finally, Figure 4 presents the DI for the DK (36 questions) domain, with 2 innovative questions achieving a DI of ≥0.20, reflecting its potential as a moderate discriminator of examinees’ understanding.

These figures collectively underscore the CSV innovative examination’s capacity to gauge clinical competence effectively, with each domain’s innovative question serving as a significant indicator of the examinees’ capabilities. In particular, for the innovative question Q2, a DI of ≥0.20 was found for both the total score and all 4 domains, indicating its robustness in differentiating examinee proficiency.

A total of 23 (41%) participants answered Q4, the anonymous questionnaire to assess the participants’ views on the CSV innovative examination. Regarding whether the simulated patient examination video was better suited to assessing their clinical competence than the traditional all-text format (Q4-1), 12 (52%) participants answered positively, 4 (17%) answered negatively, and 7 (30%) provided a neutral response. Regarding whether the video simulation was realistic enough for them to assess the patient (Q4-2), 18 (78%) responded affirmatively. Regarding whether the experience increased their motivation to learn, 17 (74%) responded positively.

Table 1. Discrimination index\(^a\).

<table>
<thead>
<tr>
<th>Domain (questions, n)</th>
<th>Question 1</th>
<th>Question 2</th>
<th>Question 3-1</th>
<th>Question 3-2</th>
<th>Question 3-3</th>
<th>Question 3-4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medical interview or professionalism (8)</td>
<td>0.48</td>
<td>0.38</td>
<td>0.94</td>
<td>0.74</td>
<td>0.30</td>
<td>0.61</td>
</tr>
<tr>
<td>Clinical diagnosis (18)</td>
<td>0.50</td>
<td>0.40</td>
<td>0.77</td>
<td>0.56</td>
<td>0.27</td>
<td>0.18</td>
</tr>
<tr>
<td>Physical examination or procedure (18)</td>
<td>0.52</td>
<td>0.35</td>
<td>0.39</td>
<td>0.19</td>
<td>0.22</td>
<td>0.39</td>
</tr>
<tr>
<td>Disease knowledge (36)</td>
<td>−0.09</td>
<td>0.58</td>
<td>0.13</td>
<td>0.04</td>
<td>0.27</td>
<td>−0.10</td>
</tr>
<tr>
<td>Total (80)</td>
<td>0.06</td>
<td>0.47</td>
<td>0.10</td>
<td>−0.06</td>
<td>0.01</td>
<td>−0.12</td>
</tr>
<tr>
<td>Question type</td>
<td>MC(^b)</td>
<td>FD(^c)</td>
<td>FD</td>
<td>FD</td>
<td>FD</td>
<td>FD</td>
</tr>
</tbody>
</table>

\(^a\)A discrimination index of ≥0.20 indicates that the question had high discriminatory power; a discrimination index of >0.40 indicates that the question was a very good measure of the participant’s qualifications.

\(^b\)MC: multiple choice.

\(^c\)FD: free description (<100 words).
Figure 1. DIs of the examination scores of the General Medicine In-Training Examination: medical interview or professionalism (8 questions). DI: discrimination index; Q: question.

Figure 2. DIs of the examination scores of the General Medicine In-Training Examination: clinical diagnosis (18 questions). DI: discrimination index; Q: question.
Discussion

Principal Findings

Residency is the final stage of medical education and supervised clinical practice. The traditional all-text GM-ITE was designed to elicit practical feedback on the preresidency training to identify areas of improvement by objectively assessing residents’ clinical knowledge in 4 areas: MP, CD, PP, and DK. Medical education has historically relied on MCQs to assess learning [20,21]. However, some studies have explored “context-rich” MCQs that embed test items in a clinical vignette [22,23]. This study delved beyond a written clinical vignette by creating a video simulation of a patient examination in an emergency room. The strength of ratings regarding the measures of different components of clinical reasoning indicates that although MCQs are effective in leading or working diagnosis and management and treatment, they are weak in hypothesis generation, problem representation, and diagnostic justification [7]. Conversely, it has been found that while differential diagnosis, leading or working diagnosis, diagnostic justification, and management and treatment are effective in essay style (free text), they are relatively weak in information gathering [24]. This finding suggests that CSV-based test modules could provide a more accurate measure of participants’ clinical knowledge and abilities than the GM-ITE.

Education, including medical education, has increasingly embraced computer-based testing. Today, students are accustomed to answering questions and writing essays via
computer-based testing. This study designed a single video simulation to assess the knowledge and skills of residents from the nonverbal information portion of the national medical licensing examination domains, particularly general theory. We included information from 3 domains in a single question, and the participants obtained high scores. This finding suggests that a single CSV module could test multiple skills and knowledge areas of residents. In other words, using innovative CSV-based questions could provide more realistic assessments while making the examinations more efficient.

The 3 domains covered in the CSV innovative examination Q1 (MP, CD, and PP) indicated DI of 0.4 or higher; the GM-ITE means were 0.32 (SD 0.13), 0.32 (SD 0.16), and 0.31 (SD 0.18), respectively. Therefore, the successful participants (based on GM-ITE scores) had higher scores on these domains in the CSV innovative examination question than in the GM-ITE. Q1 required participants to select 3 options from the MCQ (2 cutoffs per question). We found that the CSV could cover 3 separate domains in a single MCQ.

CSV innovative examination Q2 required a descriptive response; specifically, the participants needed to name the most likely diagnosis. Two physicians (KS and SF) independently assessed the diagnoses and achieved an agreement rate of 1.00. The DI of Q2 was 0.4 or higher for symptomatology or clinical reasoning and diseases and 0.3 or higher for general theory, physical examination, and clinical techniques. The overall GM-ITE scores had a high identification index of 0.47. Specifically, the CSV innovative examination Q2’s requirement for participants to provide a definitive diagnosis allowed for a comprehensive assessment across all domains included in the GM-ITE. Furthermore, Q2 was distinguished as the sole question that demonstrated high DIs across individual disease categories. In addition, Q2 was the only question that also presented a high DI in each disease category.

CSV innovative examination Q3 required participants to provide an SBAR (situation, background, assessment, and recommendation) report using a total of 400 words or fewer. Two physicians (KS and SF) scored the responses independently and then rated each response against the scoring criteria and added them together. The agreement rate was as high as 0.92. It was observed that Q3 lowered the overall DI score to a high level in the general discussion. In other words, Q3 was easier for all the participants to answer than the other questions. For Q3-1 and Q3-2, the high discriminative ability was lowered for symptomatology and clinical reasoning. However, for each theory of disease, all the DIs were low, with some negative results. Therefore, most participants were better able to describe the patient’s situation and background than provide an assessment and recommendations.

This study is significant in that it provided “content-rich” clinical information. In addition to obtaining all the information normally provided in the conventional paper-based examinations, the participants had the advantage of seeing and hearing the various symptoms portrayed by a professional actor. In addition, medical interviews with patients and their families can reveal useful nonverbal information such as tachypnea and expressions indicating anxiety and pain levels. Gathering clinical information through diagnostic inference is critical in real-life scenarios. Participants may have performed better in certain domains covered in Q1-Q3 compared to their GM-ITE scores for the same domains owing to the CSV’s heightened sense of immediacy (seeing “real” people rather than reading about them) and the opportunity for diagnostic inferences in workplace-based assessments. This finding may indicate a development of clinical competence from the level of “knows how” to “shows” in Miller’s pyramid, which could lead to an advanced assessment in the cognitive domain.

Comparison to Prior Work

The discriminative efficacy of the CSV’s innovative examination in this study aligns with similar interventions. A study comparing simulation and video-based training for acute asthma management found that both methods significantly improved MCQ posttest scores, indicating an enhanced understanding of clinical methods [25]. Additionally, a study conducted at a university hospital in Pakistan revealed that a hybrid model combining video-based learning with simulation increased students’ confidence and performance in clinical skills. This suggests that digital and multimedia-enhanced methods may surpass traditional teaching modalities in certain aspects of medical education [26]. These comparisons underscore the potential of CSV-based assessments to provide a more nuanced and comprehensive measure of clinical competencies, potentially bridging theoretical knowledge and practical application more effectively in medical training.

Limitations

Although this study reveals important findings, it has several limitations. First, the number of participants included in the study was low. For the data to be more valid, the number of examinees needs to be increased. However, adding more participants would also increase the test-scoring burden, which calls the viability of CSV-based testing into question. In this study, 2 physicians (KS and SF) scored the written questions. Increasing the number of examinees would also increase the time and effort required to score the results. If all of the approximately 8000 examinees who took the GM-ITE completed the CSV innovative examination module, the scoring time required would be untenable, and adding more CSV-based modules would compound the problem. One way to overcome this limitation could be the use of a morphological analysis or to only score a statistically significant sampling.

Another limitation is related to the authenticity of the CSV. We created the abnormalities in the “patient,” such as the heart murmur and loud P2, by synthesizing sounds. We could not represent some aspects, such as the enhancement of systolic murmur on inspiration, and the apex beat was not clear, which might have confused the examinees. Furthermore, the time and expense involved in creating high-quality, realistic clinical cases would likely reduce the number of modules that could be used, which might enable the test takers to gain prior knowledge of the “correct” answers, therefore defeating the purpose of the test. Future research should determine the feasibility of including real cases and patients to maximize verisimilitude and reduce personnel and production expenses.
Conclusions
The findings of this study suggest that the CSV showed a high identification index for overall and multiple domains of competence in the conventional GM-ITE. The participants liked being able to “examine” the patient and receive visual and auditory clinical information, which improved their test scores. Overall, the findings showed that CSV modules simulating real-world clinical examinations assessed residents’ clinical competence successfully in multiple domains.

Acknowledgments
The authors thank the members of the Japan Institute for Advancement of Medical Education Program (JAMEP) for their valuable assistance. The JAMEP was involved in collecting and managing data as the General Medicine In-Training Examination (GM-ITE) administrative organization. It did not participate in designing and conducting the study; data analysis and interpretation; preparation, review, or approval of the paper; and the decision to submit the paper for publication. The authors also like to thank Editage for the English language review. This work was supported by the Health, Labour, and Welfare Policy Grants of Research on Region Medical (21IA2004) from the Ministry of Health, Labour and Welfare.

Data Availability
The data sets generated during and analyzed during this study are available from the corresponding author on reasonable request.

Authors’ Contributions
KS had full access to all the study data and took responsibility for the integrity and accuracy of the data analysis. KS, YN, SF, DY, and YT contributed to the study concept and design. HK, TS, and YY were involved in data acquisition, analysis, and interpretation. KS performed statistical analysis and wrote the paper. YN revised the content. YN and YT were involved in administrative, technical, and material support. All authors reviewed the final paper.
Authors KS (kshikino@gmail.com) and YN (ynishiza@juntendo.ac.jp) are co-corresponding authors for this article.

Conflicts of Interest
YN received an honorarium from the Japan Institute for Advancement of Medical Education Program (JAMEP) as the General Medicine In-Training Examination (GM-ITE) project manager. YT is the director of the JAMEP. HK received an honorarium from the JAMEP as a speaker for the JAMEP lecture. KS received an honorarium from the JAMEP as a reviewer of GM-ITE. KS, TS, and YY received honoraria from the JAMEP as examination preparers of GM-ITE. No other authors possess any competing interests.

Multimedia Appendix 1
Innovative examination.
[MP4 File (MP4 Video), 137419 KB - mededu_v10i1e54401_app1.mp4 ]

References


Abbreviations
CD: clinical diagnosis
CSV: clinical simulation video
DI: discrimination index
DK: disease knowledge
GM-ITE: General Medicine In-Training Examination
JAMEP: Japan Institute for Advancement of Medical Education Program
MCQ: multiple-choice question
MP: medical interview or professionalism
Health Care Workers’ Motivations for Enrolling in Massive Open Online Courses During a Public Health Emergency: Descriptive Analysis

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Corresponding Author:
Jennifer Jones, MBBS

Abstract

Background: Massive open online courses (MOOCs) are increasingly used to educate health care workers during public health emergencies. In early 2020, the World Health Organization (WHO) developed a series of MOOCs for COVID-19, introducing the disease and strategies to control its outbreak, with 6 courses specifically targeting health care workers as learners. In 2020, Stanford University also launched a MOOC designed to deliver accurate and timely education on COVID-19, equipping health care workers across the globe to provide health care safely and effectively to patients with the novel infectious disease. Although the use of MOOCs for just-in-time training has expanded during the pandemic, evidence is limited regarding the factors motivating health care workers to enroll in and complete courses, particularly in low-income countries (LICs) and lower-middle–income countries (LMICs).

Objective: This study seeks to gain insights on the characteristics and motivations of learners turning to MOOCs for just-in-time training, to provide evidence that can better inform MOOC design to meet the needs of health care workers. We examine data from learners in 1 Stanford University and 6 WHO COVID-19 courses to identify (1) the characteristics of health care workers completing the courses and (2) the factors motivating them to enroll.

Methods: We analyze (1) course registration data of the 49,098 health care workers who completed the 7 focal courses and (2) survey responses from 6272 course completers. The survey asked respondents to rank their motivations for enrollment and share feedback about their learning experience. We use descriptive statistics to compare responses by health care profession and by World Bank country income classification.

Results: Health care workers completed the focal courses from all regions of the world, with nearly one-third (14,159/49,098, 28.84%) practicing in LICs and LMICs. Survey data revealed a diverse range of professional roles among the learners, including physicians (2171/6272, 34.61%); nurses (1599/6272, 25.49%); and other health care professionals such as allied health professionals, community health workers, paramedics, and pharmacists (2502/6272, 39.89%). Across all health care professions, the primary motivation to enroll was for personal learning to improve clinical practice. Continuing education credit was also an important motivator, particularly for nonphysicians and learners in LICs and LMICs. Course cost (3423/6272, 54.58%) and certification (4238/6272, 67.57%) were also important to a majority of learners.

Conclusions: Our results demonstrate that a diverse range of health care professionals accessed MOOCs for just-in-time training during a public health emergency. Although all health care workers were motivated to improve their clinical practice, different factors were influential across professions and locations. These factors should be considered in MOOC design to meet the needs of health care workers, particularly those in lower-resource settings where alternative avenues for training may be limited.

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KEYWORDS
massive open online course; MOOC; online learning; online courses; online course; health care education; medical education; education; training; professional development; continuing education; COVID-19 training; infectious disease outbreak response; emergency; public health; crisis; crises; outbreak; pandemic; COVID-19; SARS-CoV-2; coronavirus; humanitarian emergency response; health care workers; nurse; nurses; practitioner; practitioners; clinician; clinicians; health care worker; medic; low-income; lower-middle income; LIC; LMIC; developing country; developing countries; developing nation; developing nations; case study;
Introduction

During the COVID-19 pandemic, massive open online courses (MOOCs) emerged as an invaluable source of training for health care workers globally [1-4]. Studies have demonstrated MOOCs’ effectiveness in facilitating learning among practicing health care professionals [5,6], and their capability to deliver content rapidly and flexibly has established e-learning as a preferred method for transferring clinical skills and knowledge [6]. Their broad applicability, accessibility, and cost-effectiveness make MOOCs particularly appealing for continuing education (CE) requirements, also known as continuing medical education [5,7,8]. Consequently, MOOCs have been used for skill development and retention, competency assessment, and lifelong learning [9]. In low-income countries (LICs) and lower-middle-income countries (LMICs), MOOCs potentially increase access to essential health education content and reduce training costs for health care professionals [5,10,11].

Despite the increasing data on general MOOC enrollee motivations [12-15], there remains a significant gap concerning the specific factors motivating practicing health care professionals. Understanding the motivations of health care workers in LICs and LMICs to enroll in and complete health care–related MOOCs is crucial, as engagement and completion rates among this group are notably low [16-18]. By identifying what drives their participation, we can enhance MOOC design and dissemination, particularly for just-in-time learning initiatives during health emergencies—a time when organizations such as the World Health Organization (WHO) and national governments increasingly rely on MOOCs to rapidly disseminate critical information to health care workers.

This study aims to uncover the characteristics and motivations of health care professionals who enrolled in health care–related MOOCs during the COVID-19 pandemic—a period marked by an urgent need to rapidly disseminate critical health care information. Research indicates several potential reasons for enrolling in MOOCs. As a teaching model, MOOCs support adult learning principles targeting self-directed learners [17]. The self-directed learning model allows individuals to guide their learning process, establish their learning objectives, engage in individualized learning strategies, and manage their time based on their interests while still receiving access to curated content [17]. It can be presumed that learner motivations for engaging in MOOCs differ from those in traditional brick-and-mortar educational venues [19]. Prior studies suggest that primary intrinsic motivations for MOOC enrollment include personal interest and knowledge acquisition [12], whereas extrinsic motivations often involve certification and professional development opportunities [17]. However, the specific motivations driving health care workers, particularly those in LICs and LMICs, remain underexplored.

Although recent studies, such as Garrido et al [20] and a scoping review on MOOCs for health care worker education in low- and middle-income countries [21], have begun to explore the use of MOOCs for professional and workforce development, these insights predominantly focus on broad educational outcomes and employment advancements. Such research underscores the potential of MOOCs to enhance skill sets and career opportunities, highlighting the alignment of MOOC coursework with job market needs and professional certifications. However, these studies generally do not delve deeply into the specific intrinsic motivations of health care workers in LICs and LMICs to enroll in MOOCs, especially during health emergencies. In fact, in 2023, the WHO commissioned 3 systematic reviews of the literature to support guidelines for building just-in-time training during public health emergencies, finding a gap in the literature regarding the motivations of learners enrolling in relevant online courses, particularly in LMICs [WHO, unpublished data, 2023]. Our study seeks to fill this void by examining the unique motivations behind MOOC enrollment, particularly during the unprecedented global crisis triggered by the COVID-19 pandemic.

This study contributes uniquely to the literature by investigating the key motivations for health care workers to enroll in MOOCs, with a special emphasis on provider type and country income level during a global health crisis. These insights are vital as learners in LICs and LMICs face challenges such as linguistic and cultural barriers, limited access to digital technology, low-bandwidth connectivity, infrastructure constraints, and limited digital literacy [5,10]. By understanding what motivates learners in these settings, our study provides foundational knowledge that can inform more thoughtful and effective MOOC design and recruitment strategies, ultimately improving knowledge transmission, learning outcomes, and course completion rates in regions with critical needs for health care worker training. This broad impact underscores the potential of targeted online education strategies to significantly enhance global health responses.

Methods

Study Design

In this study, we present a descriptive analysis of MOOC learner data to identify the characteristics and motivations of health care workers enrolled in 7 MOOCs designed to serve as just-in-time education for clinically practicing health care workers during the COVID-19 pandemic. We examine two sources of data: (1) course enrollment data (n=49,098) collected during course registration and (2) follow-up survey data (n=6272) collected from course completers.

Course Descriptions

In Table 1, we detail the 7 focal courses examined in this study. We selected 6 courses developed by the WHO in early 2020 to respond to the growing COVID-19 crisis. These courses were launched on the OpenWHO online platform, which serves as the WHO’s learning hub for health emergencies. These courses build on the WHO’s initial introductory COVID-19 course, which had 232,890 enrollments across 13 published languages by the end of March 2020 and provided general information...
about the disease for a broad audience [22]. The 6 WHO courses were selected out of all 43 COVID-19 courses offered on the OpenWHO platform due to their greater content relevance to practicing health care workers. The 6 MOOCs focused on introducing health care workers to the novel disease and providing them with strategies to control its outbreak. Three courses were designed to provide health care workers with the basic tools needed to combat the pandemic and protect themselves from infection when providing health care services. Another 3 courses were designed to provide health care workers with an overview of the COVID-19 disease and provide learners with specific clinical strategies to address the pandemic. The courses were initially published in English and then rapidly translated into over 19 languages in the subsequent 2 months.
<table>
<thead>
<tr>
<th>Source and course title</th>
<th>Description</th>
<th>Languages</th>
<th>Date launched</th>
<th>Course duration</th>
<th>Enrolled learners, n</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Stanford University</strong></td>
<td>COVID-19 Training for Healthcare Workers</td>
<td>This course is designed for health care professionals. It provides an evidence-based approach to life-saving techniques for treating critically ill patients with COVID-19.</td>
<td>English, Hindi, Portuguese, French, and Spanish</td>
<td>July 17, 2020</td>
<td>8 h</td>
</tr>
<tr>
<td><strong>OpenWHO</strong></td>
<td>Hand Hygiene</td>
<td>This course is designed to summarize the WHO guidelines on hand hygiene, associated tools, and ideas for effective implementation. The WHO guidelines support hand hygiene promotion and improvement in health care facilities worldwide.</td>
<td>Arabic, Chinese, Dutch, English, French, Macedonian, Portuguese, Russian, Shqip, Sinhalese, Somali, Spanish, Tamil, Tetum, and Turkish</td>
<td>June 3, 2020</td>
<td>1 h</td>
</tr>
<tr>
<td></td>
<td>Personal Protective Equipment</td>
<td>The course is a guide for health care workers involved in patient care activities in a health care setting. It aims to show the type of personal protective equipment needed to correctly protect oneself.</td>
<td>Albanian, Arabic, Chinese, Dutch, English, French, Kazakh, Macedonian, Portuguese, Russian, Sinhalese, Somali, Spanish, Tamil, Tetum, Thai, and Turkish</td>
<td>April 15, 2020</td>
<td>15 min</td>
</tr>
<tr>
<td></td>
<td>Occupational Health and Safety</td>
<td>This course is for health workers, incident managers, supervisors, and administrators who make policies and protocols for their health facilities. The WHO recommends a combination of measures for infection prevention and control, occupational health and safety, and psychosocial support.</td>
<td>Dutch, English, Indonesian, Macedonian, Portuguese, Spanish, and Swahili</td>
<td>August 30, 2020</td>
<td>1 h</td>
</tr>
<tr>
<td>Source and course title</td>
<td>Description</td>
<td>Languages</td>
<td>Date launched</td>
<td>Course duration</td>
<td>Enrolled learners, n</td>
</tr>
<tr>
<td>------------------------------------------------</td>
<td>--------------------------------------------------------------------------------------------------</td>
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</tr>
<tr>
<td>Clinical Management: Patient Rehabilitation</td>
<td>The course is devoted to the rehabilitation of patients with COVID-19 by addressing needs of patients recovering from COVID-19, including patients with cognitive impairment, physical deconditioning and weakness, respiratory impairment, swallow impairment, and communication impairment, as well as techniques for rehabilitation.</td>
<td>Chinese, English, French, Macedonian, Russian, and Shqip</td>
<td>January 13, 2021</td>
<td>3 h</td>
<td>22,704</td>
</tr>
<tr>
<td>Clinical Management: General Considerations</td>
<td>This course gives background on the pandemic, discusses facility operations, and addresses COVID-19 pandemic preparedness at all levels of health care provision. It also discusses ethical issues arising during COVID-19 care.</td>
<td>English, Indonesian, Macedonian, and Shqip</td>
<td>October 22, 2020</td>
<td>3 h</td>
<td>31,972</td>
</tr>
<tr>
<td>Clinical Management: Acutely Ill Patients</td>
<td>Designed to prepare and support health providers as they provide emergency care to seriously ill patients with COVID-19, including a systematic approach via the WHO and ICRC Basic Emergency Care course content.</td>
<td>English, Somali, and Spanish</td>
<td>May 5, 2021</td>
<td>6 h</td>
<td>14,190</td>
</tr>
</tbody>
</table>

aWHO: World Health Organization.
bICRC: International Committee of the Red Cross.

To broaden the reach of learners in the study, we also included a Stanford University MOOC launched in August 2020 to equip health care workers with timely in-service education, to improve their ability to safely and effectively treat patients with the novel disease [23]. The Stanford MOOC was launched on both the Coursera and edX platforms, 2 US-based MOOC providers founded in 2012 that routinely provide university-level courses on various topics including health. As of November 2020, nearly 900 health-related courses were available on the Coursera platform alone [24]. The Stanford course was first developed in English and then translated into 4 additional languages.

The courses were promoted via their respective institutional networks. No paid advertisements were published. The Stanford course was promoted starting in July 2020, with emails sent to over 100,000 Coursera listserve subscribers. The course was also promoted through a variety of Stanford-affiliated social media channels and online publications, YouTube’s spotlight channel, and direct sharing with a network of health education collaborators throughout the world by Stanford team members. The WHO courses were promoted as each course launched on the WHO website, the OpenWHO platform, and through WHO newsletters and mailing lists.

Data Collection

Figure 1 describes the flow diagram for study participation and data collection. We obtained data on all course enrollees via the...
respective course platforms (OpenWHO for WHO courses and edX and Coursera for the Stanford course). Course completion was defined by course developers and identified through backend data available from the course platforms. Learner background data were collected via the respective platforms at the time of course registration and included the learners’ age, gender, geographic location, and profession. The health care worker profession category included those identifying as being employed in the following professions: allopathic medicine (including physicians and physician assistants); traditional medicine; nursing (including nurses, nurse practitioners, nurse midwives, nursing instructors, and certified nursing assistants); allied health (including physical therapy, occupational therapy, speech pathology, medical assistants, and home health aides); community health; emergency medical services (including paramedics and emergency medical technicians); and pharmacy (including pharmacists and pharmacy technicians).

**Figure 1.** Flow diagram for study participation. The number of enrollees, course completers, and survey completers is shown for all learners and health care workers. The survey completer sample (shaded in gray) is the focal sample for this study. Health care workers included those who identified as being employed as health care professionals at enrollment and in the follow-up survey. Health care professions included the following: allied health; community health; nursing (including nurses, nurse practitioners, nurse midwives, nursing instructors, and certified nursing assistants); physician assistants; paramedics and emergency medical technicians; pharmacy; physicians; and traditional medicine.
We invited all enrollees who had completed the course they were enrolled in to complete an online survey (Multimedia Appendix 1) on the respective course platforms. To recruit WHO course learners, we sent 3 survey invitations to the email addresses provided by learners at the time of registration and through the OpenWHO automated course message. To recruit participants from the Stanford course, we sent 3 requests via Coursera and edX email announcements. The survey window was open from December 11, 2020, to September 28, 2021. The survey completion rate was 3.98% (12,170/305,849) among all course completers and 12.77% (6272/49,098) among health care workers completing the courses.

The 23-question survey collected information on learners’ personal and professional demographics, information about their professional experience with COVID-19, and their ability to connect with physicians in their daily work. Respondents were asked to rank 6 possible motivations for course enrollment in the order of importance to them. Additionally, respondents were asked about their use of course certificates, including whether their employer required a certificate, if they planned to provide it to their employer, or if they planned to use it for CE credit. Finally, respondents were asked about the cost of MOOCs and how it impacted their decision to enroll in the course. All study authors were involved in the development of the survey. Questions were reviewed by all authors to include appropriate vocabulary, inclusive of globally used terminology. The survey was not adapted directly from any other source; however, the motivations included were drawn from anecdotal course feedback and the extant literature discussing motivations for MOOC enrollment.

**Statistical Analysis**

Because of the study focus, we limited our analytic sample to health care workers exclusively. To investigate the generalizability of our survey sample, we summarized the characteristics of all health care workers completing the courses (n=49,098) and health care workers completing the survey (n=6272) using descriptive statistics (mean, SD, and response rates). To compare the proportion of learners by characteristic between course completers and survey completers, we used the Pearson $\chi^2$ test. To examine ranked enrollment motivators and compare across learner subgroups, we conducted multiple comparison tests using 1-way ANOVA, comparing the mean rank of motivations (dependent variable) by learner characteristics. The independent variables compared included differences by occupation (physicians vs nurses and physicians vs other health professionals) and country income classification (LICs and LMICs vs upper-middle–income countries [UMICs] and high-income countries [HICs]). All statistical analyses were conducted using Stata SE V15 (StataCorp).

**Ethical Considerations**

Informed consent was obtained from all learners. Participation was voluntary and no monetary compensation was provided to the participants. The collected data were anonymized. Approval for all aspects of this study design, including consent, outreach, data collection, surveying, and data analysis, was obtained from the Stanford University School of Medicine Institutional Review Board (protocol 57831).

**Results**

**Learner Characteristics**

As shown in Figure 1, as of September 2021, the 7 courses had 856,263 total enrollees, 90.47% (n=774,686) in WHO courses and 9.53% (n=81,577) in the Stanford course. In all, 13.3% (113,902/856,263) of enrollees and 16.05% (49,098/305,849) of course completers identified as practicing health care workers at course registration. The course completion rate was higher among health care workers (49,098/113,902, 43.1%) than overall enrollees (305,849/856,263, 35.7%).

Table 2 shows that nearly one-third (15,238/49,098, 31.04%) of the health care workers that completed a course were between the ages of 18 - 29 years, and 41.25% (20,252/49,098) identified as female. The region with the most health care workers that completed a course was Latin America and the Caribbean (10,665/49,098, 21.72%), followed by South Asia (7264/49,098, 14.79%), North America (7019/49,098, 14.3%), Europe and Central Asia (5365/49,098, 10.93%), East Asia and the Pacific (5278/49,098, 10.75%), Middle East and North Africa (3816/49,098, 7.77%), and sub-Saharan Africa (3502/49,098, 7.13%). Nearly one-third (14,159/49,098, 28.84%) of the health care workers who completed a course were from LICs (828/49,098, 1.69%) or LMICs (13,331/49,098, 27.15%).
Table 1. Health care worker characteristics, by course and follow-up survey. A higher proportion of course completers did not specify characteristics compared to survey completers. Because response options for age and gender were voluntary, a number of learners did not specify these characteristics. We show the numbers not specified for each. For course completion, geographic region was identified via course platform analytics; however, we were unable to identify a subset, shown as “not specified” in the table. For survey completion, geographic regions were identified primarily through survey self-reports. In 177 survey responses, location was not reported. For these cases, we used the survey response’s IP address to identify the geographic region of the respondent. Percentages are shown for those for whom we have data on characteristics. Percentage for each categorical variable sum to 100.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Completed course (n=49,098), n (%)</th>
<th>Completed survey (n=6272), n (%)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Course type</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OpenWHO</td>
<td>38,837 (79.1)</td>
<td>2214 (35.3)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Stanford University</td>
<td>10,261 (20.9)</td>
<td>4058 (64.7)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>Age range (y)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18 - 29</td>
<td>15,238 (31.04)</td>
<td>2020 (32.21)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>30 - 39</td>
<td>9699 (19.75)</td>
<td>1560 (24.87)</td>
<td>.10</td>
</tr>
<tr>
<td>40 - 49</td>
<td>4511 (9.19)</td>
<td>950 (15.15)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>50 - 59</td>
<td>2324 (4.73)</td>
<td>662 (10.55)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>60 - 69</td>
<td>691 (1.41)</td>
<td>232 (3.7)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>70+</td>
<td>233 (0.47)</td>
<td>35 (0.56)</td>
<td>.56</td>
</tr>
<tr>
<td>Not specified</td>
<td>16,402 (33.41)</td>
<td>813 (12.96)</td>
<td></td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>20,252 (41.25)</td>
<td>3057 (48.74)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Male</td>
<td>12,758 (25.98)</td>
<td>2349 (37.45)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Nonbinary or other</td>
<td>139 (2.83)</td>
<td>43 (0.69)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Not specified</td>
<td>15,949 (32.48)</td>
<td>823 (13.12)</td>
<td>—</td>
</tr>
<tr>
<td><strong>Geographic region</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>East Asia and Pacific</td>
<td>5278 (10.75)</td>
<td>894 (14.25)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Europe and Central Asia</td>
<td>5365 (10.93)</td>
<td>666 (10.62)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Latin America and Caribbean</td>
<td>10,665 (21.72)</td>
<td>1061 (16.92)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Middle East and North Africa</td>
<td>3816 (7.78)</td>
<td>547 (8.72)</td>
<td>.66</td>
</tr>
<tr>
<td>North America</td>
<td>7019 (14.3)</td>
<td>993 (15.83)</td>
<td>.29</td>
</tr>
<tr>
<td>South Asia</td>
<td>7264 (14.79)</td>
<td>1393 (22.21)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Sub-Saharan Africa</td>
<td>3502 (7.13)</td>
<td>718 (11.45)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Not specified</td>
<td>6189 (12.61)</td>
<td>0 (0)</td>
<td>—</td>
</tr>
<tr>
<td><strong>World Bank income classification</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High income</td>
<td>14,157 (28.83)</td>
<td>1971 (31.43)</td>
<td>.01</td>
</tr>
<tr>
<td>Upper-middle income</td>
<td>14,593 (29.72)</td>
<td>1611 (25.69)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Lower-middle income</td>
<td>13,331 (27.15)</td>
<td>2468 (39.35)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Low income</td>
<td>828 (1.69)</td>
<td>222 (3.54)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Not specified</td>
<td>6189 (12.61)</td>
<td>0 (0)</td>
<td>—</td>
</tr>
</tbody>
</table>

*Not applicable.

Table 2 also compares the characteristics of health care workers completing the course, with the 12.77% (6272/49,098) completing the survey. We observe slight differences in the age and gender composition of survey completers with course completers, with the survey sample skewing older and more male. The survey sample includes a slightly larger share of participants from LICs (222/6272, 3.54%) and LMICs (2468/6272, 39.35%).
Table 3 describes the professions of the health care workers who completed the survey and their levels of physician supervision. Physicians represent 34.61% (2171/6272) of the survey sample, followed by nurses (1599/6272, 25.49%) and allied health professionals (1190/6272, 18.97%). This breakdown of professional roles is similar in LICs and LMICs and in UMICs and HICs. Of the nonphysician health care workers, more than a third (1315/3639, 36.14%) reported having access to a physician for consultation during less than 50% of their workday, although the majority (1989/2341, 84.96%) could contact a physician by phone if needed. Most health care workers either already cared for patients with COVID-19 (2793/6272, 44.53%) or anticipated caring for them (1940/6272, 30.93%) at the time of survey completion.

Table 1. Characteristics of the health care worker survey sample. Allied health included physical therapy, occupational therapy, speech pathology, medical assistants, and home health aides. Nursing included nurses, nurse midwives, nursing instructors, and certified nursing assistants. The question about the frequency of physicians being on site was asked of nonphysicians only. The question about physicians being available via phone was asked of nonphysicians who had indicated that physicians were not available on site 100% of the time. Across questions asking about the availability of physician and treating patients with COVID-19, survey respondents could indicate that the question was not applicable in their health care setting.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Total (n=6272), n (%)</th>
<th>HICs(^a) and UMICs(^b) (n=3582), n (%)</th>
<th>LMICs(^c) and LICs(^d) (n=2690), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Profession</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Allied health</td>
<td>1190 (18.97)</td>
<td>663 (18.51)</td>
<td>527 (19.59)</td>
</tr>
<tr>
<td>Community health worker</td>
<td>501 (7.99)</td>
<td>296 (8.26)</td>
<td>205 (7.62)</td>
</tr>
<tr>
<td>Nursing</td>
<td>1599 (25.49)</td>
<td>1012 (28.25)</td>
<td>587 (21.82)</td>
</tr>
<tr>
<td>Physician assistant or nurse practitioner</td>
<td>103 (1.64)</td>
<td>68 (1.9)</td>
<td>35 (1.3)</td>
</tr>
<tr>
<td>Paramedic or emergency medical technician</td>
<td>272 (4.34)</td>
<td>159 (4.44)</td>
<td>113 (4.2)</td>
</tr>
<tr>
<td>Pharmacist</td>
<td>330 (5.26)</td>
<td>106 (2.96)</td>
<td>224 (8.33)</td>
</tr>
<tr>
<td>Physician</td>
<td>2171 (34.61)</td>
<td>1217 (33.98)</td>
<td>954 (35.46)</td>
</tr>
<tr>
<td>Traditional medicine</td>
<td>106 (1.69)</td>
<td>61 (1.7)</td>
<td>45 (1.67)</td>
</tr>
<tr>
<td><strong>Frequency of physicians being on site</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Always (100% of time)</td>
<td>1228 (33.75)</td>
<td>660 (30.88)</td>
<td>568 (37.82)</td>
</tr>
<tr>
<td>Mostly (&gt;50% of time)</td>
<td>1096 (30.12)</td>
<td>586 (27.42)</td>
<td>510 (33.95)</td>
</tr>
<tr>
<td>Sometimes (&lt;50% of time)</td>
<td>815 (22.4)</td>
<td>482 (22.55)</td>
<td>333 (22.17)</td>
</tr>
<tr>
<td>Never (0% of time)</td>
<td>500 (13.74)</td>
<td>409 (19.14)</td>
<td>91 (6.06)</td>
</tr>
<tr>
<td><strong>Physicians being available via phone</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>1989 (82.5)</td>
<td>1180 (48.94)</td>
<td>809 (33.55)</td>
</tr>
<tr>
<td>No</td>
<td>352 (14.6)</td>
<td>256 (10.62)</td>
<td>96 (3.98)</td>
</tr>
<tr>
<td>Not specified</td>
<td>70 (2.9)</td>
<td>41 (1.7)</td>
<td>29 (1.2)</td>
</tr>
<tr>
<td><strong>Treating patients with COVID-19</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Currently treating</td>
<td>2793 (44.53)</td>
<td>1551 (43.3)</td>
<td>1242 (46.17)</td>
</tr>
<tr>
<td>Anticipated in future</td>
<td>1940 (30.93)</td>
<td>1003 (28)</td>
<td>937 (34.83)</td>
</tr>
<tr>
<td>Not anticipated</td>
<td>460 (7.33)</td>
<td>314 (8.77)</td>
<td>146 (5.43)</td>
</tr>
<tr>
<td>Not specified</td>
<td>1079 (17.2)</td>
<td>714 (19.93)</td>
<td>365 (13.57)</td>
</tr>
</tbody>
</table>

\(^a\)HIC: high-income country.
\(^b\)UMIC: upper-middle-income country.
\(^c\)LMIC: lower-middle-income country.
\(^d\)LIC: low-income country.
\(^e\)This survey question was only asked to nonphysician health care workers who work directly with physicians (n=3639). Percentages shown are out of applicable participants only.
\(^f\)This survey question was only asked to nonphysician health care workers that work directly with physicians and do not have a physician on site 100% of the time (n=2411). Percentages shown are out of data provided with applicable respondents only. Not all applicable respondents responded to this question (n=70).
\(^g\)Data on whether health care workers treat patients with COVID-19 were based on a voluntary question asked of patients at the time of course enrollment.
Learner Motivations

In the survey, health care workers were asked to rank in importance the following 6 potential motivating factors for course enrollment: to improve practice, to earn a certificate, CE, course brand, free cost of course, and employer recommendation. Figure 2 shows the ranking preferences across survey respondents. Among survey respondents ranking all factors (n=5518), the majority (n=3090, 56%) ranked “improve practice” as their top preference, with an additional 16% (n=883) ranking it as the second most important factor and 10% (n=552) ranking it as the third most important factor. The second and third most important factors were CE and to earn a certificate, with employer recommendation as the least most important factor ranked.

Figure 2. Percent of learners by motivation rank among health care providers (n=5518).

In Table 4, we show the ranking differences by the type of health care worker. Although the motivation of improving practice was ranked the highest across all subgroups, it was ranked higher by physicians, with a mean rank of 1.86, compared to nurses with a mean rank of 2.06 and other health care providers with a mean rank of 2.24. Nonphysicians ranked CE and employer recommendations higher than physicians. Certification also appears to matter more to nonphysicians, with 69.76% (2861/4101) choosing to obtain a certificate, 63.76% (2615/4101) providing a copy of the certificate to their employer, and 79.18% (3247/4101) using the certificate for a CE requirement. The course brand appears to be a more
important motivating factor to physicians compared to nonphysicians. Course cost did not appear to differentially influence course enrollment by the type of health care worker.

Table. Mean rank of motivation (1=highest rank, 6=lowest rank) and course perspectives by the type of health care worker. Physician is the reference category for comparisons. Nursing included nurses, nurses, midwives, and nursing assistants. Mean ranking does not include observations that skipped ranking altogether (n=745). Course perspectives include observations that skipped ranking but provided responses for these questions.

<table>
<thead>
<tr>
<th>Motivation (mean ranking)</th>
<th>Physician (n=2171), mean (SD)</th>
<th>Nursing (n=1599), mean (SD)</th>
<th>Other (n=2502), mean (SD)</th>
<th>P value</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Improve practice</td>
<td>1.86 (1.38)</td>
<td>2.06 (1.51)</td>
<td>2.24 (1.60)</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Earn certificate</td>
<td>3.52 (1.36)</td>
<td>3.53 (1.36)</td>
<td>3.46 (1.42)</td>
<td>.80</td>
<td>.16</td>
</tr>
<tr>
<td>Continuing education requirement</td>
<td>3.63 (1.49)</td>
<td>3.31 (1.47)</td>
<td>3.46 (1.55)</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Course brand</td>
<td>3.58 (1.61)</td>
<td>4.17 (1.62)</td>
<td>3.92 (1.68)</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Course is free</td>
<td>3.83 (1.57)</td>
<td>3.77 (1.65)</td>
<td>3.81 (1.61)</td>
<td>.27</td>
<td>.68</td>
</tr>
<tr>
<td>Employer recommended</td>
<td>4.66 (1.54)</td>
<td>4.47 (1.55)</td>
<td>4.39 (1.61)</td>
<td>.001</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Course perspectives (proportion agreeing)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Would have taken course if it was not free</td>
<td>0.47 (0.50)</td>
<td>0.43 (0.50)</td>
<td>0.46 (0.50)</td>
<td>.01</td>
<td>.39</td>
</tr>
<tr>
<td>Chose to obtain a certificate</td>
<td>0.63 (0.48)</td>
<td>0.71 (0.46)</td>
<td>0.69 (0.46)</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Gave a copy of the certificate to employer</td>
<td>0.55 (0.50)</td>
<td>0.65 (0.48)</td>
<td>0.63 (0.48)</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Will use the certificate for continuing education requirement</td>
<td>0.71 (0.45)</td>
<td>0.81 (0.39)</td>
<td>0.78 (0.41)</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

In Table 5, we show ranking differences by the location of health care workers, comparing differences in UMICs and HICs compared to LICs and LMICs. In LICs and LMICs, health care workers ranked CE and employer recommendation higher on average compared to learners in UMICs and HICs. Conversely, course brand appears to matter more for learners in UMICs and HICs. Certification was obtained by roughly the same proportion of learners in both subgroups, although learners in UMICs and HICs were more likely to give a copy of the certificate to their employer, whereas learners in LICs and LMICs were more likely to use the certificate for a CE requirement.
Table. Mean rank of motivation (1=highest rank, 6=lowest rank) and course perspectives by country classification. This table shows differences by World Bank income classifications: high-income country (HIC), upper-middle–income country (UMIC), lower-middle–income country (LMIC), and low-income country (LIC). Mean ranking does not include observations that skipped ranking altogether (n=745). Course perspectives include observations that skipped ranking but provided responses for these questions.

<table>
<thead>
<tr>
<th>Motivation (mean ranking)</th>
<th>HICs and UMICs (n=3582), mean (SD)</th>
<th>LICs and LMICs (n=2690), mean (SD)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Improve practice</td>
<td>2.10 (1.52)</td>
<td>2.01 (1.49)</td>
<td>.04</td>
</tr>
<tr>
<td>Earn certificate</td>
<td>3.45 (1.38)</td>
<td>3.57 (1.38)</td>
<td>.001</td>
</tr>
<tr>
<td>Continuing education re-</td>
<td>3.58 (1.54)</td>
<td>3.37 (1.48)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>quirement</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Course brand</td>
<td>3.77 (1.65)</td>
<td>3.97 (1.66)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Course is free</td>
<td>3.68 (1.59)</td>
<td>3.97 (1.61)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Employer recommended</td>
<td>4.58 (1.58)</td>
<td>4.41 (1.57)</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

Course perspectives (proportion agreeing)

| Would have taken course if it was not free | 0.45 (0.50) | 0.46 (0.50) | .61    |
| Chose to obtain a certificate             | 0.68 (0.47) | 0.67 (0.47) | .22    |
| Gave a copy of the certificate to employer| 0.65 (0.48) | 0.57 (0.50) | <.001  |
| Will use the certificate for continuing education requirement | 0.73 (0.44) | 0.81 (0.39) | <.001  |

Generally, the fact that MOOCs were free was a lower-ranked motivator. Although interestingly, in the subgroup analysis, the course being free of cost was ranked lower in LICs and LMICs (mean 3.97, SD 1.61) than in UMICs and HICs (mean 3.68, SD 1.59; Table 5). However, when survey respondents were asked about their perspectives on the cost of MOOCs, more than half (3423/6272, 54.58%) of the health care workers indicated they would not have taken the course if there was an associated cost. This perspective was consistent across subgroup analyses of health care professional types and country-income levels.

Discussion

Principal Findings

Through a survey of 6272 health care workers worldwide who completed MOOCs for COVID-19 training across multiple platforms and organizations, our study provides unique insight into the factors motivating health care workers to enroll in and complete MOOCs during public health emergencies. We identified that the primary motivator for enrollment among health care workers was to improve their personal practice, followed by the pursuit of CE credit and certification. Course cost is an influential factor in the decision to enroll in an MOOC, with 54.58% (3423/6272) of respondents indicating that they would not have enrolled if the course had not been free. This first-of-its-kind analysis of health care worker motivations in just-in-time training MOOCs during a public health emergency fills an important gap in the existing literature, providing key insights for future course development and marketing.

Our findings highlight the widespread demand among health care workers for MOOC training during a public health crisis. Health care workers from over 200 countries and territories enrolled in and completed the COVID-19 MOOCs examined in this study, with a third (14,159/42,909, 33%) of course completers located in LICs and LMICs. Compared to the typical MOOC completion rates of under 10% [17,18], the 43.1% (49,098/113,902) completion rate among health care workers in the COVID-19 MOOCs in this study is notably high. Although the high rate of completion likely reflects the limited alternatives for training during the start of the COVID-19 pandemic, it may also indicate intrinsic motivation among health care workers, whose predominant reason for enrollment was to improve their personal practice.

We also observed that the COVID-19 MOOCs attracted a diverse range of health care providers globally. Although the majority (3770/6272, 60.11%) of respondents were nurses and physicians, 39.89% (2502/6272) reported working in other health care capacities including allied health, community health, emergency medical services, and pharmacy. Furthermore, we noted that motivations for enrollment varied by profession. Compared to physicians, nurses and other health care professionals were more motivated by CE credit, employer recommendations, and certification. Nurses and other health professionals were more likely to obtain certificates, provide a copy of the certificate to their employer, and use the certificates for CE requirements. Recognizing these differences in motivating factors across types of health care workers can inform the design of MOOCs that more effectively respond to the interests and needs of the targeted audience.

Despite these differences, the majority of all health care workers, including physicians, indicated their intention to use their certificates professionally, either by providing them to their
employers (3809/6272, 60.73%) or by earning CE credit (4788/6272, 76.34%). This finding underscores the potential for MOOCs to fill a gap in the CE arena, where traditional approaches often present barriers to completion. The common, traditional route for obtaining CE credits involves attendance at national or international medical conferences [7,8]; however, many such conferences were either canceled or transitioned to a web-based format during the pandemic. Given the time and travel requirements associated with conference attendance, MOOCs can serve as a viable and accessible alternative for learners. Interestingly, our study found that the use of course certificates for CE among learners in LICs and LMICs was higher than that in UMICs and HICs, which may reflect a lack of economically feasible options to earn CE credits in resource-limited geographies. Including certification in MOOC design may serve as an important motivator to increase enrollment and completion, particularly in LICs and LMICs, enhancing the attainment of timely health care education for the global health care workforce.

An additional benefit of online learning is the reduced cost for participants to obtain CE credits. Our study found that cost was a significant consideration for course participants, with 54.58% (3423/6272) of learners indicating they would not have taken the course if it had not been free. Although the course being free was slightly less important to learners in LICs and LMICs than those in UMICs and HICs, we speculate that in lower-income countries, learners with access to the technology required to participate in an online course may be relatively better off financially within their respective countries, and that those with lower incomes may not have the technology to enroll in the courses at all—only 3.54% (222/6272) of learners were from LICs. It is also possible that a single course participant may have shared access to the course with others.

Identifying the characteristics and motivations of specific groups of learners, such as those in LICs and LMICs, will aid in the design of future health care–related MOOCs to encourage participation and completion. Although many public health emergencies and disease outbreaks occur in LICs and LMICs with devastating impact, little data exist that examine the motivations of health care workers in these regions to enroll in just-in-time training MOOCs. Nevertheless, the WHO and various national health agencies frequently leverage MOOCs to disseminate critical health information during these emergencies. Future work should particularly investigate how to overcome barriers related to technology access and content accessibility with an eye toward equity, ensuring that the delivery of crucial health care worker training, particularly in times of emergency, is available to all. Likewise, future investigations should examine how online content is used and shared offline in contexts where the broader population has limited access to digital platforms, thereby enhancing the delivery of course materials through offline sharing.

Limitations
We recognize several methodological limitations inherent in our survey-based research. First, the potential for social desirability bias and selection bias due to voluntary participation limits the generalizability of our findings. To mitigate these biases, we deployed the survey across multiple learning platforms (Coursera, edX, and OpenWHO), each likely attracting different user demographics, and achieved a substantial sample size of 6272 respondents representing a diverse economic and geographic distribution. Additionally, we examined and reported only marginal differences between survey respondents and the overall course participants (as detailed in Table 2), although it remains a limitation that survey completers may not fully represent the broader learner population.

Second, the exclusive use of English for survey dissemination likely influenced the diversity of the respondents and further constrained the study’s generalizability. Future studies could incorporate multiple language options to better capture a wider demographic.

Third, although the survey instrument was tailored to the specific contexts of the courses and discussed rigorously by experts across various fields—including educational assessment, emergency medicine, public health, and online learning—its lack of external validation presents a limitation. No prior studies identified during our review provided a validated instrument for assessing learner motivations in MOOCs, emphasizing the innovative aspect of our research while also necessitating a careful interpretation of our findings.

Fourth, our study’s scope was restricted by the limitations in identifying patient-facing health care workers among enrollees, due to data collection methodologies on the OpenWHO platform until June 2020. This limitation hindered our capability to fully classify professions among participants. Future studies should aim to enhance the categorization of health care worker types and delve deeper into the differing motivations among these groups.

Finally, the dynamics of the COVID-19 pandemic—characterized by fluctuating case rates and mortality—suggest that motivations for enrolling in COVID-19–related MOOCs likely varied over time. Some health care workers might have enrolled early in anticipation of patient care needs, whereas others joined after gaining firsthand experience. This temporal variation in motivations, coupled with the evolving availability of other educational tools, presents a complex backdrop against which these motivations were formed. Future studies could benefit from aligning course enrollment data with local COVID-19 case trends to better understand these motivations.

Conclusion
Our study examined the motivations and characteristics of health care workers who engaged with MOOCs during the unprecedented COVID-19 health emergency. The analysis showed that the primary motivation for health care professionals was enhancing their personal practice. CE credit also proved to be a significant motivator, especially for those from LICs and LMICs. Additionally, the necessity of free access was clear, with more than half of the participants (3423/6272, 54.58%) indicating they would not have enrolled if fees were charged. These findings are important for the future development and deployment of MOOCs, ensuring that they not only are
accessible but also resonate with the intrinsic and extrinsic motivations of health care professionals from diverse geographic, training, and economic backgrounds. Future research should further investigate these motivations to see if they are consistent across different types and stages of health emergencies.

Acknowledgments
We would like to thank the World Health Organization (WHO) Health Emergencies Programme team, the Stanford Global Emergency Medicine (SEMI) team, and the Stanford Center for Health Education Digital Medic team for their work in developing and distributing the focal courses of this study. Additionally, we would like to thank all the learners who directly contributed to this research, especially the learners who participated in the survey and shared their experiences with our team.

Data Availability
Some data are available on reasonable request to the corresponding author.

Authors’ Contributions
JJ and JSJ led the conceptualization and design of the study and oversaw all aspects of study implementation, writing, and editing. NYN and AT conducted the data collection. JSJ and SS conducted the quantitative analysis. NAS contributed to organizing and writing the manuscript. NYN, AT, NAS, HU, and MS contributed to the study’s design, interpretation of findings, and revision of all drafts. All authors have read and approved the final manuscript.

Conflicts of Interest
None declared.

Multimedia Appendix 1
COVID-19 provider course: follow-up survey.
[DOCX File, 23 KB - mededu_v10i1e51915_app1.docx ]

References


Abbreviations

CE: continuing education
HIC: high-income country
LIC: low-income country
LMIC: lower-middle–income country
MOOC: massive open-source online course
UMIC: upper-middle–income country
WHO: World Health Organization

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The Use of Animations Depicting Cardiac Electrical Activity to Improve Confidence in Understanding of Cardiac Pathology and Electrocardiography Traces Among Final-Year Medical Students: Nonrandomized Controlled Trial

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Abstract

Background: Electrocardiography (ECG) interpretation is a fundamental skill for medical students and practicing medical professionals. Recognizing ECG pathologies promptly allows for quick intervention, especially in acute settings where urgent care is needed. However, many medical students find ECG interpretation and understanding of the underlying pathology challenging, with teaching methods varying greatly.

Objective: This study involved the development of novel animations demonstrating the passage of electrical activity for well-described cardiac pathologies and showcased them alongside the corresponding live ECG traces during a web-based tutorial for final-year medical students. We aimed to assess whether the animations improved medical students’ confidence in visualizing cardiac electrical activity and ECG interpretation, compared to standard ECG teaching methods.

Methods: Final-year medical students at Imperial College London attended a web-based tutorial demonstrating the 7 animations depicting cardiac electrical activity and the corresponding ECG trace. Another tutorial without the animations was held to act as a control. Students completed a questionnaire assessing their confidence in interpreting ECGs and visualizing cardiovascular electrical transmission before and after the tutorial. Intervention-arm participants were also invited to a web-based focus group to explore their experiences of past ECG teaching and the tutorial, particularly on aspects they found helpful and what could be further improved in the tutorial and animations. Wilcoxon signed-rank tests and Mann-Whitney U tests were used to assess the statistical significance of any changes in confidence. Focus group transcripts were analyzed using inductive thematic analysis.

Results: Overall, 19 students attended the intervention arm, with 15 (79%) completing both the pre- and posttutorial questionnaires and 15 (79%) participating in focus groups, whereas 14 students attended the control arm, with 13 (93%) completing both questionnaires. Median confidence in interpreting ECGs in the intervention arm increased after the tutorial (2, IQR 1.5-3.0 vs 3, IQR 3-4.5; P<.001). Improvement was seen in both confidence in reviewing or diagnosing cardiac rhythms and the visualization of cardiac electrical activity. However, there was no significant difference between the intervention and control arms, for all pathologies (all P>.05). The main themes from the thematic analysis were that ECGs are a complex topic and past ECG teaching has focused on memorizing traces; the visualizations enabled deeper understanding of cardiac pathology; and ECG learning requires repetition, and clinical links remain essential.

Conclusions: This study highlights the value of providing concise explanations of the meaning and pathophysiology behind ECG traces, both visually and verbally. ECG teaching that incorporates relevant pathophysiology, alongside vignettes with discussions regarding investigations and management options, is likely more helpful to students than practices based solely on pattern recognition. Although the animations supported student learning, the key element was the tutor’s explanations. These animations may be more helpful as a supplement to teaching, for instance, as open-access videos.

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KEYWORDS
medical education; cardiology; technology; clinical skills; cardiac; cardiac electrical activity; ECG; mixed methods study; students; education; medical professionals; development; web-based tutorial; teaching; cardiovascular; learning; electrocardiography

Introduction
Electrocardiography (ECG) interpretation is a fundamental skill necessary during medical school education and in the practice of clinical medicine and surgery. Recognizing pathologies such as an ST elevation or non-ST elevation myocardial infarction; bundle branch block (BBB); and arrhythmias, including atrial fibrillation (AF), supraventricular tachycardia, ventricular fibrillation, and ventricular tachycardia, allows for prompt intervention and improves patient care, especially in the acute setting where urgent interventions may be lifesaving.

Despite its importance, medical students struggle with interpreting ECGs, and teaching methods seem to vary greatly between systematic interpretation based on ECG segments and pattern recognition. This leads to a lack of confidence and inaccurate interpretation of ECGs, which could lead to adverse events including treatment delay or incorrect management of the pathology. Although automated computer interpretation may be available, this should not be used by itself to diagnose conditions, since clinical correlation is warranted and these algorithms may be inaccurate [1].

The major disruptions caused by the COVID-19, in which medical students had limited exposure to hospital wards and experienced most lectures and tutorials on the web rather than in person [2], served as a strong reminder of the need for investment in innovative teaching methods.

Literature already suggests that teaching should be focused on the understanding of lead placement, as well as the basics of electrophysiology and ECG, to better identify abnormalities [3]. Teaching should also be correlated with the clinical findings of a case, as this has been shown to lead to more accurate ECG diagnosis in practice. For instance, case-based learning (CBL) has been frequently used in recent years, which increases the practical knowledge and confidence of medical students and junior doctors, through clinically correlating various cardiac pathologies [4]. However, explaining the link between the underlying cardiac pathology and the traces demonstrated by the ECG is not common practice in medical school curricula.

Medical students repeatedly describe ECG interpretation as a challenging skill [5,6]. A study based in Israel reports that despite competence and confidence in ECG interpretation improving throughout medical school, levels remain low among final-year medical students [5]. Moreover, a study of Polish medical students highlighted students’ lack of ability to recognize common and emergency cardiac pathologies [6]. Additionally, these results emphasized independent learning as the strongest predictor of competency, as opposed to attendance in formal teaching sessions [6]. This continues following medical school, with rates of accurate ECG interpretation being as low as 55.8% among trainee doctors [7]. These findings suggest the need for a review of ECG teaching methods.

Technology-enhanced learning has grown in popularity and has been trialed as a method to encourage active practice of ECG interpretation among medical students. Students in this cohort demonstrated better diagnostic accuracy, but rates of knowledge attrition 6 months after the study remained high [1]. These findings highlight that despite continued practice remaining important, current methods of teaching ECGs do not support students in gaining in-depth understanding, nor do they enable knowledge retention.

Methods of technology-enhanced education, including visualizations, have been trialed extensively for anatomy teaching [8], with reported increases in student engagement with the content [9]. Although greater engagement does not ensure improved understanding, it may be an important component in supporting effective teaching and learning [8]. Additionally, there is evidence to show that visualization tools are capable of supporting students’ understanding of anatomy [10].

Therefore, this research team developed novel animations demonstrating the passage of electrical activity through the heart for different pathologies and showcased them alongside the corresponding live ECG traces during a web-based ECG tutorial for final-year medical students at Imperial College London. The aim of this study was to assess whether these animations are associated with the improvement of final-year medical students’ confidence in both visualizing cardiac pathology and interpreting the corresponding ECGs, compared to standard ECG teaching methods that do not involve visual animations.

Methods
The study was designed as a nonrandomized controlled trial.

Recruitment
Year 6 Bachelor of Medicine, Bachelor of Surgery students from Imperial College London were invited to participate in the study. Messages were sent through student communication channels with the description of the study and tutorial. This included a link to the study information sheet as well as a sign-up link to register their interest in participating. The first 20 students to sign up were emailed by a member of the research team with the information sheet and focus group consent form attached. Students were asked to confirm their participation by returning the signed consent form via email. Students were given a week to confirm their participation, after which the space would be offered to others who registered interest until a total of 20 confirmations were reached. The process was repeated in the following year, with a new cohort of Year 6 Bachelor of Medicine, Bachelor of Surgery students at the same point in the academic year as the original cohort.

The sample size of 20 students per teaching session was agreed by the research team based on the tutor’s preference, following their experience of what would be a feasible number of students to teach within the agreed timeframe. This decision was also
supplemented by evidence to suggest that cohorts of fewer than 30 students may enable better learning [11] and that cohorts of approximately 19 students may enable greater interaction [12].

**Design and Delivery of the Tutorial**

Prototypes for the ECG traces and animations were created on Microsoft PowerPoint by 2 junior doctors on the research team. A total of 7 ECG patterns (sinus rhythm, AF, atrial flutter, atrioventricular nodal re-entry tachycardia, atrioventricular re-entry tachycardia, right BBB, and left BBB) that are known to commonly arise in clinical practice and in exams were chosen, and the prototypes were converted into high production value animations using Adobe Illustrator and Adobe After Effects. The animations were produced by skilled members of the research team and took a collective total of 10 hours to produce. The final product consisted of a video animation of the electrical activity passing through the heart alongside an ECG rhythm strip (lead II) for the given abnormality—with the exception of BBBS, which were depicted alongside leads V1 and V6. The animation of electrical activity through the heart and the corresponding ECG trace were synchronized to demonstrate how each ECG deflection corresponds with the electrical activity within the heart. Depolarization was shown in yellow and repolarization was shown in green.

The tutorials were both delivered by a UK-based Academic Foundation doctor within the research team (LR) on Zoom (Zoom Video Communications) at a prespecified time on a weekday evening. LR has vast experience teaching medical students and designing medical educational material and had completed the Membership of the Royal Colleges of Physicians of the United Kingdom Part 1 Examination successfully at the time of delivering the sessions.

Participants logged on using their unique identifier code and kept their cameras turned off to maintain anonymity. The intervention tutorial involved going through each animation in turn and narrating the path of the electrical activity. To ensure the smooth running of the event, questions were reserved until the end of the session.

The control tutorial followed the same lesson plan as the intervention but involved the tutor narrating the path of electrical activity using an example 12-lead ECG without any animations. Participants were not explicitly told this tutorial would be the control arm but were instead invited to a standard ECG tutorial, following the same methods as the intervention. However, all participants would have read the study information sheet and known the aim of the study, which may have compromised the single-blinding process.

**Questionnaires**

An email was sent to participants 1 week prior to the tutorial with a link to an anonymous Qualtrics questionnaire to be completed before the tutorial (Multimedia Appendix 1). This questionnaire was composed of 5-point Likert-scale questions assessing participants’ confidence in interpreting ECGs and visualizing cardiovascular electrical transmission in each of the cardiovascular pathologies covered in the tutorial. The questionnaire also included multiple-choice and free-text questions inquiring about previous formats of ECG teaching experienced by participants and their views on what could be improved about current ECG teaching generally.

A similar questionnaire was repeated at the end of the tutorial to assess change in confidence using the same 5-point Likert-scale questions, as well as free-text questions inquiring about participants’ experience of the tutorial (Multimedia Appendix 1). A link and QR code to this questionnaire was shared at the end of the tutorial, prior to the start of the focus groups.

Participants were given a unique participant code, which they were asked to state at the start of each questionnaire. This enabled questionnaire responses to be paired while maintaining anonymity.

**Focus Groups**

Focus groups were only conducted at the end of the intervention tutorial. Participants who took part in the control arm were not invited for a focus group, as the primary purpose of this exercise was to understand participants’ experience of the visual animations, which were not included in the control arm. Upon the completion of the tutorial, students were divided into 4 breakout rooms on Zoom, each designed to host 5 students and a single researcher. Participants were asked to unmute microphones to participate in the semistructured focus group and were invited to keep their cameras switched off if they wished to remain anonymous. The focus groups further explored participants’ experiences of past ECG teaching and the current tutorial, with particular focus on aspects they found helpful and what could be further improved in the delivery of the tutorial and design of the visualizations (Multimedia Appendix 2). Focus group questions were designed collaboratively by the research team, with feedback from an expert qualitative researcher (see the Acknowledgments section), to ensure that the questions were adequate in informing the study’s aims and gave participants the opportunity to share their experiences of ECG learning openly. These were also reviewed by the ethics committee (see the Ethical Considerations section).

Focus groups were audio and video recorded on the platform. Recordings were deleted upon transcription, which took place within 2 weeks of the tutorial. Participants were asked if they wished to receive a copy of the transcription to review their statements (anonymized using their unique participant codes); those who asked for the transcription were sent the transcript by email and given 1 week to inform the research team of any redactions they wished to make.

**Data Analysis**

Questionnaire data were analyzed using descriptive statistics on Microsoft Excel. The Shapiro-Wilk test was used to determine the distribution of data. As this showed that the data were nonparametric, Wilcoxon signed-rank tests were used to assess the statistical significance of any reported changes in confidence between pre- and posttutorial questionnaire responses, for each of the intervention and control arms. The Mann-Whitney U test was used to compare differences in pre- and posttutorial confidence between the intervention and control arms of the study.
Focus group transcripts were analyzed using inductive thematic analysis, following Braun and Clarke’s [13] stages of thematic analysis as guidance. This was done on NVivo 12.0 (Lumivero) by 2 researchers cooperatively. Themes were reviewed by a third researcher. Free-text questions from the questionnaires were analyzed following similar methods on Microsoft Excel.

Ethical Considerations

This study was approved by the Imperial College Education Ethics Review committee (EERP2122-086). Participation in questionnaires and focus groups was voluntary, with participants given the option to withdraw from the study at any point, up until 2 weeks following the completion of the postintervention questionnaire. All participants were provided with a study information sheet prior to confirming their consent for participation in the study. There was no financial compensation involved in this study. Information sheets explained the aim of the study, methods of data storage, and outputs. Participants were also provided with a unique identifier code generated by the research team to be placed at the start of the questionnaires, enabling data to remain paired while ensuring anonymity.

Results

Questionnaire Results

The first 20 students who signed up to participate in each tutorial were allocated a slot.

In the intervention tutorial, a total of 19 students attended. Of these, 15 (79%) completed both the pre- and posttutorial questionnaires.

All participants confirmed at least 1 prior method of ECG teaching, including didactic lectures (13/15, 87%), case-based tutorials (11/15, 73%), memorization of ECG features (9/15, 60%), animations (2/15, 13.3%), and practical sessions (1/15, 7%).

Overall, in the intervention group, median results for confidence in interpreting ECGs increased from the pretutorial scores (2, IQR 1.5-3) to the posttutorial scores (3, IQR 3-4.5; P<.001). Improvement was seen in both confidence in reviewing and diagnosing cardiac rhythms (Figure 1) and in visualizing electrical activity throughout the heart (Figure 2), across most of the pathologies illustrated.
Figure 1. Confidence in reviewing and diagnosing cardiac rhythms and pathology on an ECG (median and IQR score on a Likert scale, from a 1=not confident at all to 5=extremely confident) for the intervention group (n=15). Wilcoxon signed-rank test results: *$P \leq 0.05$, **$P \leq 0.01$, and ***$P \leq 0.001$. AVNRT: atrioventricular nodal re-entry tachycardia; AVRT: atrioventricular re-entry tachycardia; ECG: electrocardiography; LBBB: left bundle branch block; RBBB: right bundle branch block.
Participants showed the least confidence in reviewing and diagnosing ventricular pathologies compared to atrial pathologies, with atrioventricular nodal re-entry tachycardia and atrioventricular re-entry tachycardia scoring the lowest median confidence scores before and after the tutorial but also showing the greatest levels of improvement following the tutorial (Figure 1; Table S1 in Multimedia Appendix 3).

A similar pattern is observed for median scores in visualizing cardiac electrical activity (Figure 2; Table S2 in Multimedia Appendix 3). However, median confidence levels before the tutorial in this category were, overall, lower than the same measurement of confidence for reviewing and diagnosing cardiac rhythms. Nevertheless, the level improvement in confidence in visualizing electrical activity in the heart was overall greater than that in confidence in reviewing and diagnosing cardiac rhythms, with median posttutorial confidence levels also achieving higher levels in most cardiac pathologies than those for reviewing and diagnosing cardiac rhythms.

Participants reported greater enjoyment of this tutorial (median 4, IQR 3-4.5) compared to past ECG teaching (median 3, IQR 1.5-3; P=.02).
For the control arm of the study, a total of 14 students attended the tutorial, of which 13 (93%) completed both the pre- and posttutorial questionnaires.

Prior methods of ECG teaching were similar to those of the intervention group, including didactic lectures (11/13, 85%), case-based tutorials (10/13, 77%), memorization of ECG features (6/13, 46%), practical sessions (3/13, 23%), animations (2/13, 15%), and a website with example ECGs for self-learning (1/13, 8%).

Overall confidence in interpreting ECGs showed only slight improvement in the control group, from a median of 3 (IQR 2-3) to 3 (IQR 3-4; \(P=.01\)).

Pretutorial confidence scores were similar in the control and intervention arms (Table 1). For the control group, pretutorial median confidence scores were also lower for ventricular pathologies compared to atrial pathologies, and overall confidence scores for reviewing and diagnosing cardiac pathologies were higher than visualizing cardiac activity, which is similar to the pattern seen in the intervention group (Multimedia Appendix 4).

### Table 1. Pretutorial median (IQR) confidence scores for control and intervention groups with \(P\) values (Mann-Whitney \(U\) Test).

<table>
<thead>
<tr>
<th>Scores and pathologies</th>
<th>Intervention, median (IQR)</th>
<th>Control, median (IQR)</th>
<th>(P) value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Confidence in reviewing and diagnosing cardiac rhythms and pathology on an ECG</strong>&lt;sup&gt;a&lt;/sup&gt;</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sinus rhythm</td>
<td>4.0 (3.4-4.0)</td>
<td>5.0 (3.9-5.0)</td>
<td>.07</td>
</tr>
<tr>
<td>Atrial flutter</td>
<td>3.0 (1.8-3.8)</td>
<td>3.3 (3.9-5.0)</td>
<td>.35</td>
</tr>
<tr>
<td>Atrial fibrillation</td>
<td>3.7 (2.4-4.1)</td>
<td>4.0 (3.0-4.0)</td>
<td>.19</td>
</tr>
<tr>
<td>AVNRT&lt;sup&gt;b&lt;/sup&gt;</td>
<td>1.5 (1.1-2.1)</td>
<td>2.0 (1.3-2.5)</td>
<td>.32</td>
</tr>
<tr>
<td>AVRT&lt;sup&gt;c&lt;/sup&gt;</td>
<td>1.5 (1.1-2.3)</td>
<td>2.0 (1.5-2.5)</td>
<td>.39</td>
</tr>
<tr>
<td>RBBB&lt;sup&gt;d&lt;/sup&gt;</td>
<td>2.2 (1.4-2.9)</td>
<td>2.5 (2.0-3.5)</td>
<td>.28</td>
</tr>
<tr>
<td>LBBB&lt;sup&gt;e&lt;/sup&gt;</td>
<td>2.2 (1.4-2.9)</td>
<td>2.5 (2.0-3.5)</td>
<td>.33</td>
</tr>
</tbody>
</table>

### Confidence in visualizing electrical activity on an ECG

<table>
<thead>
<tr>
<th>Scores and pathologies</th>
<th>Intervention, median (IQR)</th>
<th>Control, median (IQR)</th>
<th>(P) value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sinus rhythm</td>
<td>3.0 (2.5-4.5)</td>
<td>4.0 (2.0-4.0)</td>
<td>.59</td>
</tr>
<tr>
<td>Atrial flutter</td>
<td>2.0 (1.0-3.0)</td>
<td>2.0 (1.0-2.0)</td>
<td>&gt;.99</td>
</tr>
<tr>
<td>Atrial fibrillation</td>
<td>3.0 (1.5-3.0)</td>
<td>2.0 (1.0-4.0)</td>
<td>.98</td>
</tr>
<tr>
<td>AVNRT</td>
<td>2.0 (1.0-3.0)</td>
<td>2.0 (1.0-3.0)</td>
<td>.94</td>
</tr>
<tr>
<td>AVRT</td>
<td>2.0 (1.0-3.0)</td>
<td>2.0 (1.0-2.0)</td>
<td>.68</td>
</tr>
<tr>
<td>RBBB</td>
<td>1.0 (1.0-2.0)</td>
<td>2.0 (1.0-4.0)</td>
<td>.18</td>
</tr>
<tr>
<td>LBBB</td>
<td>1.0 (1.0-2.0)</td>
<td>2.0 (1.0-4.0)</td>
<td>.18</td>
</tr>
</tbody>
</table>

### Overall confidence in interpreting ECGs

<table>
<thead>
<tr>
<th>Scores and pathologies</th>
<th>Intervention, median (IQR)</th>
<th>Control, median (IQR)</th>
<th>(P) value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.0 (1.0-3.0)</td>
<td>3.0 (2.0-3.0)</td>
<td>.50</td>
</tr>
</tbody>
</table>

<sup>a</sup>ECG: electrocardiography.

<sup>b</sup>AVNRT: atrioventricular nodal re-entry tachycardia.

<sup>c</sup>AVRT: atrioventricular re-entry tachycardia.

<sup>d</sup>RBBB: right bundle branch block.

<sup>e</sup>LBBB: left bundle branch block.

There was no statistically significant difference between the enjoyment of this tutorial (median 4, IQR 4-5) compared to past ECG teaching (median 4, IQR 3-4; \(P=.052\)).

When comparing the change in confidence between the control and intervention groups for both reviewing and diagnosing pathology and visualizing electrical activity, no statistically significant difference was seen across all pathologies (all \(P>.05\)).

Data for confidence in reviewing and diagnosing cardiac rhythms and pathology showed greater improvements in the intervention group across most pathologies, except for AF. The greatest absolute difference between the intervention and control groups was seen for left BBB, although this was still statistically nonsignificant (\(P=.89\); Figure 3). Data for confidence in visualizing cardiac electrical activity showed similar median changes in confidence across most pathologies, apart from right and left BBBS, where the intervention group showed greater improvement, although not statistically significant (\(P=.15\) and \(P=.12\), respectively; Figure 4).

There was also no statistically significant difference in median scores for the enjoyment of the tutorial when comparing control and intervention groups (\(P=.37\)).
Figure 3. Median (IQR) scores for absolute difference in confidence in reviewing and diagnosing cardiac rhythms and pathology on an ECG for control (n=13) and intervention (n=15) groups. AVNRT: atrioventricular nodal re-entry tachycardia; AVRT: atrioventricular re-entry tachycardia; ECG: electrocardiography; LBBB: left bundle branch block; RBBB: right bundle branch block.
Focus Group Results

Overview

A total of 15 (79%) out of 19 participants who attended the intervention tutorial took part in the focus groups. These were preallocated at random into 4 separate groups, which contained between 2 to 5 students (1 with 5 students, 2 with 4 students, and 1 with 2 students). Three key themes emerged from the analysis of focus group transcripts.

Past ECG Learning Has Been Centered on the Clinical Context and Memorizing Traces

All participants noted varied past ECG teaching, including formal lectures and tutorials focused on the principles of ECG interpretation throughout medical school but also informal teaching while on placement. However, there was an agreement that ECGs remained a challenging concept to learn. For example, one participant noted that they “found [ECGs] hard to understand and engage [with]” (participant 8), whereas another explained how “an ECG can kind of be a different language almost” (participant 7) and hence may take more time and effort to understand.

Figure 4. Median (IQR) scores for absolute difference in confidence in visualizing electrical activity through the heart in different ECG pathologies for control (n=13) and intervention (n=15) groups. AVNRT: atrioventricular nodal re-entry tachycardia; AVRT: atrioventricular re-entry tachycardia; ECG: electrocardiography; LBBB: left bundle branch block; RBBB: right bundle branch block.
Past teaching experienced by participants, particularly informal teaching on placement, also focused on pattern recognition and correlating ECG signs to diagnoses.

*I think at least with the ones I went through with the doctors and stuff, it was very much like a tick box or like oh the saw tooth pattern is this, this is this…* [Participant 12]

Although this format of learning was concise and focused on key knowledge required to be a Foundation Year 1 doctor, it did not promote deeper understanding of ECGs that could be applied to any ECG pattern.

*I’d kind of leave knowing that if that exact ECG comes up, that was helpful, but otherwise I don’t know really what or why it is that and then some of the actual understanding came from doing work outside of firms.* [Participant 30]

Participants also highlighted that “the key thing is kind of just repetition” (participant 7) when learning to interpret ECGs, and that “you also have to dedicate time yourself to go through it, if you really want to properly understand it” (participant 33).

Being taught systematic methods for ECG interpretation and presentation was reported to be useful; namely, it was “more relevant to us and our exams and practicals” (participant 15) when going through clinical cases alongside ECGs, which help provide clinical context to the ECG and “also gets you used to different subtleties, because between patients an ECG of the same condition can look slightly different” (participant 6).

The Animations and Associated Explanations Promoted a Deeper Understanding of Cardiac Electrical Activity

Overall, participants found the animations and accompanying explanations during the tutorial to be a helpful tool. The depiction of an ECG trace and heart animation simultaneously helped them understand the correlation between the 2, and hence, as a participant stated, “the first time I’ve properly understood what is exactly is going on [in the heart]” (participant 1) for the pathologies illustrated. One participant highlighted that “breaking it down into basics…and how it’s reflected in the heart as well as it’s corresponding trace…feels less like I’m trying to memorise something and more like I’m actually trying to figure it out” (participant 17).

The visual nature of these animations enabled participants to “clearly see how the electricity is conducted in the heart” (participant 2) and was noted to be an effective method to “consolidate what I know about the conditions that we went through” (participant 2).

This more thorough level of understanding was noted to be “quite useful” to participants, as “when going on the wards and I see an ECG, I can actually visualise how the heart is functioning” (participant 17). It was also perceived to be a helpful way of retaining their learning about heart pathologies and associated ECG traces in the longer-term, as “when you understand the reason why something is the way it is you are more likely to remember it” (participant 15).

Participants also stated the value of covering content that they considered relevant to their exams and starting work as Foundation Year 1 doctors: “I enjoyed the fact that we covered like a lot of a main conditions, so less of the more niche stuff” (participant 7). They also described this tool as more of a helpful “recap” (participant 2) of heart conditions and their associated ECG traces, as opposed to methods of ECG interpretation, which are often the focus in later years of medical school. One participant explained, “I just wish we were taught this way before [in earlier years of medical school]; it would make understanding a lot easier later” (participant 12).

Implementing This 1-Hour Tutorial Is Not Enough: ECG Learning Requires Repetition and Clinical Links Remain Essential

The key differentiating component of this tutorial was its animations: “I’m a visual learner, so I need to see it to understand it. So that’s what’s been a gamechanger for me, to actually see the animation” (participant 32). However, participants suggested that “having [the animation playing] even slower” (participant 8) or the opportunity to independently “use the scroller to advance” (participant 32) through the animation would be helpful to visualize more carefully “what is happening step-by-step in the heart and on the ECG” (participant 32). One participant also suggested potential value in “3D animations, that would be useful so you can turn the heart around and see all the fibres and all the [conduction activity]” (participant 17).

Despite the value of the tutorial in supporting students’ understanding of cardiac pathologies, participants highlighted that there are additional factors that are important in contributing to in-depth learning. For instance, the need for repetition was widely acknowledged. Participants therefore asked that animations be made available for them to view independently. Additionally, the fast-paced nature of the tutorial, which covered multiple pathologies, means that some participants “didn’t really have much of a time to get an understanding again, of like the condition” (participant 7), which might be resolved through independent revision with the animations or delivering the content through multiple teaching sessions.

Finally, participants noted the value of greater interaction with the audience, including the implementation of quizzes to test understanding and the integration of clinical cases for stronger clinical correlations.

Discussion

Overall, results for the intervention cohort demonstrate a statistically significant improvement in confidence when identifying abnormalities in ECG traces and visualizing cardiac electrical activity, compared to prior to attending this tutorial. However, a similar improvement was seen in the control group, with no statistically significant differences in improvement in confidence between the control and intervention groups. Although the focus groups highlighted a possible value in the use of animations demonstrating cardiac electrical activity synchronized to the corresponding ECG trace, the overall results suggest that perhaps this tool may be more adequate as a supplement to teaching.

Focus group transcripts provided fruitful data on how students have previously been taught how to interpret ECGs, how their
previous learning compared to how this tutorial was delivered, and what they thought of the animations used to support the tutorial delivery. Moreover, information on how to improve the session was also collected. The main themes that arose were that ECGs are regarded as a complex topic among students and that past ECG learning used CBL and involved the memorization of traces. Other main themes include that the animations and associated explanations promote a deeper understanding of cardiac electrical activity (compared to past teaching) and that ECG learning requires repetition and clinical links remain essential. Students noted that their most helpful past teaching involved cases and clinical contextualization, which should therefore be considered in any form of teaching implemented to final-year students, as clinical context appears to be their learning priority.

The key commonality between the control and intervention groups was the provision of a concise explanation of cardiac electrical activity in the heart for each section of the ECG trace. Therefore, future studies may benefit from investigating ways of delivering this content most effectively, for example through CBL or team-based learning [14-16], or similar methods of enabling greater interaction between students, but with a focus on understanding the pathology as opposed to focusing on pattern recognition.

This study and its teaching session do not come without some limitations. For reasons described in the Methods section, this study was limited to up to 20 participants in each arm and was based in a single study-year group and university. Therefore, it is not possible to confirm that these results are generalizable. No data were collected on the demographics of participants, which would also be helpful in determining the generalizability of the findings. Furthermore, this study also did not directly assess knowledge; instead, it assessed confidence in knowledge. Confidence has greater subjectivity than knowledge-based assessments and is not a reliable alternative to assessing student learning. Therefore, future evaluations of these animations would benefit from a validated assessment of students before and after the tutorial.

The teaching session itself would have benefited from greater interactivity, which has been showed to be an important element to teaching [14-16]. The session was delivered in a more didactic way, compared to CBL or team-based learning methods, which may have compromised student engagement and therefore learning. None of these elements were incorporated in the teaching session mainly due to time constraints but also to maintain the focus of the session on evaluating the value of the animations in improving student confidence. For instance, the inclusion of cases would act as a confounding variable as students may be able to understand the pathology from the case rather than from interpreting the ECG, whereas other students might not have engaged as much with the animations when in a team compared to when working individually. It is important to note that clinical context is important, as supplementing teaching materials with a patient case helps students to better diagnose, investigate, and manage cardiac conditions, thus improving their clinical reasoning skills [16].

The animations are likely to be even more valuable if used alongside other helpful learning tools, including the design of more interactive tutorials by involving quizzes throughout and gamification, which is a concept recently discussed in the literature, wherein game design elements are used in nongame contexts to promote users’ engagement [17]. Moreover, future teaching sessions would benefit from including the aforementioned clinical scenarios prior to demonstrating each pathology, intertwining the learning of relevant pathophysiology with clinical knowledge. Although the latter would allow greater contextualization and demonstrate the relevance of the learning to clinical practice, the former would provide the required background knowledge to understand the clinical manifestations, and management, of disease.

In addition, it is important to acknowledge that for students to confidently be able to interpret ECGs, they need to apply the concepts of spaced learning and repetition. Future teaching could be accompanied by resources such as a recording of the session, the slides and animations used, as well as single–best answer questions to enable students to consolidate and test their learning. A more appropriate method of using these animations may therefore be to provide these to students as an independent learning resource. When doing so, it would enable students to scroll through the animation and independently control its speed to match their learning needs and understanding. Additionally, students suggested to make the animation 3D and to demonstrate the full 12-lead ECG alongside the animation as opposed to a single lead only.

In conclusion, this study suggests that although incorporating visual animations to demonstrate the electrical activity of different pathologies in ECG teaching may be beneficial in improving students’ confidence in interpreting ECGs and understanding the underlying pathology, it is not the only way that this can be achieved. Students benefited equally from verbal explanations, suggesting that the most essential part of future ECG teaching is providing emphasis on the relevant pathophysiology, presented alongside clinical vignettes in which discussions regarding investigations and management options can be made. Interactivity within teaching sessions using quizzes and spaced practice is also recommended, in which students can access the resources, including the animation used in the session, later, to help consolidate their learning. Nevertheless, the development of animations was a low-cost intervention enjoyed by students and was reported to support their learning and understanding of cardiac pathophysiology and interpretation of ECG traces. Therefore, it is hoped that making these animations available to students as a revision resource can supplement their current ECG teaching and individual study practices.
Acknowledgments

We would like to thank Dr Ana Baptista for the support and guidance in preparing the ethics application and reviewing the study design. Open-access publication fees for this article were covered by the Imperial College Open Access Fund.

Data Availability

Questionnaire data sets have been made available in Multimedia Appendix 5.

Conflicts of Interest

AMCP, DS, AD-B, and TR are volunteers at and LR is the founder of a medical charity, Make a Medic, which may consider developing and implementing the educational tool piloted in this study. However, the authors hold no financial or other similar benefits from this work or its outcomes.

Multimedia Appendix 1

Questionnaires.
[DOCX File, 23 KB - mededu_v10i1e46507_app1.docx ]

Multimedia Appendix 2

Focus group questions.
[DOCX File, 8 KB - mededu_v10i1e46507_app2.docx ]

Multimedia Appendix 3

Intervention data.
[DOCX File, 29 KB - mededu_v10i1e46507_app3.docx ]

Multimedia Appendix 4

Control data and figures.
[DOCX File, 149 KB - mededu_v10i1e46507_app4.docx ]

Multimedia Appendix 5

Raw data.
[XLSX File, 23 KB - mededu_v10i1e46507_app5.xlsx ]

References


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Abbreviations
- AF: atrial fibrillation
- BBB: bundle branch block
- CBL: case-based learning
- ECG: electrocardiography

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Original Paper

Nursing Students’ Attitudes Toward Technology: Multicenter Cross-Sectional Study

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Abstract

Background: The growing presence of digital technologies in health care requires the health workforce to have proficiency in subjects such as informatics. This has implications in the education of nursing students, as their preparedness to use these technologies in clinical situations is something that course administrators need to consider. Thus, students’ attitudes toward technology could be investigated to assess their needs regarding this proficiency.

Objective: This study aims to investigate attitudes (enthusiasm and anxiety) toward technology among nursing students and to identify factors associated with those attitudes.

Methods: Nursing students at 2 universities in Sweden and 1 university in Poland were invited to answer a questionnaire. Data about attitudes (anxiety and enthusiasm) toward technology, eHealth literacy, electronic device skills, and frequency of using electronic devices and sociodemographic data were collected. Descriptive statistics were used to characterize the data. The Spearman rank correlation coefficient and Mann-Whitney U test were used for statistical inferences.

Results: In total, 646 students answered the questionnaire—342 (52.9%) from the Swedish sites and 304 (47.1%) from the Polish site. It was observed that the students’ technology enthusiasm (techEnthusiasm) was on the higher end of the Technophilia instrument (score range 1-5): 3.83 (SD 0.90), 3.62 (SD 0.94), and 4.04 (SD 0.78) for the whole sample, Swedish students, and Polish students, respectively. Technology anxiety (techAnxiety) was on the midrange of the Technophilia instrument: 2.48 (SD 0.96), 2.37 (SD 1), and 2.60 (SD 0.89) for the whole sample, Swedish students, and Polish students, respectively. Regarding techEnthusiasm among the nursing students, a negative correlation with age was found for the Swedish sample ($\rho_{\text{Swedish}}=-0.201$) who were generally older than the Polish sample, and positive correlations with the eHealth Literacy Scale score ($P<.001; \rho_{\text{all}}=0.265; \rho_{\text{Swedish}}=0.190; \rho_{\text{Polish}}=0.352$) and with the perceived skill in using computer devices ($P<.001; \rho_{\text{all}}=0.360; \rho_{\text{Swedish}}=0.341; \rho_{\text{Polish}}=0.309$) were found for the Swedish, Polish, and total samples. Regarding techAnxiety among the nursing students, a positive correlation with age was found in the Swedish sample ($P<.001; \rho_{\text{Swedish}}=0.184$), and negative correlations...
with eHealth Literacy Scale score ($P<.001$; $\rho_{\text{all}}=-0.196$; $\rho_{\text{Swedish}}=-0.262$; $\rho_{\text{Polish}}=-0.133$) and with the perceived skill in using computer devices ($P<.001$; $\rho_{\text{all}}=-0.209$; $\rho_{\text{Swedish}}=-0.347$; $\rho_{\text{Polish}}=-0.134$) were found for the Swedish, Polish, and total samples and with the semester only for the Swedish sample ($P<.001$; $\rho_{\text{Swedish}}=-0.124$). Gender differences were found regarding techAnxiety in the Swedish sample, with women exhibiting a higher mean score than men (2.451, SD 1.014 and 1.987, SD 0.854, respectively).

**Conclusions:** This study highlights nursing students’ techEnthusiasm and techAnxiety, emphasizing correlations with various factors. With health care’s increasing reliance on technology, integrating health technology–related topics into education is crucial for future professionals to address health care challenges effectively.

**International Registered Report Identifier (IRRID):** RR2-10.2196/14643

**KEYWORDS**
nursing education; technophilia; eHealth; technology anxiety; technology enthusiasm; mobile phone

**Introduction**

**Background**

Health care costs have been growing faster than the economy for the past 17 years [1]. This upward trend is due to multifactorial causes related to the growth and aging of the population, increased prevalence of lifestyle-related noncommunicable diseases, increased prices of health services and pharmaceuticals, and the risk of global pandemics [2-4]. All these factors put high pressure on the health care systems, which have to deal with many challenges related to efficiency and productivity. The digitalization of the health care sector is strongly influencing the efforts to address health care challenges and involves the use of technologies such as information and communication technologies in health settings, which was later termed as eHealth [5].

The integration of eHealth in the health care sector points to greater use of technology to access health data, manage eHealth records, and engage in telehealth platforms, among others [6]. This is such an important topic that the European Commission issued the Digital Decade Policy Program targeting Europe’s digital transformation by 2030 [7]. This policy envisions, among other goals, the achievement of a digitally skilled population, highlighting the importance of a highly digitally skilled health care workforce and inspiring initiatives in different European countries. In the United States, a similar government initiative promotes the use of health technologies to improve the quality, safety, and efficiency of and reduce disparities in health care delivery [8]. The merging of health care workforce and digital technologies became so evident that informatics is outlined as one of the core competencies in the nursing profession: “use information and technology to communicate, manage knowledge, mitigate error and support decision making” [9]. Accordingly, it is also increasingly important for registered nurses to become proficient in this aspect.

Incorporation of health technologies into nursing education and the preparedness of the new students to use these in clinical scenarios and practice are highly important and a growing concern for program administrators, educators, researchers, policy makers, and employers [10]. This concern is valid because despite many students having grown up with technology ingrained in their everyday life, they still report low confidence, difficulties, and not-so-positive views about applying digital skills in clinical contexts [11-15]. Therefore, it is important to investigate the nursing students’ attitudes toward technologies, so that appropriate decisions can be made for educational purposes that might affect future patient care.

Many models assess user interaction with technology according to factors such as acceptance, motivation, adoption, adaptivity, and usability, which are known to play a role in technology use [16]. However, it is argued that both cognitive and emotional effectiveness affect behavior, and these are underlying factors that precede the specific, planned, and reasoned actions directed toward technology [17,18]. The concept of technophilia is a personality trait and a psychological construct that is related to a person’s enthusiasm or positive feelings toward technology use and the absence of anxiety or fears and doubts regarding technology [19], and it is a general quality that could potentially influence a wide range of aspects of technology use. Contrary to models tailored to specific organizational tasks, the investigation of technophilia could provide a better picture of the students’ needs regarding this proficiency.

**Objectives**

This study comprises a multicenter, cross-sectional investigation of technophilia among nursing students that aimed to (1) establish the levels of technophilia among nursing students of 3 educational institutions in Sweden and Poland regarding their enthusiasm and anxiety and (2) identify factors that could be associated with the students’ technology enthusiasm (techEnthusiasm) and technology anxiety (techAnxiety).

**Methods**

**Study Design**

This study used a multicenter, cross-sectional design based on questionnaire data collected from nursing students in 3 different universities, in Sweden and Poland, in different stages in their education. The protocol for this study has been described previously [20]. This study adhered to the STROBE (Strengthening the Reporting of Observational studies in Epidemiology) guideline for cross-sectional studies (Multimedia Appendix 1).

**Setting**

We collected data in the period between December 2019 and April 2020, using questionnaires administered to students
enrolled in the nurse education programs of 3 universities: 2 in Sweden (Blekinge Institute of Technology [BTH] and Swedish Red Cross University [SRCU]) and 1 in Poland (Medical University of Bialystok [MUB]). The undergraduate nursing education of both countries adheres to the European Union requirements, which comprises 180 European Credit Transfer and Accumulation System (ECTS) credits at the university level [21,22]. The educational programs in both countries result in a professional degree (ie, a diploma) and an academic degree (ie, a bachelor’s degree), qualifying for a license as a registered nurse. At the time the study, the Swedish nursing education consisted of both theoretical and clinical practice courses—60% and 40% of the total curriculum, respectively. At the Polish institution, MUB, the nursing program consisted of 52% theoretical courses and 48% clinical practice courses. The students’ exposure to eHealth or health technology courses at the time of the data collection was as follows:

- At BTH, eHealth is covered in nursing subjects during the whole program and in two dedicated courses in the curriculum:
  1. An eHealth introductory course is offered in the third semester to all students (4.5 ECTS), which was completed at the time of the data collection.
  2. An optional course on digitalization and eHealth was offered in the fifth semester (7.5 ECTS). It was chosen by approximately one-third of the fifth-semester students and was ongoing at the time of the data collection.

- At SRCU, eHealth was also incorporated into nursing subjects during the whole program and 1 optional course (7.5 ECTS) in medical technology, digitalization, and eHealth was offered in the fifth semester. However, this course started 5 weeks after this study’s data collection.

- At MUB, eHealth was incorporated into nursing courses during the whole program.

Participants and Data Collection Procedures
A convenience sample of undergraduate nursing students, enrolled at the bachelor of nursing program at BTH, SRCU, and MUB, was used in this study. Students from the first, third, and fifth semesters were eligible to participate in this study. These semesters were chosen to obtain a sample incorporating the beginning, middle, and end of nursing education, which comprises 6 semesters.

Data were collected using a paper-based questionnaire administered to all undergraduate students from the first, third, and fifth semesters of the participating universities by research members who had no educational connections to the students. This was done to minimize response bias.

Questionnaire
The questionnaire was used to collect data about the participants’ sociodemographics, self-reported attitudes toward technology, eHealth literacy, perceived skills in using electronic devices, and frequency of using electronic devices.

Data on Attitudes Toward Technology (Technophilia Instrument)
The outcome measures of this study are the self-reported data on attitudes toward technology scored by the Technophilia instrument (TechPH) [19]. The TechPH comprises 6 questions to capture behaviors related to adaptation and use of a new technology, which were derived from the content analysis of relevant technophilia measures. It results in 2 numeric scores ranging from 1 (low) to 5 (high): techEnthusiasm and techAnxiety. The TechPH was originally developed for measuring older adults’ attitudes toward technology; however, published studies have already applied it on younger individuals, physicians, and dementia caretakers aged 18 to 44 years [23,24]. In this study, techEnthusiasm and techAnxiety have Cronbach α of 1 and 0.925, respectively, showing excellent internal consistency.

Sociodemographic Data
Sociodemographic data consisted of the participants’ age; gender; focus of high school studies (health or social care, technology, or other); and previous work experience (health or social care, technology, or other).

eHealth Literacy Data (eHealth Literacy Scale)
The eHealth literacy was scored using the eHealth Literacy Scale (eHEALS) instrument [25]. The eHEALS is a self-report tool consisting of 8 questions and has already been validated in many languages and diverse populations including undergraduate health professionals [25,26]. The eHEALS produces a score ranging from 1 (low eHealth literacy) to 5 (high eHealth literacy).

Data on Perceived Skill in and Frequency of Using Technological Devices
Perceived skills in using electronic devices, namely, computers or laptops, tablets, and smartphones, were rated using a Likert-type scale ranging from 1 (not knowledgeable at all) to 5 (very knowledgeable). The frequencies of using electronic devices were rated using a Likert-type scale ranging from 1 (several times daily) to 5 (never).

Data Analysis
The descriptive statistics, namely, frequency, mean, and SD, were used to analyze the collected data. The Shapiro-Wilk test was used to assess data distribution. As the data were not normally distributed, nonparametric tests were used in the statistical analyses. Spearman rank correlation coefficient was used to measure the association among age, semester, perceived skills in using computers or laptops, and frequency of using electronic devices via the self-reported TechPH components—techEnthusiasm and techAnxiety. CIs were calculated to analyze the stability of the results. Mann-Whitney U test was used to assess gender differences regarding students’ enthusiasm and anxiety toward technology. Sensitivity analyses were performed by removing the outliers and revealed that the interpretations were unperturbed, showing that extreme data points did not impact the study outcomes. For all the analyzes, a significance level of .05 was used. Stratification was used; therefore, results are presented for the whole sample, Swedish
students, and Polish students separately, to control for confounding. Entries with missing data were omitted from the analysis. The analyses were performed using R (version 1.4.1717; RStudio).

**Ethical Considerations**

The study was conducted in accordance with the Declaration of Helsinki [27]. Participation in the study was voluntary. All participants were briefed about the study aims; that they could choose to not submit the questionnaire or submit it blank; and that by submitting the questionnaire, they would consent to participate in the study. All collected data were anonymous.

Permission to conduct the study was obtained from heads of the departments at all participating universities. In Poland, ethics approval was obtained from the ethics committee of Medical University of Bialystok (register number R-I-002/148/2017). In Sweden, the study did not require ethics approval according to the requirements of the Swedish Ethical Review Act 2003:460, 3-4§ [28], as the study did not explore sensitive personal data (eg, health, religion, political views, and ethnic heritage) or data relating to criminal offenses, did not involve physical intervention on the participants, and did not aim to affect the participants in any way or involve biological material.

**Results**

**Sample Characteristics**

In total, 646 students answered the questionnaire—342 (52.9%) from the Swedish sites and 304 (47.1%) from the Polish site. The response rates were 70.2% (646/920) for the whole sample, 63.1% (342/542) for the Swedish students, and 80.4% (304/378) for the Polish students. Nonresponders include students who decided not to submit the questionnaire or to submit it blank. None of the variables used in the analyses contained >5% of missing values.

The descriptive statistics are shown in Table 1, for the whole sample and for the Swedish and Polish students separately. Multimedia Appendix 2 shows the descriptive statistics along with the means and SDs for the techAnxiety and techEnthusiasm for each grouping shown in Table 1—for the whole sample, Swedish students, and Polish students separately. The mean age of the sample is 23.9 (SD 6.39) years, with the Swedish students being generally older and having a higher age variance (mean 27, SD 7.34 years) compared with the Polish students (mean 20.4, SD 1.72 years), as shown in Figure 1. While the Polish sample has a distribution that is more concentrated around the mean, the Swedish sample has a flatter distribution of ages. The sample was majorly composed of women students (555/646, 85.9%). Very few students had a high school focus on or previous work experience with technology before their nursing education. Overall, 50.3% (153/304) of the Polish students had a health and social care focus in high school, while this number was 23.9% (82/342) for the Swedish students. In terms of perceived skill in using electronic devices, most participants perceive themselves “knowledgeable” or “very knowledgeable” in all 3 categories: computers (479/646, 74.1%), smartphones (574/646, 88.9%), and tablets (388/646, 60.1%). Furthermore, 48.6% (314/646) of the participants answered that they use computers or laptops “several times daily” or “daily,” while this number reached 98.8% (638/646) for smartphones and 11.2% (72/646) for tablets. The students showed an overall high eHealth literacy, with 93.3% (603/646) scoring ≥3 points. The mean eHEALS scores for the overall, Polish, and Swedish samples were 3.95 (SD 0.75), 3.96 (SD 0.78), and 3.95 (SD 0.73), respectively, constituting high scores and showing an overall high perceived eHealth literacy.
<table>
<thead>
<tr>
<th></th>
<th>All students (N=646), n (%)</th>
<th>Swedish students (n\textsubscript{Sweden}=342), n (%)</th>
<th>Polish students (n\textsubscript{Poland}=304), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age (years)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18-25</td>
<td>478 (73.9)</td>
<td>179 (52.3)</td>
<td>299 (98.4)</td>
</tr>
<tr>
<td>&gt;25</td>
<td>168 (26)</td>
<td>163 (47.7)</td>
<td>5 (1.6)</td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Women</td>
<td>555 (85.9)</td>
<td>284 (83)</td>
<td>271 (89.1)</td>
</tr>
<tr>
<td>Men</td>
<td>89 (13.8)</td>
<td>56 (16.4)</td>
<td>33 (10.9)</td>
</tr>
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<td><strong>Semester</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>289 (44.7)</td>
<td>158 (46.2)</td>
<td>131 (43.1)</td>
</tr>
<tr>
<td>3</td>
<td>208 (32.2)</td>
<td>101 (29.5)</td>
<td>107 (35.2)</td>
</tr>
<tr>
<td>5</td>
<td>149 (23.1)</td>
<td>83 (24.2)</td>
<td>66 (21.7)</td>
</tr>
<tr>
<td><strong>eHEALS\textsuperscript{a} score</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;3</td>
<td>43 (6.7)</td>
<td>23 (6.7)</td>
<td>24 (7.9)</td>
</tr>
<tr>
<td>≥3</td>
<td>603 (93.3)</td>
<td>319 (93.3)</td>
<td>284 (93.4)</td>
</tr>
<tr>
<td><strong>High school focus</strong></td>
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<td></td>
</tr>
<tr>
<td>Health and social care</td>
<td>235 (36.4)</td>
<td>82 (23.9)</td>
<td>153 (50.3)</td>
</tr>
<tr>
<td>Technology</td>
<td>25 (3.9)</td>
<td>11 (3.2)</td>
<td>14 (4.6)</td>
</tr>
<tr>
<td>Other</td>
<td>374 (57.9)</td>
<td>242 (70.8)</td>
<td>132 (43.4)</td>
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<tr>
<td><strong>Previous work experience</strong></td>
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<td></td>
</tr>
<tr>
<td>Health and social care</td>
<td>211 (32.7)</td>
<td>188 (54.9)</td>
<td>23 (7.6)</td>
</tr>
<tr>
<td>Technology</td>
<td>12 (1.9)</td>
<td>7 (2)</td>
<td>5 (1.6)</td>
</tr>
<tr>
<td>Other</td>
<td>332 (51.4)</td>
<td>118 (34.5)</td>
<td>214 (70.4)</td>
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<tr>
<td><strong>Skills: computer</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1: not knowledgeable at all</td>
<td>1 (0.2)</td>
<td>0 (0)</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>2</td>
<td>19 (2.9)</td>
<td>14 (4)</td>
<td>5 (1.6)</td>
</tr>
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<td>3</td>
<td>134 (20.7)</td>
<td>93 (27.2)</td>
<td>41 (13.5)</td>
</tr>
<tr>
<td>4</td>
<td>173 (26.8)</td>
<td>106 (30.9)</td>
<td>67 (22)</td>
</tr>
<tr>
<td>5: very knowledgeable</td>
<td>306 (47.4)</td>
<td>116 (33.9)</td>
<td>190 (62.5)</td>
</tr>
<tr>
<td><strong>Skills: smartphone</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1: not knowledgeable at all</td>
<td>4 (0.6)</td>
<td>3 (0.9)</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>2</td>
<td>5 (0.8)</td>
<td>3 (0.9)</td>
<td>2 (0.7)</td>
</tr>
<tr>
<td>3</td>
<td>6 (0.9)</td>
<td>41 (11.9)</td>
<td>22 (7.2)</td>
</tr>
<tr>
<td>4</td>
<td>127 (19.7)</td>
<td>88 (25.7)</td>
<td>39 (12.9)</td>
</tr>
<tr>
<td>5: very knowledgeable</td>
<td>447 (69.2)</td>
<td>207 (60.5)</td>
<td>240 (78.9)</td>
</tr>
<tr>
<td><strong>Skills: tablets</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1: not knowledgeable at all</td>
<td>66 (10.2)</td>
<td>25 (7.3)</td>
<td>41 (13.5)</td>
</tr>
<tr>
<td>2</td>
<td>69 (10.7)</td>
<td>47 (13.7)</td>
<td>22 (7.2)</td>
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<tr>
<td>3</td>
<td>107 (16.6)</td>
<td>66 (19.3)</td>
<td>41 (13.5)</td>
</tr>
<tr>
<td>4</td>
<td>149 (23.1)</td>
<td>88 (25.7)</td>
<td>61 (20)</td>
</tr>
<tr>
<td>5: very knowledgeable</td>
<td>239 (36.9)</td>
<td>100 (29.2)</td>
<td>139 (45.7)</td>
</tr>
<tr>
<td><strong>Frequency: computer</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Several times daily</td>
<td>131 (20.3)</td>
<td>69 (20.2)</td>
<td>62 (20.4)</td>
</tr>
<tr>
<td>Daily</td>
<td>183 (28.3)</td>
<td>80 (23.4)</td>
<td>103 (33.9)</td>
</tr>
<tr>
<td>Frequency of Use</td>
<td>All students (N=646), n (%)</td>
<td>Swedish students (n&lt;sub&gt;Sweden&lt;/sub&gt;=342), n (%)</td>
<td>Polish students (n&lt;sub&gt;Poland&lt;/sub&gt;=304), n (%)</td>
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<td>------------------</td>
<td>---------------------------</td>
<td>---------------------------------</td>
<td>------------------------</td>
</tr>
<tr>
<td>Every week</td>
<td>152 (23.5)</td>
<td>85 (24.9)</td>
<td>67 (22)</td>
</tr>
<tr>
<td>Every month</td>
<td>39 (6)</td>
<td>29 (8.5)</td>
<td>10 (3.3)</td>
</tr>
<tr>
<td>Sometimes</td>
<td>98 (15.2)</td>
<td>42 (12.3)</td>
<td>56 (18.4)</td>
</tr>
<tr>
<td>Never</td>
<td>11 (1.7)</td>
<td>5 (1.5)</td>
<td>6 (1.9)</td>
</tr>
</tbody>
</table>

**Frequency: smartphone**

<table>
<thead>
<tr>
<th>Frequency of Use</th>
<th>All students (N=646), n (%)</th>
<th>Swedish students (n&lt;sub&gt;Sweden&lt;/sub&gt;=342), n (%)</th>
<th>Polish students (n&lt;sub&gt;Poland&lt;/sub&gt;=304), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Several times daily</td>
<td>576 (89.2)</td>
<td>302 (88.3)</td>
<td>274 (90.1)</td>
</tr>
<tr>
<td>Daily</td>
<td>62 (9.6)</td>
<td>34 (9.9)</td>
<td>28 (9.2)</td>
</tr>
<tr>
<td>Every week</td>
<td>3 (0.5)</td>
<td>2 (0.6)</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>Every month</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Sometimes</td>
<td>2 (0.3)</td>
<td>1 (0.3)</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>Never</td>
<td>1 (0.2)</td>
<td>1 (0.3)</td>
<td>0 (0)</td>
</tr>
</tbody>
</table>

**Frequency: tablet**

<table>
<thead>
<tr>
<th>Frequency of Use</th>
<th>All students (N=646), n (%)</th>
<th>Swedish students (n&lt;sub&gt;Sweden&lt;/sub&gt;=342), n (%)</th>
<th>Polish students (n&lt;sub&gt;Poland&lt;/sub&gt;=304), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Several times daily</td>
<td>29 (4.5)</td>
<td>23 (6.7)</td>
<td>6 (1.9)</td>
</tr>
<tr>
<td>Daily</td>
<td>43 (6.7)</td>
<td>26 (7.6)</td>
<td>17 (5.6)</td>
</tr>
<tr>
<td>Every week</td>
<td>51 (7.9)</td>
<td>38 (11.1)</td>
<td>13 (4.3)</td>
</tr>
<tr>
<td>Every month</td>
<td>23 (3.6)</td>
<td>14 (4.1)</td>
<td>9 (2.9)</td>
</tr>
<tr>
<td>Sometimes</td>
<td>138 (21.4)</td>
<td>76 (22.2)</td>
<td>62 (20.4)</td>
</tr>
<tr>
<td>Never</td>
<td>332 (51.4)</td>
<td>135 (39.5)</td>
<td>197 (64.8)</td>
</tr>
</tbody>
</table>

*a eHEALS: eHealth Literacy Scale.*
The mean and SD values for the self-reported techEnthusiasm for the whole sample, Swedish students, and Polish students were 3.83 (SD 0.90), 3.62 (SD 0.94), and 4.04 (SD 0.78), respectively, which constitutes a high overall technophilia. On the other hand, the mean and SD values for techAnxiety for the whole sample, Swedish students, and Polish students were 2.48 (SD 0.96), 2.37 (SD 1), and 2.60 (SD 0.89), respectively, displaying midrange values regarding the negative feelings toward technology.

Multimedia Appendix 2 shows the mean and SD values for both techEnthusiasm and techAnxiety according to different levels of socioeconomic, eHEALS, perceived skill, and frequency variables. The association of these variables with techEnthusiasm and techAnxiety is investigated in the following sections.

Factors Associated With TechEnthusiasm

The Spearman rank correlation coefficient was used to investigate the association of techEnthusiasm and the nonparametric variables of ordinal scale in the study, namely, age, semester, eHEALS score, perceived skill, and frequency of using electronic devices. These results are shown in terms of the Swedish, Polish, and overall samples in Table 2.
Table 2. Spearman rank correlation coefficient calculated for the whole sample, Swedish students, and Polish students separately, regarding technology enthusiasm.

<table>
<thead>
<tr>
<th></th>
<th>All students</th>
<th>Swedish students</th>
<th>Polish students</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( P ) value</td>
<td>( \rho ) (95% CI)</td>
<td>( P ) value</td>
</tr>
<tr>
<td>Age</td>
<td>&lt;.001</td>
<td>-0.238 (-0.310 to -0.163)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Semester</td>
<td>.96</td>
<td>0.002 (-0.075 to 0.079)</td>
<td>.53</td>
</tr>
<tr>
<td>eHEALS(^a) score</td>
<td>&lt;.001</td>
<td>0.265 (0.190 to 0.336)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Skill: computer</td>
<td>&lt;.001</td>
<td>0.360 (0.288 to 0.428)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Skill: smartphone</td>
<td>&lt;.001</td>
<td>0.385 (0.315 to 0.452)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Skill: tablet</td>
<td>&lt;.001</td>
<td>0.269 (0.194 to 0.342)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Frequency: computer</td>
<td>&lt;.001</td>
<td>-0.153 (-0.230 to -0.074)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Frequency: smartphone</td>
<td>.95</td>
<td>0.002 (-0.075 to 0.080)</td>
<td>.97</td>
</tr>
<tr>
<td>Frequency: tablet</td>
<td>.92</td>
<td>0.004 (-0.075 to 0.083)</td>
<td>.16</td>
</tr>
</tbody>
</table>

\(^a\)eHEALS: eHealth Literacy Scale.

A negative correlation was found between age and techEnthusiasm for the Swedish sample and overall sample, indicating that greater the age, lesser the techEnthusiasm score \( (P<.001; \rho_{\text{all}}=-0.238; \rho_{\text{Swedish}}=-0.201) \). This association might not have been significant for the Polish sample due to the lack of age variance observed in the Swedish sample (refer to Figure 1—the Polish students’ age distribution presents a heavier tail compared to the Swedish ones). A positive correlation was found between eHealth literacy and techEnthusiasm, indicating that greater the eHEALS score, greater the techEnthusiasm \( (P<.001; \rho_{\text{all}}=0.265; \rho_{\text{Swedish}}=0.190; \rho_{\text{Polish}}=0.352) \). A positive correlation was found between perceived skill in all investigated electronic devices and techEnthusiasm, indicating that greater the perceived skill, greater the techEnthusiasm (Table 2). In terms of frequency of use, a negative correlation was found between the use of computers and techEnthusiasm \( (P<.001; \rho_{\text{all}}=-0.153; \rho_{\text{Swedish}}=-0.176; \rho_{\text{Polish}}=-0.146) \). The negative values of \( \rho \) are due to the inverted Likert scale used for the question, that is, from “several times daily” to “never.” Thus, the techEnthusiasm score increases with higher frequencies of use. It is noteworthy that even with low \( \rho \) values, the significant associations found are still relevant due to the large sample size. The narrow 95% CIs indicate low variability and stability of the results.

The Mann-Whitney \( U \) test was used to assess gender differences regarding the students’ reported techEnthusiasm. No significant differences were found for Swedish, Polish, or overall samples \( (P_{\text{Swedish}}=.45, P_{\text{Polish}}=.38, \text{and } P_{\text{all}}=.68) \).

Factors Associated With TechAnxiety

Analogous statistical analyses were performed on the techAnxiety scores for the Swedish, Polish, and overall samples. Table 3 shows the Spearman rank correlation coefficients calculated for the same variables as for techEnthusiasm. A positive correlation was found between age and techAnxiety in the Swedish sample, indicating that greater the age, greater the techAnxiety \( (P<.05; \rho_{\text{Swedish}}=0.184) \). Similar to techEnthusiasm, this association might not have been significant for the Polish sample due to the lack of age variance (Figure 1). A negative correlation was found between higher semesters and techAnxiety in the Swedish and overall samples, indicating that higher the students were in their education, lesser the techAnxiety \( (P<.05; \rho_{\text{all}}=-0.101; \rho_{\text{Swedish}}=-0.124) \).
Table 3. Spearman rank correlation coefficient calculated for the whole sample, Swedish students, and Polish students separately, regarding technology anxiety.

<table>
<thead>
<tr>
<th>Feature</th>
<th>All students</th>
<th>Swedish students</th>
<th>Polish students</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>P value</td>
<td>$\rho$ (95% CI)</td>
<td>P value</td>
</tr>
<tr>
<td>Age</td>
<td>.54</td>
<td>0.024 (−0.101 to 0.053)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Semester</td>
<td>.01</td>
<td>−0.101 (−0.178 to −0.024)</td>
<td>.02</td>
</tr>
<tr>
<td>eHEALS$^a$ score</td>
<td>&lt;.001</td>
<td>−0.196 (−0.270 to −0.120)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Skill: computer</td>
<td>&lt;.001</td>
<td>−0.209 (−0.283 to −0.132)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Skill: smartphone</td>
<td>&lt;.001</td>
<td>−0.165 (−0.240 to −0.088)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Skill: tablet</td>
<td>&lt;.001</td>
<td>−0.251 (−0.324 to −0.175)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Frequency: computer</td>
<td>.495</td>
<td>0.028 (−0.052 to 0.107)</td>
<td>.16</td>
</tr>
<tr>
<td>Frequency: smartphone</td>
<td>.17</td>
<td>0.055 (−0.023 to 0.132)</td>
<td>.27</td>
</tr>
<tr>
<td>Frequency: tablet</td>
<td>.19</td>
<td>0.053 (−0.026 to 0.132)</td>
<td>.77</td>
</tr>
</tbody>
</table>

$^a$eHEALS: eHealth Literacy Scale.

A negative correlation was found between eHealth literacy and techAnxiety ($P<.001$; $\rho_{\text{all}}=−0.196$; $\rho_{\text{Swedish}}=−0.262$; $\rho_{\text{Polish}}=−0.133$). A negative correlation was found between the perceived skill in all investigated devices and techAnxiety, indicating that greater the perceived skill, lesser the techAnxiety score (Table 3). Similar to techEnthusiasm, the low $\rho$ values still show relevant associations due to the sample size. In addition, similar to techEnthusiasm, the narrow 95% CIs indicate low variability and stability of the results.

Gender differences regarding the students’ reported techAnxiety were observed through the Mann-Whitney $U$ test for the whole sample and the Swedish students ($P_{\text{Swedish}}=.002$; $P_{\text{Polish}}=.69$; $P_{\text{all}}=.01$). A considerable difference in the mean scores of the reported techAnxiety can be observed between men (1.987, SD 0.854) and women (2.451, SD 1.014) in the Swedish sample of students. This was not observed for the whole sample, with means of 2.240 (SD 0.90) and 2.521 (SD 0.963) for men and women students, respectively. However, upon closer inspection of the boxplots shown in Figure 2, the attributed gender differences can be observed when the distribution is analyzed. The Swedish women students present a higher dispersion of techAnxiety scores, whereas men present a heavier tail distribution, which in turn increases the distance between these groups.
Discussion

Principal Findings

Overview

This cross-sectional, multicenter study aimed to determine Swedish and Polish students’ attitudes toward technology, specifically directed to enthusiasm and anxiety, and factors associated with those attitudes. The principal findings of this study are as follows: (1) in the Swedish sample (mean age 27, SD 7.34 years), the older the students were, the more anxious and less enthusiastic they were about technology; (2) the higher the students’ eHealth literacy score was, the more enthusiastic and less anxious they were regarding technology (both Swedish and Polish samples); (3) the higher the perceived skill in using electronic devices was, the more enthusiastic and less anxious about technology the students were (both Swedish and Polish samples); (4) in the Swedish sample, the more senior the students were in their education (higher semesters), the less anxious they were toward technology they were; and (5) gender differences were found in the Swedish sample regarding anxiety toward technology. These will be further discussed in the following sections.

Attitudes Toward Technology and Age

The positive correlation between age and techAnxiety and negative correlation between age and techEnthusiasm, meaning that greater the age, lesser the enthusiasm and higher the anxiety toward technology, is an interesting finding, as many Swedish students (163/342, 47.6%) fall into the mature student category. This concept does not have a definition, but published literature usually considers the individuals who enter higher education at the age of 26 to 30 as mature students who are believed to be different from their younger colleagues [29]. The fact that many universities have a changing cohort with a higher rate of accepted mature students, meanwhile adopting more and more technologies as teaching enhancements [30], raises concerns about how the students’ attitudes toward technology could affect their learning. Technology-enhanced learning methods in the classroom can promote high-order thinking, that is, rationalizing on a level higher than memorizing or telling facts as told [31]. These teaching approaches affect the attainment of the subject being taught and decrease subject anxieties [29,32,33]. In the specific case of nursing, a systematic review of literature by Labrague et al [34] shows positive results in using high-fidelity simulations for enhancing the self-confidence of nursing students in managing their duties. Identifying the students’ needs could be important in these scenarios, so that learning could be efficiently delivered. A recent study investigated mature students’ attitudes toward technology and found no significant differences from younger students. However, the attitudes considered in the study instrument were confidence and a sense of utility [29]. The hypothesis suggests that the observed phenomenon related to age may not be applicable to the Polish sample due to its younger ages and lower variability (mean 20.4, SD 1.72 years).

Attitudes Toward Technology and eHealth Literacy

The positive correlation between eHealth literacy score and enthusiasm toward technology is not surprising because computer literacy is one of the domains assessed in the eHEALS instrument. The negative correlation between eHealth literacy
score and anxiety toward technology is also important to be considered. Even with different approaches to eHealth in nursing education, it seems important for the nursing students’ attitudes toward technology, which would later influence their use of technology in clinical scenarios. Registered nurses commonly rely on advice from their colleagues as their primary information source to inform daily clinical practice [35-37]. However, this information channel has an inherent risk of diverging from the best evidence available in published literature, which could impact the quality of patient care [38]. The best clinical practices can be readily accessed through reference materials and web-based publications in nursing journals. Thus, if anxiety toward technology is a factor that is identified as a barrier to pursuing such information, this means that it should be addressed in their education.

**Attitudes Toward Technology and Perceived Skills in Using Electronic Devices**

Another study finding suggests that students exhibiting higher perceived skill in using electronic devices (computers or laptops, smartphones, and tablets) also demonstrated more enthusiastic and less anxious attitudes toward technology. Only few studies have investigated electronic device use in nursing education. However, investigating this topic is important because despite nursing students reporting proficiency in computer skills, a lack of exposure to new devices can still lead to hesitancy in their use [39]. In the recent years, mobile apps have been trialed and shown to support the education and practice training of nursing students [40]. This technology facilitates access to patient care resources, fostering self-directed learning and problem-solving [41]. A study by Kenny et al [42] investigated the impact of using smartphones and tablets with a QR code scanning app linking to educational information on the nursing students’ anxiety levels while performing psychomotor skills in the patient care setting. The study found that providing students with access to these tools helped to reduce anxiety by offering quick access to reputable patient care information [42]. Previous studies of bank employees also found an inverse relationship between techAnxiety and computer skills [43]. The study did not find any significant associations with the frequency of use, which is consistent with this study, with the exception of techEnthusiasm related to computer or notebook. However, it can be argued that this could simply be a direct result of being enthusiastic and wanting to engage with it daily. While no studies in the literature approached the topic of techEnthusiasm and skill, a study by Revilla Muñoz et al [44] reported lower levels of techAnxiety in high school teachers after information and communications technology training.

**Attitudes Toward Technology and Semester**

In the Swedish sample, students exhibited lower levels of anxiety toward technology the further in their education they were. This could be related to how health technology topics are being addressed in specific courses given in higher semesters, which was not the case for the Polish university at the time of the study. This could indicate that having specific courses with eHealth and health technology curricula could be useful to address techAnxiety in students. A scoping review by Nes et al [45] highlights that the current state of nursing education indicates a prevalent lack of focus on technology and technological literacy, favoring teaching over engaging with technological advancements in the clinical field, resulting in limited exposure to such developments. This holds significance because practitioners are likely to navigate ongoing technological advancements throughout their careers. Therefore, nursing education should be viewed as a platform that fosters lifelong learning, placing emphasis on proactive engagement and critical thinking in response to technological progress [46].

**Implications to Practice**

Understanding the factors that influence techEnthusiasm and techAnxiety holds important practical implications, particularly in the context of health care innovation and access to care. TechAnxiety and techEnthusiasm can impact the technology acceptance level of a new health care solution. Low levels of acceptance are related to implementation delays and even complete system failures [51]. According to the systematic literature review by AlQudah et al [52], which included 142 studies, the key factors associated with health technology acceptance are its ease of use and perceived usefulness, which are measured using the widespread Technology Acceptance Model instrument. In addition, anxiety and computer self-efficacy are the next extensively studied factors related to health care technology acceptance, which aligns with the focus of this study.

A qualitative study conducted with nurses who have lower levels of digital literacy [53] explored factors related to health IT acceptance in this population. The results portrayed that these nurses show little enthusiasm toward technology and even considered the use of such technological tools as “bad patient-centered care.” Addressing those attitudes toward technology is a challenge and should be tailored to special needs, as these individuals also reported that the training sessions are conducted in large groups and that the pace is too fast for them. Telemedicine, eHealth records, health IT systems, and mobile apps emerge as important health technologies that are directed to improve productivity and effectiveness of the health care sector. During the COVID-19 pandemic, digital health strategies, which include such systems, were imperative for providing continuity of care; economic, social, geographical, time, and cultural accessibility; and coordination of care, among others [54]. However, during those difficult times, several health
professionals were unprepared to use such technologies [54]. Having health personnel that is trained to use different health technologies proved to be imperative to build preparedness for unusual health emergency situations. Strategies to address the problem of accessibility of health care in remote or rural areas could also use such technologies [52]. Hence, it is important to understand students’ digital savviness to devise strategies to address health technology topics accordingly in the curricula of health-related undergraduate programs.

Limitations
As this was a self-reported survey study, care must be taken when extrapolating the results shown in this paper. Response bias was mitigated by involving researchers with no educational connections with the surveyed participants. An earlier study of self-reported technology use presented only marginal errors to the respondents’ true use [55]. Another important limitation of this study is the disproportionate number of women and men participants, with the former consisting of 85.9% (555/646) of the whole sample. Although the statistical tests used in the analyses are robust against data imbalance, the magnitude of such imbalance could have affected the results. In addition, the use of a convenience sample can limit how the findings of this study can be generalized. However, in this study, the involvement of different universities from different countries as data sources helped to reduce this risk. Finally, the instrument used in this study was initially crafted and validated for use with older adults. Although published evidence exists for its use in younger populations [23,24], the results should be interpreted with caution, recognizing the potential for age-related bias.

Conclusions
This cross-sectional, multicenter study emphasized the importance of nursing students’ enthusiasm and anxiety toward technology and highlighted the factors associated with these attitudes. As health care increasingly relies on technologies such as telemedicine, eHealth records, health IT systems, and mobile apps, the integration of health technology topics into educational curricula becomes imperative, taking the students’ attitudes toward technology into consideration, so that in the future, these professionals are prepared to address future health care challenges. Future qualitative studies should investigate nursing students who portray high anxiety and low enthusiasm toward technology to further validate the results presented in this paper and understand their points of view, so that pedagogical strategies can be developed to incorporate health technology topics in the curricula.

Acknowledgments
The authors are especially grateful to the study participants for their time and interest in participating in the study. This study is part of the eHealth in Nursing Education (eNurseEd) study and was supported financially by the participating universities as an educational improvement effort. The funding source was not involved in the review design, analysis, interpretation of findings, writing of the paper, or the decision to submit the paper for publication.

Data Availability
The data sets generated during and analyzed during this study are available from the corresponding author on reasonable request.

Authors’ Contributions
ALD, DB, and PA conceived the study design. EKA, DB, LS, GB, and LM performed the data collection. ALD and BGP performed the data analysis. ALD, EKA, BGP, and PA drafted the paper. All authors have contributed to the authorship and approved the final version of this paper.

Conflicts of Interest
None declared.

Multimedia Appendix 1
STROBE (Strengthening the Reporting of Observational studies in Epidemiology) statement—checklist of items that should be included in the reports of cross-sectional studies.

[DOCX File, 32 KB - mededu_v10i1e50297_app1.docx ]

Multimedia Appendix 2
Descriptive statistics in terms of sociodemographic variables, technology anxiety, and technology enthusiasm. The first panel shows the frequency and percentages, and the second and third panels show the results in terms of the technology anxiety and technology enthusiasm scores.

[PDF File (Adobe PDF File), 102 KB - mededu_v10i1e50297_app2.pdf ]

References

https://mededu.jmir.org/2024/1/e50297


Abbreviations

**BTH**: Blekinge Institute of Technology
**ECTS**: European Credit Transfer and Accumulation System
**eHEALS**: eHealth Literacy Scale
**MUB**: Medical University of Bialystok
**SRCU**: Swedish Red Cross University
**STROBE**: Strengthening the Reporting of Observational studies in Epidemiology
**TechAnxiety**: technology anxiety
**TechEnthusiasm**: technology enthusiasm
**TechPH**: Technophilia instrument
Exploring the Performance of ChatGPT-4 in the Taiwan Audiologist Qualification Examination: Preliminary Observational Study Highlighting the Potential of AI Chatbots in Hearing Care

Shangqiguo Wang¹, PhD; Changgeng Mo², PhD; Yuan Chen³, PhD; Xiaolu Dai⁴, PhD; Huiyi Wang⁵, MSc; Xiaoli Shen⁶, MSc

Corresponding Author:
Yuan Chen, PhD

Abstract

Background: Artificial intelligence (AI) chatbots, such as ChatGPT-4, have shown immense potential for application across various aspects of medicine, including medical education, clinical practice, and research.

Objective: This study aimed to evaluate the performance of ChatGPT-4 in the 2023 Taiwan Audiologist Qualification Examination, thereby preliminarily exploring the potential utility of AI chatbots in the fields of audiology and hearing care services.

Methods: ChatGPT-4 was tasked to provide answers and reasoning for the 2023 Taiwan Audiologist Qualification Examination. The examination encompassed six subjects: (1) basic auditory science, (2) behavioral audiology, (3) electrophysiological audiology, (4) principles and practice of hearing devices, (5) health and rehabilitation of the auditory and balance systems, and (6) auditory and speech communication disorders (including professional ethics). Each subject included 50 multiple-choice questions, with the exception of behavioral audiology, which had 49 questions, amounting to a total of 299 questions.

Results: The correct answer rates across the 6 subjects were as follows: 88% for basic auditory science, 63% for behavioral audiology, 58% for electrophysiological audiology, 72% for principles and practice of hearing devices, 80% for health and rehabilitation of the auditory and balance systems, and 86% for auditory and speech communication disorders (including professional ethics). The overall accuracy rate for the 299 questions was 75%, which surpasses the examination’s passing criteria of an average 60% accuracy rate across all subjects. A comprehensive review of ChatGPT-4’s responses indicated that incorrect answers were predominantly due to information errors.

Conclusions: ChatGPT-4 demonstrated a robust performance in the Taiwan Audiologist Qualification Examination, showcasing effective logical reasoning skills. Our results suggest that with enhanced information accuracy, ChatGPT-4’s performance could be further improved. This study indicates significant potential for the application of AI chatbots in audiology and hearing care services.

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KEYWORDS
ChatGPT; medical education; artificial intelligence; AI; audiology; hearing care; natural language processing; large language model; Taiwan; hearing; hearing specialist; audiologist; examination; information accuracy; educational technology; healthcare services; chatbot; health care services

Introduction

In recent years, the rapid advancement of large language models (LLMs) has significantly expanded their usage in various domains. Among the leading artificial intelligence (AI) chatbots—such as Bard, Bing, and ChatGPT—there has been a notable increase in diverse applications in everyday life. Prominently, ChatGPT, launched by OpenAI in November 2022 [1], stands out in the realm of AI chatbots. This model, known for its proficiency in generating and comprehending human-like text, showcases remarkable natural language processing skills. It has the capability to grasp complex queries, furnish insightful responses, and participate in meaningful conversations, thus
ChatGPT represents a significant advancement in the field of natural language processing, exemplifying the latest developments in LLMs, particularly within the subset of autoregressive language models. Such generative LLMs, including ChatGPT, are predominantly trained on extensive text corpora. They use the decoder element of a transformer model, a groundbreaking architecture introduced by Vaswani et al. [4] in 2017. This model is adept at predicting subsequent tokens in text sequences, a capability that has been progressively refined in subsequent research [5,6]. The transformer model, upon which ChatGPT is built, has revolutionized natural language processing. Its core strength lies in its ability to process text sequences efficiently, facilitating tasks such as language translation, question answering, and text summarization. One of the key features of this architecture is the self-attention mechanism, which allows it to understand long-range dependencies between words in a sentence without the need for sequential processing. This feature not only enhances efficiency compared to older recurrent neural network architectures but also offers improved interpretability, linking the semantic and syntactic structures of language inputs more effectively [4].

In addition to these capabilities, ChatGPT has evolved to incorporate real-time and knowledge-based information through various plug-ins. The introduction of GPT-4 by OpenAI in 2023 has expanded ChatGPT’s proficiency to include processing both image and text inputs [1], marking a new milestone in the versatility and applicability of AI in diverse contexts.

ChatGPT has received considerable attention and exploration in its application within health care. The integration of ChatGPT into health care demonstrates its significant potential in enhancing patient education and handling general inquiries, marking it as a vital informational and supportive tool [7]. The broad applicability of AI chatbots in health care extends beyond patient interaction, serving clinicians, researchers, and students, with ChatGPT showing effectiveness in personalizing patient interactions and providing consumer health education [8,9]. This trend aligns with the overarching aim in health care AI to increase accessibility to medical knowledge and make care more affordable. Chatbots offer continuous health advice and support, potentially improving patient outcomes by reducing the need for in-person consultations. Additionally, they provide health care professionals with valuable insights for more informed decision-making, though concerns regarding data transparency have been noted [10]. ChatGPT is capable of generating empathetic, high-quality responses to health-related queries, often comparable to those of physicians, and shows promise in producing emotionally aware responses with potential for continuous improvement [11,12]. In low- and middle-income countries, ChatGPT has great potential as a pivotal tool in public health efforts. Its advantages span various domains such as health literacy, screening, triage, remote support, mental health, multilingual communication, medical training, and professional support, addressing numerous challenges in these health care systems [13]. Furthermore, ChatGPT’s role as a supplementary educational tool in areas requiring aptitude, problem-solving, critical thinking, and reading comprehension has been highlighted. The ChatGPT-4 version, in particular, shows potential in applications such as discharge summarization and group learning, enhancing human-computer interaction through verbal fluency [14,15]. However, the need for embracing these advancements while ensuring patient safety and recognizing the limitations of AI in intricate clinical cases is emphasized [16].

The evolution of computational sciences in hearing care services and research has given rise to the field of computational audiology. This approach combines algorithms, machine learning, and data-driven modeling for audiological diagnosis, treatment, and rehabilitation, using biological, clinical, and behavioral theories to augment care for patients and professionals [17]. The rapid development of AI technologies, especially LLMs such as ChatGPT, has significantly contributed to this field’s growth. ChatGPT’s advanced capabilities position it as a potential tool for patient interaction, education, aural rehabilitation program, and preliminary diagnostics in audiology [18,19]. However, it is crucial to recognize its current limitations. While it can handle complex interactions, it is not a substitute for human expertise in specialized areas such as audiology and is limited in interpreting nuanced medical information or performing physical diagnostics. AI chatbots have shown immense potential in hearing health care, aiding patients, clinicians, and researchers. Their applications range from initial screenings, educational support, and teleaudiology services for patients, to data analysis and decision support for clinicians and researchers [19]. In countries with vast geographical areas and imbalanced hearing care resources, AI chatbots could significantly enhance the development of hearing care services. Very recently, explorations into the use of AI chatbots for answering questions pertaining audiological knowledge have shown that AI chatbots can serve as a tool to access basic audiological information [20]. However, the accuracy and reliability of information provided by these tools remain a concern [19].

Despite the significant potential of AI chatbots to enhance hearing care services, research in this area remains sparse. AI chatbots’ ability to understand questions and provide logical responses based on available information is crucial. This capability suggests promising applications in hearing care, including educational support, patient assistance in clinical settings, and aid for clinical staff. By engaging with AI chatbots, students, teachers, patients, and clinical personnel could significantly improve learning outcomes, patient care, and clinical practice efficiency. Therefore, this study starts from the most fundamental aspects to explore the performance of the current commercial version of ChatGPT-4 in taking an audiologist qualification examination (ie, the Taiwan Audiologist Qualification Examination). This investigation not only assesses the accuracy of responses to test questions but also explores the ability of the current AI chatbot to comprehend and logically respond to examination questions. These capabilities form the cornerstone for future integration of AI chatbots into educational support or clinical service assistance.
Methods

Materials
This study used the 2023 Taiwan Audiologist Qualification Examination [21]—a professional licensing examination for audiologists in Taiwan. Candidates of this examination are required to have a bachelor’s or master’s degree in audiology and at least 6 months or 375 hours of clinical practice. The examination comprises six subjects: (1) basic auditory science, (2) behavioral audiology, (3) electrophysiological audiology, (4) principles and practice of hearing devices, (5) health and rehabilitation of the auditory and balance systems, and (6) auditory and speech communication disorders (including professional ethics). Each subject consists of 50 multiple-choice questions, except for behavioral audiology, which has 49 questions, totaling 299 questions in all. The examination papers featured 7 images, pivotal for answering 13 of the questions. Notably, these images were embedded directly within the PDF version of the examination rather than being provided as separate attachments. However, it is important to highlight that the images’ resolution was relatively low, and they were presented without color. When extracted and saved in JPEG format, the images ranged in size from 12.7 to 27.2 KB and had resolutions spanning from 82 to 150 DPI. All related PDFs are accessible for download from the official source [21].

Prompt Engineering
Recognizing the significant influence of prompt engineering (where “prompt” refers to the input text provided by the user, which the model responds to) on the outputs of generative LLMs, a standardized prompt format was used in this research: “Please answer the following multiple-choice question as a hearing care professional, providing reasoning and explanation.” This format was chosen to assess the logic and reasoning behind ChatGPT’s responses. The original examination questions, a blend of Traditional Chinese and English, often used bilingual terminology for specialized concepts. For this study, ChatGPT was instructed to respond in English. Additionally, ChatGPT was not informed that these questions were from the Taiwan Audiologist Qualification Examination to prevent it from sourcing specific information to increase the accuracy of its responses. An example of a prompt and response is illustrated in Figure 1.
Figure 1. A template of a question posed to ChatGPT-4 and its corresponding responses. The example provided is the first question from the basic auditory science examination. The italicized English translations in the question stem are solely for reader comprehension and are not included in the actual prompt.

Procedure
All questions and correct answers were downloaded from the official website of the Taiwan Ministry of Examination in PDF format [21]. Subsequently, all questions were pre-edited in a Word (Microsoft Corp) document to avoid formatting issues. ChatGPT-4, enhanced with DALL-E (Decoder-Only Autoregressive Language and Image Synthesis), browsing, and analysis capabilities, was used for the test from December 10 to 12, 2023. A separate chat was used for each subject of the examination. Despite being within the same subject, the questions essentially had no overlapping content. For questions presented as images, both the image and the text format of the question were provided to leverage ChatGPT-4’s image recognition capabilities. It is important to note that the resolution of the images supplied in the test was relatively poor, which could have potentially impacted the accuracy of image recognition. Following the approach of Gilson et al [9], the reasons for errors in incorrectly answered questions were categorized as follows: (1) logical errors: the response correctly identifies relevant information but fails to translate this information into an appropriate answer; (2) information errors: ChatGPT either overlooks a key piece of information, whether present in the question stem or from external sources, or shows a lack of expected knowledge; and (3) statistical errors: the error is due to a miscalculation, including explicit arithmetic errors.
or incorrect estimations of statistical data. Authors SW and CM, both having a PhD in audiology, reviewed the original questions in Chinese and the GPT’s responses in English, and then compared ChatGPT-4’s responses to the official correct answers provided for the examination (all multiple-choice questions) to determine whether each question was answered correctly. They then performed a cross-check to ensure the accuracy of this step. Subsequently, SW and CM classified the incorrect answers into the 3 aforementioned categories and compared their classification results. In case of any discrepancies, they consulted with HW, who has a master’s degree in public health, to reach a consensus and make a final decision together.

Ethical Considerations
This research did not involve human participants or private data and was therefore exempt from ethics approval by the ethics committee of Ningbo College of Health Sciences.

Data Analysis
The data analysis for this study was straightforward and conducted using Excel (Microsoft Corp). Our primary objective was to calculate the accuracy rate of ChatGPT-4 when tasked with taking the Taiwan Audiologist Qualification Examination.

Results

Overall Performance
ChatGPT-4 demonstrated commendable performance in the Taiwan Audiologist Qualification Examination. The accuracy rates for the 6 subjects were as follows: 88% for basic auditory science, 63% for behavioral audiology, 58% for electrophysiological audiology, 72% for principles and practice of hearing devices, 80% for health and rehabilitation of the auditory and balance systems, and 86% for auditory and speech communication disorders (including professional ethics). The overall accuracy rate for the 299 questions was 75% (see Table 1). The examination’s passing criteria include an average accuracy rate of 60% across all subjects. Thus, ChatGPT-4 successfully passed this examination. Records of all ChatGPT-4’s responses to the test questions can be found in the supplements (Multimedia Appendices 1-6). A detailed review of ChatGPT-4’s responses revealed that errors were not caused by logical or statistical errors; instead, all incorrect answers resulted from information errors.

Table . Performance of ChatGPT-4 in the 2023 Taiwan Audiologist Qualification Examination.

<table>
<thead>
<tr>
<th>Questions, n</th>
<th>Correct responses, n</th>
<th>Accuracy rate, %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Basic auditory science</td>
<td>50</td>
<td>44</td>
</tr>
<tr>
<td>Behavioral audiology</td>
<td>49</td>
<td>31</td>
</tr>
<tr>
<td>Electrophysiological audiology</td>
<td>50</td>
<td>29</td>
</tr>
<tr>
<td>Principles and practice of hearing devices</td>
<td>50</td>
<td>36</td>
</tr>
<tr>
<td>Health and rehabilitation of the auditory and balance systems</td>
<td>50</td>
<td>40</td>
</tr>
<tr>
<td>Auditory and speech communication disorders (including professional ethics)</td>
<td>50</td>
<td>43</td>
</tr>
<tr>
<td>Total questions</td>
<td>299</td>
<td>233</td>
</tr>
<tr>
<td>Questions with images</td>
<td>13</td>
<td>8</td>
</tr>
<tr>
<td>Images</td>
<td>7</td>
<td>4</td>
</tr>
</tbody>
</table>

Information Errors Leading to Incorrect Answers

Lack of Correct Information Sources
Most incorrect answers were due to ChatGPT-4 relying on inaccurate information. For example, in the basic auditory science examination, question 43 involved identifying an incorrect statement about temporal masking among options A, B, C, and D. Option B stated that forward masking occurs when a signal appears after the masking noise, even with a 200-millisecond gap between the 2 stimuli (which is a misconception). The correct answer was that this statement is false, but ChatGPT-4’s explanation suggested otherwise:

*Forward Masking with 200 ms Gap (B): This is correct. Forward masking can occur when the signal appears after the masking noise, even with a gap as long as 200 ms.*

This response indicates that ChatGPT-4 did not have accurate information to answer this question. As a matter of fact, no masking occurs when the time interval between the masker and the signal equals or exceeds 200 milliseconds [22]. Similarly, for option D, which stated that forward masking is more effective than backward masking, ChatGPT-4’s choice and explanation were as follows:

*Forward Masking More Effective Than Backward Masking (D): This is typically incorrect. Backward masking is often found to be more effective than forward masking.*

While this appears correct at first glance, it lacks the clarification that backward masking is more effective than forward masking when the same time interval exists between the masker and signal, with more masking occurring when the masker follows the signal [23]. However, from the perspective of the
information available to ChatGPT-4, option D was the most reasonable choice.

**Conflicting Information Sources**

Multiple sources of information also led to incorrect responses from ChatGPT-4. For example, question 22 in the electrophysiological audiology examination asked about the most appropriate frequency for tympanometry in newborns, with the correct answer being 1000 Hz. Despite its simplicity and lack of complexity in reasoning, ChatGPT-4 provided an incorrect response:

(A) 112 Hz is typically used for infants and young children. Newborns and young children have a more compliant ear canal than adults, and lower frequencies such as 226 Hz can sometimes overestimate middle ear pressure and compliance. Therefore, a lower frequency probe tone is often recommended.

Considering the straightforward nature of this question, the authors expected an accurate answer from ChatGPT-4. Therefore, after the conclusion of all tests, the question was posed to ChatGPT-4 twice more in separate new dialogues to avoid information cross-over. Two completely different responses were generated by ChatGPT-4:

226 Hz Standard: The 226 Hz probe tone is the standard frequency used in clinical tympanometry for all ages, including newborns. This frequency has been proven to provide reliable and accurate measurements of middle ear function in this age group. It is effective in identifying middle ear fluid, a common issue in newborns, and other conditions that might affect hearing. ... In conclusion, 226 Hz (option B) is the most suitable probe tone frequency for tympanometry in newborns, due to its effectiveness in assessing middle ear function accurately in this specific age group.

and

When performing tympanometry on a newborn, the most appropriate probe tone frequency is typically 1000 Hz (Option C). Let me explain why:

Age-Related Differences: The middle ear mechanics in infants, especially newborns, differ significantly from those in older children and adults. These differences are mainly due to the size and composition of the middle ear and ear canal, as well as the compliance of the tympanic membrane.

High-Frequency Probe Tones: A 1000 Hz probe tone is recommended for newborns and infants up to around six months of age. This higher frequency provides more accurate assessments of middle ear function in this age group, as it is less affected by the high compliance of the infant ear canal.

Therefore, the most appropriate option for tympanometry in newborns is 1000 Hz (Option C), as it offers the most reliable assessment of middle ear function in this specific age group.

This indicates that ChatGPT-4 may provide different answers each time based on varying sources of information, particularly when these sources have conflicts or inconsistencies.

**Image Information Recognition**

In the examination, 13 questions could be answered only through the recognition of images to extract information. ChatGPT-4 correctly answered 8 of these questions. Images 1 to 4 are from the behavioral audiology subject, images 5 and 6 are from the electrophysiological audiology subject, and image 7 is from the principles and practice of hearing devices subject. Out of the 7 images provided in total, ChatGPT-4 successfully recognized 4. The criterion for determining successful recognition was assessing the accuracy of ChatGPT-4’s interpretation of image content and its ability to extract pertinent information for answering questions. Authors SW and CM independently evaluated this aspect and subsequently performed a cross-check of their assessments.

**Discussion**

**Principal Findings**

This study evaluated ChatGPT-4’s performance in the 2023 Taiwan Audiologist Qualification Examination. The eligibility criteria for this examination are having a degree in audiology or a related field and a minimum of 6 months or 375 hours of clinical practice. The minimum required accuracy rate to pass the examination is set at 60%. In the 2023 examination, 88.5% of candidates achieved this accuracy rate or higher, effectively passing the examination. ChatGPT-4 achieved an overall accuracy rate of 75%, meeting the passing criterion necessary for candidates to obtain the basic qualification for practicing as clinical audiologists in Taiwan. It performed notably well in subjects that required more analytical reasoning and contextual decision-making, such as health and rehabilitation of the auditory and balance systems and auditory and speech communication disorders (including professional ethics). The proficiency of LLMs in integrating and interpreting information logically was evident in subjects demanding contextual knowledge. However, in fields such as electrophysiological audiology, which depend more on precise knowledge points, the accuracy of ChatGPT-4 was challenged when confronted with incorrect or insufficient information. In our study, the original questions were in both Chinese and English. We requested ChatGPT to provide responses in English, and the translation between the 2 languages did not negatively impact either the comprehension or the accuracy of the responses. In addition, although this research was a preliminary examination of ChatGPT-4’s capabilities in image recognition within audiology examinations, it is important to note that the number of images used was limited, and their quality and resolution were suboptimal. Nevertheless, despite these constraints, ChatGPT-4 demonstrated a moderately acceptable level of image recognition performance, successfully identifying over half of the content within the images.

Comparative analysis with the existing literature indicates that LLMs such as ChatGPT have shown promising results in medical examinations [24-26], particularly GPT-4 [27]. The model’s ability to pass examinations that are challenging for
ChatGPT's capacity to process and analyze extensive data makes it an appealing tool for research, especially in the field of audiology. The introduction of advanced AI models such as ChatGPT-4 has the potential to transform the way audiologists approach data analysis and improve the accuracy and reliability of their findings. This is particularly relevant in audiology, where data collection and analysis are crucial for making informed decisions about patient care.

In this study, we evaluated the performance of ChatGPT-4 in answering questions related to audiological knowledge. The model was tasked with answering multiple-choice questions, short-answer questions, and questions that required logical reasoning. The results showed that ChatGPT-4's accuracy rate in answering multiple-choice questions was significantly higher than that of its predecessors, with an average accuracy rate of 75.1% compared to 53.6% for GPT-3 [27]. This performance is promising and suggests that ChatGPT-4 could be a valuable tool for audiologists in the future.

However, like any AI model, ChatGPT-4 has limitations. For instance, it lacks the ability to understand context and nuance, which could be crucial in audiological cases. Additionally, ChatGPT-4's performance in answering questions that require logical reasoning was not as high as that in multiple-choice questions. This suggests that further refinement of LLMs is needed to improve their ability to handle complex reasoning tasks.

In conclusion, ChatGPT-4 has the potential to revolutionize the field of audiology by providing a comprehensive and accurate data source. However, future research should focus on improving the model's ability to handle complex reasoning tasks and to provide nuanced answers that are relevant to the context of the question. This could be achieved through advancements in LLMs and the integration of more domain-specific knowledge into the model's training.

**Limitations**

This study represents a preliminary exploration of an AI chatbot's performance in an audiologist qualification examination. However, several limitations must be acknowledged. First, the selected examination questions were exclusively multiple-choice, with a subset requiring integrated information for reasoning. This format lacks open-ended questions that typically mirror the complexity of real-world clinical scenarios in hearing care, where audiologists address diverse and intricate issues beyond isolated knowledge points. Future research could extend to evaluating AI chatbots in handling complex audiology cases. Second, while this study included an assessment of ChatGPT-4's image recognition capabilities, the quality of the images in the original test files was suboptimal. Additionally, the number of questions involving image information was limited, which constrained the ability of this study to draw substantial conclusions about this functionality.
Conclusions
In conclusion, the findings of this study show that ChatGPT 4 achieved a 75% accuracy rate in the 2023 Taiwan Audiologist Qualification Examination, thus successfully passing it. The primary reason for ChatGPT-4’s incorrect responses was identified to be information errors, including both a lack of correct information sources and the presence of conflicting information sources. Therefore, a fine-tuned model containing accurate hearing care information sources has the potential to further enhance the feasibility of AI chatbot applications in hearing care services. However, passing the examination does not imply that ChatGPT-4 can become a qualified clinical audiologist in Taiwan; rather, it only indicates that ChatGPT-4 has some basic knowledge required for the audiology profession. Adequate clinical internship hours are also a crucial requirement for the actual practice of audiology in Taiwan, and its performance in handling real clinical cases remains unknown.

Acknowledgments
The authors wish to express gratitude for the rapid development of large language models, which brings hope for future improvement in hearing care globally. ChatGPT was used to proofread and correct grammatical issues in this article.

Data Availability
The data supporting the findings of this study are available from the corresponding author upon request.

Authors’ Contributions
SW led the study’s design, managed the data, performed the analysis, and contributed to drafting the manuscript. CM, YC, and XD helped conceptualize the study. HW also participated in the analysis, while XS oversaw the study’s administration.

Conflicts of Interest
None declared.

Multimedia Appendix 1
ChatGPT transcripts: basic auditory science.
[PDF File, 10148 KB - mededu_v10i1e55595_app1.pdf]

Multimedia Appendix 2
ChatGPT transcripts for behavioral audiology.
[PDF File, 9601 KB - mededu_v10i1e55595_app2.pdf]

Multimedia Appendix 3
ChatGPT transcripts for auditory and speech communication disorders (including professional ethics).
[PDF File, 9737 KB - mededu_v10i1e55595_app3.pdf]

Multimedia Appendix 4
ChatGPT transcripts for electrophysiological audiology.
[PDF File, 8874 KB - mededu_v10i1e55595_app4.pdf]

Multimedia Appendix 5
ChatGPT transcripts for principles and practice of hearing devices.
[PDF File, 10975 KB - mededu_v10i1e55595_app5.pdf]

Multimedia Appendix 6
ChatGPT transcripts for health and rehabilitation of the auditory and balance systems.
[PDF File, 9752 KB - mededu_v10i1e55595_app6.pdf]

References


Abbreviations
- **AI**: artificial intelligence
- **DALL-E**: Decoder-Only Autoregressive Language and Image Synthesis
- **LLM**: large language model
Using ChatGPT in Psychiatry to Design Script Concordance Tests in Undergraduate Medical Education: Mixed Methods Study

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Alexandre Hudon, BEng, MD

Abstract

Background: Undergraduate medical studies represent a wide range of learning opportunities served in the form of various teaching-learning modalities for medical learners. A clinical scenario is frequently used as a modality, followed by multiple-choice and open-ended questions among other learning and teaching methods. As such, script concordance tests (SCTs) can be used to promote a higher level of clinical reasoning. Recent technological developments have made generative artificial intelligence (AI)–based systems such as ChatGPT (OpenAI) available to assist clinician-educators in creating instructional materials.

Objective: The main objective of this project is to explore how SCTs generated by ChatGPT compared to SCTs produced by clinical experts on 3 major elements: the scenario (stem), clinical questions, and expert opinion.

Methods: This mixed method study evaluated 3 ChatGPT-generated SCTs with 3 expert-created SCTs using a predefined framework. Clinician-educators as well as resident doctors in psychiatry involved in undergraduate medical education in Quebec, Canada, evaluated via a web-based survey the 6 SCTs on 3 criteria: the scenario, clinical questions, and expert opinion. They were also asked to describe the strengths and weaknesses of the SCTs.

Results: A total of 102 respondents assessed the SCTs. There were no significant distinctions between the 2 types of SCTs concerning the scenario (P=.84), clinical questions (P=.99), and expert opinion (P=.07), as interpreted by the respondents. Indeed, respondents struggled to differentiate between ChatGPT- and expert-generated SCTs. ChatGPT showcased promise in expediting SCT design, aligning well with Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition criteria, albeit with a tendency toward caricatured scenarios and simplistic content.

Conclusions: This study is the first to concentrate on the design of SCTs supported by AI in a period where medicine is changing swiftly and where technologies generated from AI are expanding much faster. This study suggests that ChatGPT can be a valuable tool in creating educational materials, and further validation is essential to ensure educational efficacy and accuracy.

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KEYWORDS

psychiatry; artificial intelligence; medical education; concordance scripts; machine learning; ChatGPT; evaluation; education; medical learners; learning; teaching; design; support; tool; validation; educational; accuracy; clinical questions; educators

Introduction

Undergraduate Medical Education

Undergraduate medical studies offer a wide range of learning opportunities through various teaching methods for medical students [1]. The competencies required are partly dictated by the Medical Council of Canada, and these skills are regularly assessed throughout the undergraduate medical education (UGME) program. Training programs must incorporate clinical reasoning instruction to aid students in developing this crucial competency [2]. The Bloom taxonomy is a useful tool for clearly identifying the cognitive level targeted by different teaching methods [3]. The taxonomy helps determine the appropriate methods for teaching and evaluating students based on the desired level of competency. Although various teaching methods are used, clinical situations followed by multiple-choice questions, as well as open-ended questions, are commonly used initially [4]. However, these types of questions have limitations when it comes to assessing a student’s analysis and clinical reasoning [5]. To address this, script concordance tests (SCTs) can be used to enhance the development of higher-level clinical reasoning skills [6].

The Use of SCTs

Methods such as SCTs are grounded in clinical cases designed to mirror real-life clinical scenarios, where information may be incomplete or unclear. The process involves presenting an initial vignette with some preliminary hypotheses, followed by additional information given to the student. SCTs assess how
this new information influences the likelihood of the initial hypotheses being considered as correct or relevant [6]. Students express the impact on the initial hypothesis using a 5-level Likert scale ranging from “much less likely” to “much more likely.” This process serves as a proxy for clinical reasoning, aiming to replicate decision-making in actual clinical practice. Typically, specialists in the subject develop the cases, and a robust SCT should comprise a minimum of 60 questions for strong internal validity [7-9]. The student’s responses are then compared to those of an expert panel, ideally consisting of at least 10 experts. Research suggests that 15 experts are necessary for high-impact testing, with minimal added benefit beyond 20 experts [10]. A notable limitation of SCTs is acceptability; a study on SCT acceptability with surgical residents revealed that experts tend to be more satisfied than students. Experts found the questions to be representative of real-life clinical settings [11]. However, SCTs may potentially provide a more precise assessment of students’ clinical reasoning compared to multiple-choice questions [12]. In psychiatry, the use of SCTs is emerging. Early data indicate good internal validity, with a correlation between learners’ education level, test scores, and improvement in evaluations tested before and after a psychiatry rotation [13].

The creation of SCTs demands a substantial investment of human resources [14]. Moreover, the questions are influenced by the designers’ inherent biases, necessitating multiple rounds of refinement with field experts [15]. This iterative process can lead to delays in developing educational materials. In a time when efficiency is crucial—such as during the COVID-19 pandemic or in situations with limited teaching resources—swift adaptations and improvements in the effectiveness of certain teaching methods may be imperative to uphold the quality of medical training [16,17].

Large Language Models and Their Uses in SCT Design

For clinician-educators seeking assistance in crafting educational materials, recent advancements include the availability of generative artificial intelligence (AI) tools, including large language models (LLM) such as ChatGPT (OpenAI) [18,19]. Originally designed for the public, these tools are currently under scrutiny by various companies and educational institutions to assess their limitations and advantages [20]. Numerous studies highlight the tool’s utility in developing clinical vignettes within medical studies and other health science domains [21]. However, to date, there is no study demonstrating the educational quality of SCT vignettes produced using ChatGPT. Before integrating tools such as ChatGPT into the design of educational materials, it is crucial to evaluate the quality of scenarios, questions, and related expertise generated by ChatGPT, as well as its ability to assess clinical reasoning. It is equally important to consider the potential limitations in using such tools for medical education material design. Although these generative models can be beneficial, they may also introduce errors that limit their usefulness [18]. As for medical students’ attitude toward AI, a recent study on the subject reported that medical students viewed AI in medicine as reliable, trustworthy, and technically competent, although they expressed limited confidence in its capabilities. While acknowledging AI’s intelligence, they did not consider it to be anthropomorphic. The consensus was that fundamental AI knowledge, covering its operation, ethics, applications, reliability, and potential risks, should be integrated into medical education [22].

Objective and Hypotheses

The primary goal of this project is to investigate how SCTs generated by ChatGPT compare to those produced by clinical experts in 3 key aspects: the scenario (stem), clinical questions, and expert opinion. A secondary objective is to assess whether blind evaluators can distinguish between an SCT generated by ChatGPT and one crafted by experts. Additionally, another subobjective aims to identify the advantages and limitations of the clinical vignettes under examination. Our hypothesis posits that the clinical SCTs created by ChatGPT will likely be considered acceptable by the medical community in terms of scenarios and clinical questions. However, we anticipate that their use with learners may necessitate supervision from clinical experts. Preliminary studies have indicated that AI is a promising tool to aid clinician-educators in designing clinical scenarios. Still, given that the underlying algorithms rely on potentially erroneous data, it is crucial to validate and fine-tune the content before using them as educational materials for learners.

Methods

Ethical Considerations

This study received the approval of the ethics of research committee of the Université de Montréal (approval 2023-4906). Participants were given a description of the study in the letter they received and were asked for their consent for their data to be used. Data were anonymized. The participants received no compensation for this study.

Recruitment

The project was aimed at residents and clinician-educators in the field of psychiatry since SCTs are already used in UGME programs. To be included in the study, participants needed to be either clinician-educators in the field of psychiatry or medical residents in psychiatry affiliated with 1 of Québécs’s 4 universities that offer UGME programs (McGill University, Université de Montréal, Université de Sherbrooke, and Université Laval). Psychiatrists not involved in an UGME program were excluded. A total of 100 participants were anticipated for this study, according to similar studies to determine whether there were significant differences between clinical vignettes developed by ChatGPT or those developed by experts [23,24]. Convenience sampling was conducted with the help of the departments of psychiatry of the 4 universities listed above, and a letter was sent out by email that includes a link to a survey that contained all the questions from this study.

Data Collection

A web-based survey, hosted on LimeSurvey (LimeSurvey GmbH), featured 3 SCTs generated by ChatGPT and 3 SCTs previously crafted by experts in the field, currently used in the digital learning environment at the Université de Montréal. The experts consisted of experienced psychiatrists and primary care physicians who underwent training in SCT concepts. As the primary language for the participants is French, the survey was...
conducted in French. The original, comprehensive survey in French is available in Multimedia Appendix 1, with an English translation provided in Multimedia Appendix 2. Participants assessed the SCTs based on their respective roles. Due to the anonymous nature of the survey and the inclusion criteria requiring respondents to be either psychiatry residents or physicians, additional demographic data were not collected. The study did, however, document information on the participants’ level of training (resident doctors vs clinician-educators) and their level of clinical experience (0-5, 6-10, or ≥10 y).

Each SCT was evaluated by the participants using the conceptual framework developed by Fournier et al [9] for creating SCTs. This conceptual framework provides a general guideline for SCTs. The SCTs involve real-life medical situations, each describing as a short scenario with some uncertainty. To solve the problem presented in each scenario, there are multiple relevant options available for the medical student. Each scenario, along with its questions, is considered an item. The questions are divided into 3 parts. The first part provides a relevant diagnostic or management option. The second part introduces a new clinical finding, such as a physical sign or test result. The third part uses a 5-point Likert scale for examinees to express their decision on how the new finding affects the option, considering direction (positive, negative, or neutral) and intensity. Examinees are tasked with determining the impact of the new information, and the Likert scale is used to capture their decisions, as script theory suggests that clinical reasoning involves qualitative judgments.

Three components are evaluated by this framework when constructing SCTs: the scenario, clinical questions, and expert opinion. The scenario refers to the stem presented by the SCTs. The clinical questions are the individual questions adding a key element to the stem to stimulate clinical reasoning. The expert opinion refers to the opinion of an expert in the field giving a subjective appreciation as to the ability of the SCT to generate clinical reasoning. The elements of this framework are presented in Table 1. A common SCT template was used for both SCTs generated by ChatGPT and the experts in the field to ensure that the presentation of the SCTs does not create bias.

Table 1. The script concordance test (SCT) components with their relevant questions as per the framework by Fournier et al [9] for the evaluation and conception of SCTs.

<table>
<thead>
<tr>
<th>SCT components and questions</th>
<th>Potential answers</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Scenarios</strong></td>
<td></td>
</tr>
<tr>
<td>S1. Describes a challenging circumstance, even for experts</td>
<td>Yes or no</td>
</tr>
<tr>
<td>S2. Describes an appropriate situation for test takers</td>
<td>Yes or no</td>
</tr>
<tr>
<td>S3. The scenario is necessary to understand the question and to set the context</td>
<td>Yes or no</td>
</tr>
<tr>
<td>S4. The clinical presentation is typical</td>
<td>Yes or no</td>
</tr>
<tr>
<td>S5. The scenario is well written</td>
<td>Yes or no</td>
</tr>
<tr>
<td><strong>Clinical questions</strong></td>
<td></td>
</tr>
<tr>
<td>Q1. The questions are developed using a key element approach</td>
<td>Yes or no</td>
</tr>
<tr>
<td>Q2. In the opinion of experts, the options are relevant</td>
<td>Yes or no</td>
</tr>
<tr>
<td>Q3. The same option is not found in 2 consecutive questions</td>
<td>Yes or no</td>
</tr>
<tr>
<td>Q4. The new information (second column) makes it possible to test the link between the new information and the option (first column) in the context described</td>
<td>Yes or no</td>
</tr>
<tr>
<td>Q5. Likert-scale anchors are clearly defined and unambiguous</td>
<td>Yes or no</td>
</tr>
<tr>
<td>Q6. Questions are expanded to distribute responses equally across all Likert-scale values</td>
<td>Yes or no</td>
</tr>
<tr>
<td>Q7. Questions are designed to provide a balance between low and high variability</td>
<td>Yes or no</td>
</tr>
</tbody>
</table>

**Expert Opinion**

The participants needed to state if the SCT was generated (or not) by ChatGPT (single-blinded mode), give their main hypothesis as to the main diagnosis studied in the SCT, and state in free-text style the strengths and weaknesses of each SCT.
Creating SCTs With ChatGPT

The ChatGPT tool operates through commands or prompts to enhance its performance. These prompts must offer a context of use, an expertise level, and a specific task. Following the typical steps involved in creating SCTs, we designed the prompts based on the approach outlined in Fournier et al [9]. In this initial study on the subject, we did not explore different sets of prompts, and the generated SCTs were used without modification.

The following commands were entered into ChatGPT to create the SCTs:

1. Act as an expert in university pedagogy of health sciences, in the field of psychiatry.
2. Also acts as an expert in designing thumbnails by script matching.
3. Generates a script matching vignette that includes three questions for the following diagnosis: (diagnosis name), according to DSM-5.
4. Create questions linked to the vignette which start with if you think of "a diagnostic hypothesis" and you find "a sign or a symptom", this hypothesis is probable or not (from -2 to 2, using a Likert scale)

Choosing the ChatGPT 3.5 algorithm as the main LLM for this task made sense for a few key reasons. This algorithm has a vast knowledge base covering a wide array of medical topics, making it an adequate tool for instructors crafting medical questions for medical students [25]. Its natural language comprehension, used in various medical fields, aids in question development [26]. The model’s flexibility allows educators to create different types of questions to suit various learning styles and assessment methods. Notably, ChatGPT 3.5 supports multiple languages, including French, making it accessible for instructors in French-speaking regions. The model’s ability to grasp context enables the creation of questions that build on existing knowledge, providing a more cohesive learning experience [27]. Educators can save time with the model’s human-like text generation based on specific prompts or instructions. It is also crucial to highlight that this algorithm is open access and free, a substantial consideration when cost is a factor in choosing educational tools. Additionally, it is noteworthy that generating an SCT takes less than a minute on average with this tool.

Selecting Existing Expert-Created SCTs

Three SCTs were chosen at random from the 10 SCTs currently available to learners on the digital learning platform for the clinical psychiatry clerkship rotation at Université de Montréal. As stated above, a total of 3 ChatGPT-generated SCTs and 3 expert-created SCTs were chosen to limit the possibility that chance alone would identify the SCTs generated by ChatGPT from those produced by experts.

Statistical Analysis

A combined mixed method analysis was conducted with qualitative and quantitative components.

Qualitative Analysis

We conducted a content analysis by examining participants’ open responses regarding the advantages and drawbacks of the presented SCTs. The objective was to pinpoint the primary types of benefits and limitations for emphasis. After receiving the open-ended survey responses, we individually extracted emergent themes from respondents using the grounded theory design framework [28]. Subsequently, AH and MP created an initial classification scheme based on these emerging themes. They applied this scheme to annotate the open-ended responses using the Qualitative Data Analysis Miner program (Provalis Research). Any discrepancies in annotations among responders were deliberated upon until a consensus was reached.

Quantitative Analysis

We conducted a descriptive statistical analysis to showcase the proportion of participants accurately identifying SCTs generated by ChatGPT compared to those crafted by experts. This same approach was applied to diagnostic hypotheses.

Additionally, we performed a descriptive statistical analysis to compare SCT scores based on the domains of the scenario and clinical questions, following the conceptual framework by Fournier et al [9]. Using a $\chi^2$ test, we assessed the average results within each domain for the SCTs generated by ChatGPT and those by the experts. This allowed us to observe any statistical differences in the responses (yes or no) for various criteria within the scenario and clinical questions domains. We established a statistical significance threshold of $P<.05$ to identify noteworthy observations between the 2 types of SCTs.

Results

Participants Characterististics

A total of 102 participants completed the survey. Considering that there are an estimated 400 teaching clinicians in psychiatry in Quebec (about a third of the 1200 practicing psychiatrists), as well as 235 medical residents in psychiatry, this represents 16.1% (102/635) of the pool of potential responders. From the 102 participants, 45 (44.1%) identified as medical residents in psychiatry, 2 (2%) identified as teaching psychiatrists with less than 5 years of experience, 16 (15.7%) identified as teaching psychiatrists with between 6 and 10 years of experience, and 39 (38.2%) identified as teaching psychiatrists with more than 10 years of experience.

SCT Evaluation

The pooled averages of evaluations of the SCTs for each domain of assessment, stratified by the respondent categories, are shown in Table 2. A complete table reporting the evaluations of the respondents for each individual component of the domains of assessment is available in Multimedia Appendix 3. SCTs 2, 3 and 4 were generated by ChatGPT. It can be observed that there was no significant distinction between the pooled results for the SCTs generated by ChatGPT as compared to those generated by experts in the field. The questions related to the scenario component of the SCTs received better approval from the participants as compared to the clinical questions component.
Table. Responses for every component of the script concordance test (SCT) evaluations for the 6 SCTs, stratified by respondent categories. “Yes” indicates that the respondents agreed that the domain was elaborated appropriately.

<table>
<thead>
<tr>
<th>SCT and evaluated component</th>
<th>Medical residents (n=45), n (%)</th>
<th>Teaching physicians (≤5 y; n=2), n (%)</th>
<th>Teaching physicians (6-10 y; n=16), n (%)</th>
<th>Teaching physicians (≥10 y; n=39), n (%)</th>
<th>Pooled average (N=102), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCT 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario (yes)</td>
<td>30 (67)</td>
<td>2 (100)</td>
<td>12 (75)</td>
<td>31 (79)</td>
<td>75 (74)</td>
</tr>
<tr>
<td>Clinical questions (yes)</td>
<td>29 (64)</td>
<td>2 (100)</td>
<td>13 (81)</td>
<td>28 (72)</td>
<td>72 (71)</td>
</tr>
<tr>
<td>Is it a ChatGPT-generated scenario? (correct answers)</td>
<td>25 (44)</td>
<td>1 (50)</td>
<td>6 (38)</td>
<td>18 (54)</td>
<td>50 (49)</td>
</tr>
<tr>
<td>SCT 2 a</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario (yes)</td>
<td>29 (64)</td>
<td>2 (100)</td>
<td>13 (81)</td>
<td>25 (64)</td>
<td>69 (68)</td>
</tr>
<tr>
<td>Clinical questions (yes)</td>
<td>30 (67)</td>
<td>2 (100)</td>
<td>14 (88)</td>
<td>25 (64)</td>
<td>71 (70)</td>
</tr>
<tr>
<td>Is it a ChatGPT-generated scenario? (correct answers)</td>
<td>22 (49)</td>
<td>0 (0)</td>
<td>6 (38)</td>
<td>18 (46)</td>
<td>46 (45)</td>
</tr>
<tr>
<td>SCT 3 a</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario (yes)</td>
<td>28 (62)</td>
<td>2 (100)</td>
<td>12 (75)</td>
<td>26 (67)</td>
<td>68 (67)</td>
</tr>
<tr>
<td>Clinical questions (yes)</td>
<td>28 (62)</td>
<td>2 (100)</td>
<td>13 (81)</td>
<td>25 (64)</td>
<td>68 (67)</td>
</tr>
<tr>
<td>Is it a ChatGPT-generated scenario? (correct answers)</td>
<td>16 (36)</td>
<td>0 (0)</td>
<td>4 (25)</td>
<td>16 (41)</td>
<td>36 (35)</td>
</tr>
<tr>
<td>SCT 4 a</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario (yes)</td>
<td>28 (62)</td>
<td>2 (100)</td>
<td>11 (69)</td>
<td>26 (67)</td>
<td>67 (66)</td>
</tr>
<tr>
<td>Clinical questions (yes)</td>
<td>25 (56)</td>
<td>2 (100)</td>
<td>14 (88)</td>
<td>28 (72)</td>
<td>69 (68)</td>
</tr>
<tr>
<td>Is it a ChatGPT-generated scenario? (correct answers)</td>
<td>19 (42)</td>
<td>1 (50)</td>
<td>6 (38)</td>
<td>12 (31)</td>
<td>38 (37)</td>
</tr>
<tr>
<td>SCT 5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario (yes)</td>
<td>26 (58)</td>
<td>2 (100)</td>
<td>11 (69)</td>
<td>26 (67)</td>
<td>65 (64)</td>
</tr>
<tr>
<td>Clinical questions (yes)</td>
<td>27 (60)</td>
<td>2 (100)</td>
<td>13 (81)</td>
<td>28 (72)</td>
<td>70 (69)</td>
</tr>
<tr>
<td>Is it a ChatGPT-generated scenario? (correct answers)</td>
<td>21 (53)</td>
<td>2 (100)</td>
<td>8 (50)</td>
<td>23 (59)</td>
<td>54 (53)</td>
</tr>
<tr>
<td>SCT 6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scenario (yes)</td>
<td>27 (60)</td>
<td>2 (100)</td>
<td>12 (75)</td>
<td>26 (67)</td>
<td>67 (66)</td>
</tr>
<tr>
<td>Clinical questions (yes)</td>
<td>24 (53)</td>
<td>2 (100)</td>
<td>13 (81)</td>
<td>27 (69)</td>
<td>66 (65)</td>
</tr>
<tr>
<td>Is it a ChatGPT-generated scenario? (correct answers)</td>
<td>21 (53)</td>
<td>1 (50)</td>
<td>8 (50)</td>
<td>18 (46)</td>
<td>48 (47)</td>
</tr>
</tbody>
</table>

Participants could not identify which SCT was created by ChatGPT from those created by experts in the field, as observed in Table 2. Teaching clinicians with more than 10 years of experience tended to better recognize SCTs generated by ChatGPT than their peers with less experience and medical residents, except for SCT 4.
Comparisons Between ChatGPT- and Expert-Generated SCTs

When using the pooled observations for the scenario and clinical questions domains across the SCTs generated by ChatGPT and those generated by experts, no statistically significant distinctions were observed when comparing both types of SCTs (all \( P > .05 \)), as seen in Table 3.

<table>
<thead>
<tr>
<th>Components</th>
<th>SCTs 1, 5, and 6 (experts), average score (%)</th>
<th>SCTs 2, 3, and 4 (ChatGPT), average score (%)</th>
<th>( P ) value (ChatGPT-generated vs expert-generated SCTs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario</td>
<td>66.40</td>
<td>67.27</td>
<td>.84</td>
</tr>
<tr>
<td>Clinical questions</td>
<td>70.05</td>
<td>68.86</td>
<td>.99</td>
</tr>
<tr>
<td>Identifying if generated by AI(^a)</td>
<td>54</td>
<td>40</td>
<td>.07</td>
</tr>
</tbody>
</table>

\(^a\)AI: artificial intelligence.

Reported Strengths and Weaknesses of the SCTs

Overview

Only 39 (38.2%) of the 102 participants wrote at least 1 comment on the strengths or weaknesses for each of individual SCT. The strengths and weaknesses of the SCTs generated by ChatGPT were similarly reported across all the respondents and resembled those identified for the SCTs generated by experts in the field. Respondents reported that SCTs generated by ChatGPT were well aligned with the *Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5)* but were also too caricatural.

Strengths of the SCTs Generated by Experts in the Field

Overall, 3 (8%) of the 39 respondents indicated for 1 or more SCTs generated by experts in the field that the scenario represented typical clinical challenges. Most of the respondents (27/39, 69%) reported that the SCTs used clear prompts to test clinical reasoning. Sample responses included the following:

*This concordance test was easy to follow as because the scenarios were concise and the prompts were clear.* [Respondent 1]

*In terms of clarity, the prompts were well written and it was very simple to see how they could elicit clinical reasoning.* [Respondent 9]

Strengths of the SCTs Generated by ChatGPT

Almost all respondents (32/39, 82%) mentioned that the SCTs were using typical clinical signs and symptoms reported in the *DSM-5*. Some (5/39, 13%) indicated that the SCTs were very well nuanced. Sample responses included the following:

*This scenario corresponds to the textbook’s description of the presented diagnosis.* [Respondent 4]

*I see that these prompts do not try to derive too much from the differential diagnoses intended for the suggested clinical presentation. They offered a degree of flexibility to enable the student to use their clinical reasoning.* [Respondent 71]

Limitations of the SCTs Generated by Experts in the Field

In all, 2 (5%) of the 39 respondents mentioned that they found the SCTs straightforward and unchallenging. There were no other comments regarding the limitations of the SCTs generated by experts in the field. Sample responses included the following:

*This scenario is too easy. I find little value as it is clear for the student that we are looking at the specific diagnosis.* [Respondent 1]

*I don’t see how this is challenging for the medical student who is going to take this test.* [Respondent 80]

Limitations of the SCTs Generated by ChatGPT

Most respondents (29/39, 74%) reported the SCTs generated by ChatGPT as caricatural or stereotypical clinical presentations as observed in textbooks with little regard to atypical presentations. A total of 7 (18%) respondents indicated that the SCTs generated by ChatGPT were too simple, as they tended to include additional information that were too trivial when attempting to challenge the responder’s clinical reasoning. Sample responses included the following:

*This is very trivial. I mean, it is not very difficult to find out what are the answers to these prompts as they clearly hint towards the same diagnosis.* [Respondent 3]

*It would be interesting to add more challenging prompts as they tend to be very simplistic and poorly represent complex clinical cases as they are very stereotypical to what is found in the DSM-5.* [Respondent 4]

Discussion

Principal Findings

The aim of this study was to compare SCTs created by ChatGPT to SCTs produced by clinical specialists on the scenario (stem), clinical questions, and expert opinions. There were no significant distinctions between the SCTs generated by ChatGPT as compared to those developed by experts in the field for the evaluated components. The strengths and weaknesses were similar across the 2 types of SCT. Respondents reported that
the SCTs generated by ChatGPT were well aligned with the DSM-5 but were also too caricatural.

Comparison With Prior Work

Since the creation of ChatGPT, it has been used in various areas of medical education such as digital teaching assistants and personalized education [29]. As a recent exploration study on the role of LLMs such as ChatGPT demonstrated, these models can provide interactive cases in a medical education context [30]. Considering these previous studies of ChatGPT in the development of medical education tools, it is possible that the inability to recognize a SCT generated by ChatGPT from one developed by experts in the field can be explained by the generative nature of this LLM. As such, a recent review on the use of ChatGPT in health care has identified that this form of AI can be used for problem-based learning and critical thinking in health care education [31]. However, it is mentioned in the literature that although the quality of the scenarios (or information) generated by ChatGPT might appear impressive, there is a need for an expert to assess the content generated, as it might be an amalgamation of erroneous information [32].

Although a few comments were provided regarding the strengths and limitations of both types of SCTs, they align with what is commonly reported in the literature for similar tasks. Some respondents noted caricature-like scenarios, possibly attributed to the robotic and dehumanized nature often associated with vignettes produced by LLMs [33]. It is plausible that more intricate prompts could have resulted in more nuanced scenarios. Therefore, the mentioned strengths of the scenarios and clinical questions, particularly their clinical alignment with the DSM-5, may be tied to the fact that this was one of the prompts used when conceptualizing interactions with ChatGPT during the creation of the SCTs.

In the field of psychiatry, applications of ChatGPT to medical education are limited. Among the limited available evidence, a novel study tested the knowledge of ChatGPT by exposing it to 100 clinical cases vignettes, and it performed extremely well [34]. Another similar use of ChatGPT was as an aid to answer clinical questions. A recent study evaluated the performance of users (psychiatrist and medical residents in the Netherlands) using ChatGPT as compared to nonusers for answering several questions in psychiatry, and it was observed that the users had better and faster responses as compared to nonusers [35].

Although these applications differ from this study, they might hint that ChatGPT currently has a database that holds relevant data in the field of psychiatry, which might explain the realism of scenarios and prompts observed for SCTs 2, 3, and 4.

There are substantial ethical considerations that must be accounted for when using such tool to assist medical educators. As an example, it is important to consider that ChatGPT (and other LLMs) are bound to the data they have been trained with along with their inherent biases [36]. Cross-validation of the generated information is often necessary to ensure that learners are not exposed to false information [37].

Limitations

Although web-based surveys offer convenience in distribution, they struggle with the challenge of accurately identifying the characteristics of the assessed population [38]. In our survey, we did not differentiate between those formally trained in SCTs and those who merely encountered them during their medical training, thus introducing potential limitations in generalizing the results. It is plausible that clinicians more experienced with SCTs were more likely to participate in the survey, but our recruitment from psychiatry departments exclusively helps mitigate this bias. Interpretation biases may also be present, as not all participants might be familiar with the framework used in this study. We did not explore acceptability regarding the use of generative AI in SCT creation, marking another limitation. Additionally, we did not compare different prompts, and it is conceivable that alternative sets of prompts could have produced better results for the SCTs generated by ChatGPT. Opting for a different language model might have yielded varied performances, and it is plausible that alternative models could outperform ChatGPT in this context.

Conclusions

In an era of rapidly evolving medicine and where technologies derived from AI are growing even more quickly, this study is the first to focus on the design of SCTs assisted by AI. The primary goal of this study highlighted that no statistical differences were found between the SCTs generated by ChatGPT and those created by clinical experts in the field of psychiatry for the elaboration of a scenario and the clinical questions presented in the SCTs. On average, the respondents incorrectly identified which SCTs were created with the help of AI. The major strength of SCTs generated by ChatGPT was that they were consistent with the DSM-5, whereas the caricatural quality or triviality of the SCTs generated by ChatGPT were the main weaknesses reported by the respondents. A possible way to mitigate this effect would be to provide more complex prompts to the generative AI or editing some details of the vignette. This study opens the door to larger-scale studies in this area to assess the impact of such aid on the academic success of medical students and how it can be used to improve efficiencies.

Acknowledgments

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Authors’ Contributions

AH, BK, MP, and VP contributed to the study conceptualization and writing of the original manuscript. All authors participated in the investigation and validation process. All authors edited the manuscript draft and reviewed the final manuscript.
Conflicts of Interest

None declared.

Multimedia Appendix 1
Original survey in French.
[PDF File, 502 KB - mededu_v10i1e54067_app1.pdf ]

Multimedia Appendix 2
Translated survey in English.
[PDF File, 949 KB - mededu_v10i1e54067_app2.pdf ]

Multimedia Appendix 3
Responses for every component of the script concordance test (SCT) evaluations for the 6 SCTs, stratified by the category of respondents.
[DOCX File, 27 KB - mededu_v10i1e54067_app3.docx ]

References


Abbreviations

AI: artificial intelligence
DSM-5: Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition
LLM: large language model
SCT: script concordance test
UGME: undergraduate medical education
Using Project Extension for Community Healthcare Outcomes to Enhance Substance Use Disorder Care in Primary Care: Mixed Methods Study

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Abstract

Background: Substance use and overdose deaths make up a substantial portion of injury-related deaths in the United States, with the state of Ohio leading the nation in rates of diagnosed substance use disorder (SUD). Ohio’s growing epidemic has indicated a need to improve SUD care in a primary care setting through the engagement of multidisciplinary providers and the use of a comprehensive approach to care.

Objective: The purpose of this study was to assess the ability of the Weitzman Extension for Community Healthcare Outcomes (ECHO): Comprehensive Substance Use Disorder Care program to both address and meet 7 series learning objectives and address substances by analyzing (1) the frequency of exposure to the learning objective topics and substance types during case discussions and (2) participants’ change in knowledge, self-efficacy, attitudes, and skills related to the treatment of SUDs pre- to postseries. The 7 series learning objective themes included harm reduction, team-based care, behavioral techniques, medication-assisted treatment, trauma-informed care, co-occurring conditions, and social determinants of health.

Methods: We used a mixed methods approach using a conceptual content analysis based on series learning objectives and substances and a 2-tailed paired-samples t test of participants’ self-reported learner outcomes. The content analysis gauged the frequency and dose of learning objective themes and illicit and nonillicit substances mentioned in participant case presentations and discussions, and the paired-samples t test compared participants’ knowledge, self-efficacy, attitudes, and skills associated with learning objectives and medication management of substances from pre- to postseries.

Results: The results of the content analysis indicated that 3 learning objective themes—team-based care, harm reduction, and social determinants of health—resulted in the highest frequencies and dose, appearing in 100% (n=22) of case presentations and discussions. Alcohol had the highest frequency and dose among the illicit and nonillicit substances mentioned in participant case presentations and discussions. The results of the paired-samples t test indicated statistically significant increases in knowledge domain statements related to polysubstance use (P=.02), understanding the approach other disciplines use in SUD care (P=.02), and medication management strategies for nicotine (P=.03) and opioid use disorder (P=.003). Statistically significant increases were observed for 2 self-efficacy domain statements regarding medication management for nicotine (P=.002) and alcohol use disorder (P=.02). Further, 1 statistically significant increase in the skill domain was observed regarding using the stages of change theory in interventions (P=.03).

Conclusions: These findings indicate that the ECHO program’s content aligned with its stated learning objectives; met its learning objectives for the 3 themes where significant improvements were measured; and met its intent to address multiple substances in case presentations and discussions. These results demonstrate that Project ECHO is a potential tool to educate multidisciplinary providers in a comprehensive approach to SUD care.
Introduction

Background

In the United States, overdose deaths continue to be a major cause of injury-related deaths. Since the onset of the COVID-19 pandemic, numbers have only accelerated, and the state of Ohio has led the nation in high substance use disorder (SUD) rates, including drug use and prescription drug use. The Centers for Disease Control and Prevention ranks the state among the top 5 across the United States with the highest rates of opioid overdose deaths [1]. While research has shown an increase in the number of people enrolled in substance use treatment in Ohio between 2015 and 2019 there was still a notable high increase in the annual average prevalence of past-year illicit drug use disorder in Ohio (3.6%) compared to the regional average (3%) and the national average (2.9%) [2]. In addition, past-month alcohol use disorder (9.3%), cannabis use disorder (5.8%), and tobacco use disorder (35.2%) were higher than the national average among young adults aged 18-25 years [2]. Ohio’s growing epidemic has highlighted the need to improve SUD care in a primary care setting by training providers to better address differences in care and social determinants of health through the use of behavioral techniques, harm-reduction philosophy of care, medication management, and a team-based care approach.

Weitzman Extension for Community Healthcare Outcomes: Comprehensive Substance Use Disorder Care Program

Beginning in 2021, Buckeye Health Plan and Ohio University Heritage College of Osteopathic Medicine have partnered with the Weitzman Institute (WI), a national primary care research, policy, and education institute, to provide targeted support and education to Ohio primary care medical and behavioral health providers working with underserved patients, especially those in the rural, southeastern Appalachian region, using the evidence-based Project Extension for Community Healthcare Outcomes (ECHO) learning model. Project ECHO uses frequent videoconference sessions to connect a target audience of learners with subject matter experts for didactic and case-based instruction and engaged discussion [3]. Through regular attendance at these sessions, Project ECHO aims to equip learners with the knowledge, confidence, and skills to better manage complex cases.

WI has over 11 years of experience in developing and delivering Project ECHO programs to meet the needs of providers working in resource-limited settings. As an early adopter of the model in 2012, Weitzman ECHO programs have been offered in 22 topic areas to over 8000 health care professionals across all 50 states, Washington D.C., and Puerto Rico. Working in collaboration, Buckeye Health Plan and Ohio University aimed to leverage this expertise and offer multiple Project ECHO programs each year for providers in topics of the greatest need and interest.

As described, one of Ohio’s most dire population health needs is to improve outcomes for patients experiencing addiction. Thus, SUD was selected as the second ECHO program developed through this partnership. More specifically, opioids are a heightened concern throughout both Ohio and the United States, and the opioid epidemic has spurred significant funding allocations, such as the Biden Administration’s US $1.5 billion award to states and territories to end the epidemic [4]. However, there are many additional substances of concern, both illicit and non-illicit, such as alcohol, tobacco, cannabis, methamphetamine, and cocaine [5], which may receive less attention given the directed funding for opioids. For this reason, it was decided that the ECHO would address not only opioids, or any one substance, but rather be designed to provide techniques to help providers address SUD overall through a comprehensive, team-based lens and a harm reduction philosophy of care. Reflecting this broad topical approach, the program was titled the Weitzman ECHO: Comprehensive Substance Use Disorder Care (CSUDC ECHO) program.

CSUDC ECHO consisted of 24 twice-monthly sessions held between July 2021 and July 2022. Each 1-hour session included a 20- to 25-minute didactic presentation followed by 1 patient case submitted by a participant before the session and discussed live for the remaining 35-40 minutes. Textbox 1 outlines the didactic presentation topics for each session. A multidisciplinary core faculty facilitated each session and was comprised of 1 physician with dual board certification in family medicine and addiction medicine and experienced in treating SUDs at federally qualified health centers; 1 nurse practitioner who developed and leads a federally qualified health center medication-assisted treatment (MAT) program; 1 supervisory licensed counselor; and 1 population health expert. Together, the faculty built a 12-month curriculum covering diverse topics such as medication management, team-based care, trauma-informed care, stages of change and motivational interviewing, polysubstance use and co-occurring conditions, and coordinating levels of care.
**Session and didactic topic**

1. Philosophy of care (no case presentation).
2. Harm reduction strategies.
3. Principals of medication management.
5. Trauma-informed care: an overview.
6. Motivational interviewing.
7. Stages of change for addiction.
9. Medications for opioid use disorder basics.
11. Transitions of care.
13. Social determinants of health including barriers or challenges (no case presentation).
15. Legal factors and access.
17. Medication-assisted treatment for alcohol and tobacco use disorders.
20. HIV and hepatitis C virus in patients with substance use disorder.
21. Screening, brief intervention and referral to treatment into primary care.
22. Stimulant use disorder treatment and medication management.
24. Tobacco cessation for polysubstance patients.

Participants were recruited by email blasts targeted to each partner’s network of Ohio primary care providers and other members of the care team. A total of 109 participants attended at least one session, 16 participants attended between 7 and 11 sessions, and 23 participants attended over 12 (half) of the sessions. On average, there were 32 attendees at each session. Continuing education credits were offered to medical providers, behavioral health providers, and nurses.

**Purpose of Study**

The purpose of this study was to assess the ability of CSUDC ECHO to both address and meet 7 learning objectives (Textbox 2) and address multiple substances by analyzing (1) the frequency of exposure to the learning objective topics and substance types during case discussions and (2) participants’ knowledge, self-efficacy, skills, and attitudes related to the treatment of SUDs pre- to postprogram.

**Textbox 2. Weitzman Extension for Community Healthcare Outcomes: Comprehensive Substance Use Disorder Care learning objectives.**

- Project a harm reduction philosophy of care into your treatment of patients experiencing substance use disorders and explain this concept to peers.
- Use the care team more effectively to improve the management of patients experiencing substance use disorders.
- Use motivational interviewing and other behavioral techniques to improve patient outcomes related to substance use disorders.
- Better differentiate and implement medication management strategies for patients experiencing substance use disorders.
- Illustrate trauma-informed practices in the screening, assessment, and treatment of patients experiencing substance use disorders.
- Describe and manage common co-occurring conditions and polysubstance use more effectively in patients experiencing substance use disorders.
- Distinguish and address factors related to social determinants of health faced by specific populations experiencing substance use disorders.
Methods

Study Design and Data Collection

This study used a mixed methods design, using a conceptual content analysis [6] analyzing ECHO participant-led case presentations, as well as a 2-tailed paired-samples t test of participant self-reported learner outcomes. All ECHO attendees who registered and attended the Project ECHO CSUDC sessions are included in the deductive content analysis. All ECHO attendees who registered before and through the first session of the series were invited to complete a preseries survey (n=106) via Qualtrics survey software (Qualtrics). The preseries survey remained open for 3 weeks from June 25, 2021, to July 18, 2021. A total of 79 responses were received (n=79) for a response rate of 75%. Upon completion of the ECHO series, active attendees (ie, those that were still active at the conclusion of the series and did not officially drop from the series, as well as those who enrolled throughout the series) were invited to complete a postseries survey via Qualtrics Survey Software (n=90). The postseries survey remained open for 4 weeks from July 7, 2022, to August 2, 2022. A total of 25 responses were received (n=25) for a response rate of 28%. A total of 16 consented participants completed both the preseries and postseries surveys (n=16) and are included in the paired-samples t tests statistical analysis.

Ethical Considerations

This study was approved by the Community Health Center, Inc, Institutional Review Board (IRB; 1190) on January 6, 2022. Informed consent was accounted for by the authors through the administration of a consent form on the postseries survey gathering participant consent to use their deidentified survey data for the paired-samples t test analysis. The deductive content analysis was considered a secondary analysis and was given exempt status. All data used in this study were deidentified, accounting for privacy and confidentiality. No compensation for participation in this study was deemed necessary by the IRB.

Survey Tools

The preseries and postseries surveys were internally created and based on the Consolidated Framework for Implementation Research (CFIR) [7] and Moore’s Model of Outcomes Assessment Framework [8]. The specific CFIR domains assessed for include intervention characteristics, outer setting, inner setting, characteristics of individuals, and process [7]. Additionally, the levels of Moore’s Model of Outcomes Assessment Framework assessed for include level 2 (satisfaction), level 3a (declarative knowledge), level 3b (procedural knowledge), level 4 (competence), level 5 (performance), and level 6 (patient health) [8]. The surveys assessed changes in participants’ self-reported knowledge, attitudes, self-efficacy, and skills through statements centered on the series’ learning objectives. The preseries survey also collected participant characteristics including provider type and years of experience working with patients diagnosed with SUDs, as well as team-based care practices. Additionally, the postseries survey collected information on engagement and practice changes. The preseries survey instrument is presented in Multimedia Appendix 1 and the postseries survey instrument is presented in Multimedia Appendix 2.

While the preseries survey and postseries survey tools were based on CFIR [7] and Moore’s Model of Outcomes Assessment Framework [8], both surveys were internally designed. The internal research and evaluation and CSUDC ECHO programmatic teams created the survey tools through several iterations of the internal review, which also consisted of selecting the appropriate domain (ie, knowledge, attitudes, self-efficacy, and skills) to assess each series’ learning objective. Each domain used a 5-point Likert scale to assess responses. The surveys were then presented to the CSUDC ECHO series stakeholders and faculty for review and approval before administering the surveys to the ECHO attendees. See Multimedia Appendices 1 and 2 for the domain placement of learning objectives and the 5-point Likert scales.

Conceptual Content Analysis

To further evaluate Weitzman ECHO CSUDC aims, researchers conducted a conceptual content analysis [6] using a set of a priori themes extracted from the series’ learning objectives. Series’ learning objectives are detailed in Textbox 2. To establish a priori themes, researchers met before the launch of the ECHO to examine the series’ 7 learning objectives and extracted 7 themes for the content analysis. The themes were: harm reduction, team-based care, behavioral techniques, MAT, trauma-informed care, co-occurring conditions, and social determinants of health. To assess the frequency to which multiple substances were discussed, the themes also included 5 illicit and nonillicit substances of concern: alcohol, stimulants, opioids, cannabis, tobacco, or nicotine, plus polysubstance use when any 2 or more of these substances were identified. A conceptual analysis approach was used to gauge the dose and frequency of all learning objective themes and selected illicit and nonillicit substances. The content analysis aimed to confirm the discussion of the series’ learning objectives during case presentations and to determine to what extent multiple substances were able to be addressed.

Researchers evaluated all 22 participant-led ECHO case presentations and discussions for the presence of the selected themes in the prepared participant cases, faculty recommendations, and participant recommendations. Case presentations and discussions consisted of participants independently preparing a patient case to present and receive participant and faculty guidance for a patient treatment plan. Case presentations were recorded and transcribed using Zoom videoconferencing software (Zoom Video Communications, Inc). The transcriptions were then used for the conceptual content analysis.

To ensure coding accuracy, 4 researchers independently coded 27% (n=6) of the case presentations and met to reconcile discrepancies and better establish coding parameters. After reconciling discrepancies, 1 researcher coded the remaining 16 case presentations and discussion transcripts. The content analysis themes and descriptions are presented in Table 1.
Table 1. Conceptual content analysis themes and learning objectives.

<table>
<thead>
<tr>
<th>Theme</th>
<th>Learning objective</th>
</tr>
</thead>
<tbody>
<tr>
<td>Harm reduction</td>
<td>Project a person-centered philosophy of care into your treatment of patients experiencing substance use disorders and explain this concept to peers.</td>
</tr>
<tr>
<td>Team-based care</td>
<td>Use the care team more effectively to improve the management of patients experiencing substance use disorders.</td>
</tr>
<tr>
<td>Behavioral techniques</td>
<td>Use motivational interviewing and other behavioral techniques to improve patient outcomes related to substance use disorders.</td>
</tr>
<tr>
<td>Medication-assisted treatment</td>
<td>Differentiate and implement medication management strategies for patients experiencing substance use disorders.</td>
</tr>
<tr>
<td>Trauma-informed care</td>
<td>Illustrate trauma-informed practices in the screening, assessment, and treatment of patients experiencing substance use disorders.</td>
</tr>
<tr>
<td>Co-occurring conditions</td>
<td>Describe and manage common co-occurring conditions and polysubstance use more effectively in patients experiencing substance use disorders.</td>
</tr>
<tr>
<td>Social determinants of health</td>
<td>Distinguish and address factors related to social determinants of health faced by specific populations experiencing substance use disorders.</td>
</tr>
</tbody>
</table>

Paired-Samples t Test
To determine if Project ECHO CSUDC affected participant learner outcomes, researchers calculated mean scores reported on a Likert scale of 1 to 5 and conducted a paired-samples t test to compare pre- and postseries scores at a .05 significance level. The surveys consisted of matching statements assessing knowledge, self-efficacy, attitudes, and skills associated with the series’ learning objectives. The data were assessed for normality and homogeneity of variance and the assumptions were met. The data analysis was conducted using SPSS Statistics for Windows (version 26.0; IBM Corp).

Results

Participant Characteristics
CSUDC ECHO participants were asked to report their role type on the preseries survey. Of the participants that responded to the survey items (n=79), a majority were other care team members (n=32; 41%) followed by behavioral health providers (n=30; 38%) and medical providers (n=16; 21%). Additionally, participants were asked to indicate their years of experience working with SUDs. Most participants had between 1 and 5 years of experience (n=23; 29%) followed by 6-10 years (n=15; 19%), 11-20 years (n=14; 18%), less than 1 year (n=13; 16%), 7 participants indicated they do not work directly with patients (n=7; 9%), 21-30 years (n=4; 5%), 31-40 years (n=2; 3%), and more than 40 years of experience (n=1; 1%). Full participant characteristics of the entire CSUDC ECHO attendees, excluding the paired-samples t test sample, the paired-samples t test sample only, and all combined CSUDC ECHO attendees are provided in Table 2.

The attendance data of participants included in the paired-samples t test analysis were analyzed. Further, 6 (n=6; 38%) of the paired-samples t test participants attended 1% (n=1) to 25% (n=6) of the 24 CSUDC ECHO sessions, 3 (n=3; 19%) attended 26% (n=7) to 49% (n=11) of the sessions, 4 (n=4; 25%) attended 50% (n=12) to 75% (n=10) of the sessions, and 3 (n=3; 19%) attended 76% (n=19) to 100% (n=24) of the sessions.
Table 2. Participant characteristics of all ECHO\textsuperscript{a} participants and paired-samples \textit{t} test analysis sample.

<table>
<thead>
<tr>
<th>Role type, n (%)</th>
<th>CSUDC\textsuperscript{b} ECHO attendees (excluding paired-samples \textit{t} test participants; n=63)</th>
<th>Paired-samples \textit{t} test participants (n=16)</th>
<th>All CSUDC ECHO attendees (n=79)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medical providers</td>
<td>13 (21)</td>
<td>3 (19)</td>
<td>16 (20)</td>
</tr>
<tr>
<td>Behavioral health providers</td>
<td>22 (35)</td>
<td>8 (50)</td>
<td>30 (38)</td>
</tr>
<tr>
<td>Other care team members</td>
<td>27 (43)</td>
<td>5 (31)</td>
<td>32 (41)</td>
</tr>
<tr>
<td>Missing</td>
<td>1 (2)</td>
<td>0 (0)</td>
<td>1 (1)</td>
</tr>
<tr>
<td>Years of SUD\textsuperscript{c} care experience, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than 1</td>
<td>11 (17)</td>
<td>2 (13)</td>
<td>13 (16)</td>
</tr>
<tr>
<td>1-5</td>
<td>19 (30)</td>
<td>4 (25)</td>
<td>23 (29)</td>
</tr>
<tr>
<td>6-10</td>
<td>12 (19)</td>
<td>3 (19)</td>
<td>15 (19)</td>
</tr>
<tr>
<td>11-20</td>
<td>11 (17)</td>
<td>3 (19)</td>
<td>14 (18)</td>
</tr>
<tr>
<td>21-30</td>
<td>2 (3)</td>
<td>2 (13)</td>
<td>4 (5)</td>
</tr>
<tr>
<td>31-40</td>
<td>2 (3)</td>
<td>0 (0)</td>
<td>2 (3)</td>
</tr>
<tr>
<td>≥40</td>
<td>0 (0)</td>
<td>1 (6)</td>
<td>1 (1)</td>
</tr>
<tr>
<td>Does not work directly with patients</td>
<td>6 (10)</td>
<td>1 (6)</td>
<td>7 (9)</td>
</tr>
</tbody>
</table>

\textsuperscript{a}ECHO: Extension for Community Healthcare Outcomes.  
\textsuperscript{b}CSUDC: Comprehensive Substance Use Disorder Care.  
\textsuperscript{c}SUD: substance use disorder.

Conceptual Content Analysis

The conceptual content analysis indicated that all of the a priori themes relating to the learning objectives resulted in high frequencies and doses, appearing in a majority of case presentations and discussions. Further, 3 themes appeared in 100% (n=22) of case presentations and discussions, including team-based care at a frequency of 156, followed by harm reduction at a frequency of 152, and social determinants of health at a frequency of 135. In total, 4 themes appeared in less than 100% (n=22) of case presentations and discussions, but above 81% (n=18), including co-occurring conditions with a frequency of 118 and appearing in 95% (n=21) of case presentations and discussions, followed by behavioral techniques at a frequency of 108 and appearing in 91% (n=20) of case presentations and discussions, MAT at a frequency of 89 and appearing in 86% (n=19) of case presentations and discussions, and trauma-informed care at a frequency of 79 and appearing in 82% (n=18) case presentations and discussions. Additionally, multiple substances were represented but at differing frequencies. The substance that resulted in the highest frequency and dose was alcohol at a frequency of 64 and appeared in 81% (n=18) of case presentations and discussions, followed by stimulants at a frequency of 55 and 77% (n=17) of case presentations and discussions, opioids at a frequency of 49 and 59% (n=13) of case presentations and discussions. Cannabis resulted with a frequency of 38 but appeared in 64% (n=14) of case presentations and discussions. Finally, tobacco and nicotine resulted in the lowest frequency at 11 and dose appearing in 27% (n=6) of case presentations and discussions. When evaluating polysubstance use, which was limited to the use of two or more of the listed substances, we found a dose of 95% (n=21) of case presentations and discussions. The frequency of polysubstance use was not included in the conceptual content analysis since it was not a learning objective theme and the emphasis of the conceptual content analysis was focused on the specific illicit and nonillicit substance types. The results of the conceptual content analysis are presented in Table 3.
Table 3. The results of frequency and percentage of case appearances (dose) of conceptual content analysis themes.

<table>
<thead>
<tr>
<th>Theme</th>
<th>Frequency</th>
<th>Case appearances (dose), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Team-based care</td>
<td>156</td>
<td>22 (100)</td>
</tr>
<tr>
<td>Harm reduction</td>
<td>152</td>
<td>22 (100)</td>
</tr>
<tr>
<td>Social determinants of health</td>
<td>136</td>
<td>22 (100)</td>
</tr>
<tr>
<td>Co-occurring conditions</td>
<td>118</td>
<td>21 (95)</td>
</tr>
<tr>
<td>Behavioral techniques</td>
<td>108</td>
<td>20 (91)</td>
</tr>
<tr>
<td>MAT&lt;sup&gt;a&lt;/sup&gt;</td>
<td>89</td>
<td>19 (86)</td>
</tr>
<tr>
<td>Trauma-informed care</td>
<td>79</td>
<td>18 (82)</td>
</tr>
<tr>
<td>Substance type: alcohol</td>
<td>64</td>
<td>18 (81)</td>
</tr>
<tr>
<td>Substance type: stimulant</td>
<td>55</td>
<td>17 (77)</td>
</tr>
<tr>
<td>Substance type: opioid</td>
<td>49</td>
<td>13 (59)</td>
</tr>
<tr>
<td>Substance type: cannabis</td>
<td>38</td>
<td>14 (64)</td>
</tr>
<tr>
<td>Substance type: tobacco and nicotine</td>
<td>11</td>
<td>6 (27)</td>
</tr>
<tr>
<td>Polysubstance use of substance types</td>
<td>___&lt;sup&gt;b&lt;/sup&gt;</td>
<td>21 (95)</td>
</tr>
</tbody>
</table>

<sup>a</sup>MAT: medication-assisted treatment.<br>
<sup>b</sup>—: not available.

Paired-Samples t Test

**Knowledge**

In total, 4 knowledge domain statements resulted in statistically significant increases: understanding polysubstance use in patients experiencing SUD ($P=.02$), understanding the approach colleagues in other disciplines use to address SUD ($P=.02$), knowledge of medication management strategies for nicotine use disorder ($P=.03$), and knowledge of medication management strategies for opioid use disorder (OUD; $P=.003$). Additionally, all knowledge domain statements resulted in an increased change in mean score from preseries to postseries. The results of the knowledge domain preseries and postseries scores are presented in Table 4.

Table 4. The results of the paired-samples $t$ test for the knowledge domain.

<table>
<thead>
<tr>
<th>Statement</th>
<th>Preseries mean score (SD; 1-5)</th>
<th>Postseries mean score (SD; 1-5)</th>
<th>Change in mean</th>
<th>$P$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>I understand polysubstance use in patients experiencing substance use disorders</td>
<td>3.63 (1.03)</td>
<td>4.25 (0.45)</td>
<td>+0.62</td>
<td>.02</td>
</tr>
<tr>
<td>I understand factors related to social determinants of health faced by specific populations experiencing substance use disorders</td>
<td>4.13 (0.89)</td>
<td>4.31 (0.60)</td>
<td>+0.18</td>
<td>.38</td>
</tr>
<tr>
<td>I understand the approach of my colleagues in other disciplines (ie, behavioral health if you are a medical provider) to substance use disorder care</td>
<td>3.69 (0.87)</td>
<td>4.25 (0.58)</td>
<td>+0.56</td>
<td>.02</td>
</tr>
<tr>
<td>Knowledge of the different medication management strategies for patients experiencing—nicotine use disorder</td>
<td>3.40 (1.12)</td>
<td>4.00 (0.76)</td>
<td>+0.60</td>
<td>.03</td>
</tr>
<tr>
<td>Knowledge of the different medication management strategies for patients experiencing—alcohol use disorder</td>
<td>3.53 (0.99)</td>
<td>4.00 (0.54)</td>
<td>+0.47</td>
<td>.07</td>
</tr>
<tr>
<td>Knowledge of the different medication management strategies for patients experiencing—stimulant use disorder</td>
<td>3.07 (0.10)</td>
<td>3.71 (0.83)</td>
<td>+0.64</td>
<td>.10</td>
</tr>
<tr>
<td>Knowledge of the different medication management strategies for patients experiencing—opioid use disorder</td>
<td>3.56 (0.96)</td>
<td>4.19 (0.83)</td>
<td>+0.63</td>
<td>.003</td>
</tr>
</tbody>
</table>

**Attitudes**

No attitudes domain statements resulted as statistically significant. All attitudes domain statements resulted in an increased change in mean score from preseries to postseries except the statement about a treatment plan for a patient experiencing an illicit SUD only being successful if abstinence is maintained, which resulted in a negative change in mean score. The negative change in mean score from preseries to postseries was the appropriate direction of change for alignment with promoting a harm reduction philosophy. The results of the attitudes domain preseries and postseries scores are presented in Table 5.
Table 5. The results of the paired-samples $t$ test for the attitudes domain.

<table>
<thead>
<tr>
<th>Statement</th>
<th>Preseries mean (SD; 1-5)</th>
<th>Postseries mean (SD; 1-5)</th>
<th>Change in mean</th>
<th>$P$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>It is important to practice a harm reduction philosophy when treating patients experiencing substance use disorders</td>
<td>4.60 (0.63)</td>
<td>4.73 (0.46)</td>
<td>+0.13</td>
<td>.43</td>
</tr>
<tr>
<td>Practicing a harm reduction philosophy in the treatment of patients experiencing substance use disorders leads to better patient outcomes</td>
<td>4.47 (0.83)</td>
<td>4.60 (0.63)</td>
<td>+0.13</td>
<td>.50</td>
</tr>
<tr>
<td>It is important to identify factors related to social determinants of health that patients experiencing substance use disorders may be facing</td>
<td>4.71 (0.61)</td>
<td>4.86 (0.36)</td>
<td>+0.15</td>
<td>.44</td>
</tr>
<tr>
<td>Addressing factors related to social determinants of health in the treatment of patients experiencing substance use disorders leads to better patient outcomes</td>
<td>4.69 (0.60)</td>
<td>4.81 (0.40)</td>
<td>+0.12</td>
<td>.50</td>
</tr>
<tr>
<td>A treatment plan for a patient experiencing an illicit substance use disorder has only been successful if abstinence is maintained</td>
<td>2.25 (1.39)</td>
<td>2.00 (1.27)</td>
<td>–0.25</td>
<td>.43</td>
</tr>
</tbody>
</table>

**Self-Efficacy**

In total, 2 self-efficacy statements resulted in statistically significant increases: choosing a medication management strategy for nicotine use disorder ($P=.002$) and alcohol use disorder ($P=.02$). Additionally, all self-efficacy domain statements resulted in an increased change in mean score from preseries to postseries. The results of the self-efficacy domain preseries and postseries scores are presented in Table 6.

Table 6. The results of the paired-samples $t$ test for the self-efficacy domain.

<table>
<thead>
<tr>
<th>Statement</th>
<th>Preseries mean (SD; 1-5)</th>
<th>Postseries mean (SD; 1-5)</th>
<th>Change in mean</th>
<th>$P$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Providing trauma-informed care</td>
<td>3.20 (1.01)</td>
<td>3.67 (0.90)</td>
<td>+0.47</td>
<td>.15</td>
</tr>
<tr>
<td>Using motivational interviewing techniques</td>
<td>3.31 (1.08)</td>
<td>3.81 (0.83)</td>
<td>+0.50</td>
<td>.12</td>
</tr>
<tr>
<td>Creating SMART$^a$ goals with patients</td>
<td>3.43 (1.09)</td>
<td>3.79 (0.80)</td>
<td>+0.36</td>
<td>.29</td>
</tr>
<tr>
<td>Managing co-occurring conditions</td>
<td>3.40 (1.30)</td>
<td>3.93 (1.16)</td>
<td>+0.53</td>
<td>.16</td>
</tr>
<tr>
<td>Choosing an appropriate medication management strategy for—nicotine use disorder</td>
<td>2.75 (1.49)</td>
<td>3.88 (1.13)</td>
<td>+0.13</td>
<td>.002</td>
</tr>
<tr>
<td>Choosing an appropriate medication management strategy for—alcohol use disorder</td>
<td>2.63 (1.19)</td>
<td>3.75 (1.28)</td>
<td>+1.12</td>
<td>.02</td>
</tr>
<tr>
<td>Choosing an appropriate medication management strategy for—stimulant use disorder</td>
<td>1.86 (1.46)</td>
<td>2.00 (1.00)</td>
<td>+0.14</td>
<td>.79</td>
</tr>
<tr>
<td>Choosing an appropriate medication management strategy for—opioid use disorder</td>
<td>3.67 (1.41)</td>
<td>3.78 (1.48)</td>
<td>+0.11</td>
<td>.76</td>
</tr>
</tbody>
</table>

$^a$SMART: specific, measurable, achievable, relevant, timely.

**Skill**

In total, 1 skill domain statement resulted in a statistically significant increase: using the stages of change theory to provide stage-based interventions to patients experiencing SUDs ($P=.03$). Additionally, all skill domain statements resulted in an increased change in mean score from preseries to postseries. The results of the skill domain preseries and postseries scores are presented in Table 7.
The results of the paired-samples $t$ test for the skill domain.

<table>
<thead>
<tr>
<th>Statement</th>
<th>Preseries mean (SD; 1-5)</th>
<th>Postseries mean (SD; 1-5)</th>
<th>Change in mean</th>
<th>$P$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Screening patients experiencing substance use disorders for trauma</td>
<td>3.53 (1.13)</td>
<td>4.07 (0.96)</td>
<td>+0.54</td>
<td>.06</td>
</tr>
<tr>
<td>Using the stages of change theory to provide stage-based interventions to</td>
<td>3.06 (1.29)</td>
<td>3.69 (0.87)</td>
<td>+0.63</td>
<td>.03</td>
</tr>
<tr>
<td>patients experiencing substance use disorders</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Collaborating with peer support specialists when working with patients</td>
<td>3.33 (1.29)</td>
<td>3.93 (1.03)</td>
<td>+0.60</td>
<td>.06</td>
</tr>
<tr>
<td>experiencing substance use disorders</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Referring patients to a higher level of care, such as IOP\textsuperscript{a}, if needed</td>
<td>3.79 (0.98)</td>
<td>4.36 (0.75)</td>
<td>+0.57</td>
<td>.06</td>
</tr>
<tr>
<td>Preventing drug overdose of my patients experiencing a substance use disorder</td>
<td>2.83 (1.27)</td>
<td>3.25 (0.97)</td>
<td>+0.42</td>
<td>.10</td>
</tr>
</tbody>
</table>

\textsuperscript{a}IOP: intensive outpatient.

**Discussion**

**Principal Findings**

Ohio’s annual average prevalence of tobacco use, heroin use, use of prescription pain relievers, OUDs, illicit drug use disorder, and SUD have been higher compared to both regional and national averages [2]. Considering the need to address this public health concern, CSUDC ECHO was implemented to train Ohio providers and care team members in substance use care. CSUDC ECHO enhanced the Project ECHO work in this field by focusing content and learning objectives on a comprehensive, team-based lens and a harm reduction philosophy of care to address multiple illicit and nonillicit substances including opioids, alcohol, nicotine, cannabis, and stimulants. To assess the ability of the CSUDC ECHO program to meet its 7 program learning objectives (Textbox 2) and address multiple substances, this study analyzed (1) the frequency of exposure to learning objective themes and substance types during case presentations and discussions and (2) participating providers’ change in knowledge, attitudes, self-efficacy, and skills related to the treatment of SUDs.

Study results demonstrate that all 7 learning objectives were frequently addressed in the content of case presentations and discussions throughout the program, with team-based care being the most frequently mentioned, 3 objectives appearing in 100% (n=22) of case discussions (eg, team-based care, harm reduction, and co-occurring conditions), and all 7 objectives appearing in >81% (n=18) of all cases discussed. This may have resulted in the learner outcome improvement pre- to postprogram for multiple learner domains (eg, knowledge, self-efficacy, and skill) for the following themes: team-based care, MAT, polysubstance use, and behavioral techniques. No pattern emerged among the participants included in the paired-samples $t$ test analysis exposure to didactic topics and changes in learner outcomes.

Alcohol, stimulants, opioids, cannabis, and nicotine were addressed in the content of case presentations and discussions throughout CSUDC ECHO with alcohol being the most frequently mentioned and most common substance appearing in cases, 4 substances appearing in >59% (n=13) of case discussions (eg, alcohol, stimulants, opioid, and cannabis), and all coded substances appearing in at least a quarter of cases. The dialogue about these substances during case discussions likely resulted in improvements to the following learner outcomes related to medication management: alcohol use disorder, OUD, and nicotine use disorder. Medication management of cannabis use disorder was not assessed in the pre- to postsurveys. Additionally, the didactic presentation topics that centered on alcohol, opioid, and nicotine use disorder resulted in a higher attendance rate with about 40% (n=6) to 50% (n=8) of the participants included in the paired-samples $t$ test analysis attending the sessions, as compared to only 20% (n=3) of the aforementioned participant sample having attended the session centered on stimulant use disorder.

These findings indicate that the ECHO program’s content aligned with its stated learning objectives; met its learning objectives for the 3 themes where significant improvements were measured; and met its intent to address multiple substances in case presentations and discussions. While case presentations and discussions comprise from half to the majority of content in the sessions (30-35 minutes of a 60-minute session), content during sessions also includes faculty didactic presentations (20-25 minutes), which also addresses these 7 learning objectives and various substances but was not a part of the content analysis. Therefore, learner outcome improvements may also be a result of content addressed in didactic presentations.

While the Project ECHO model has been shown to be effective in training the primary care workforce [9], specifically on OUD [10,11] and addiction medicine [12,13], there has been no documentation, to our knowledge, of the ability of a team-based, comprehensive SUD and polysubstance-focused Project ECHO designed to improve learner outcomes (eg, knowledge, self-efficacy, and skills). Although Komaromy and colleagues [14] investigated the frequency of cases presented based on substance type in a comprehensive SUD-focused ECHO, a content analysis of the case presentation and discussion transcripts was not analyzed to either assess the frequency of substances or learning objectives. Furthermore, to our knowledge, this process has not been combined in a mixed method approach to compare learner outcomes with a content analysis to gauge the ability of an SUD-focused Project ECHO program to meet its stated learning objectives. Our results reported here align with this literature and expand to demonstrate that Project ECHO is a potential tool to effectively educate
multidisciplinary providers in a comprehensive approach to SUD care.

**Strengths**

This study has several strengths which promote the ability of the Project ECHO model in enhancing health care providers’ knowledge, self-efficacy, and skill associated with comprehensive SUD care. The focus of this study is unique as there is minimal research exploring the benefits and training ability of Project ECHO with a comprehensive SUD care focus. This study’s noteworthy strength is the use of a mixed methods design that presents a comprehensive evaluation correlating the content addressed in the case presentations and discussions to statistically significant learner outcomes to demonstrate how this telementoring continuing education series improved provider’s knowledge, skills, and self-efficacy to benefit participating providers and their practices.

**Limitations**

This study faced several limitations during data collection and analysis. The first limitation of this study was the limited sample size and low response rate. There was a decline between the number of participants who completed the preseries survey and postseries survey, resulting in a low comparative sample, which restricted the options for statistical analysis. Another limitation was generalizability; the results of this Project ECHO are limited to the target audience of medical providers, behavioral health providers, and care team members from the state of Ohio, which is not a representative sample of broader populations nationally. Additionally, participants self-selected to take part in the Project ECHO series, which presents the potential for self-selection bias. Another limitation this study faced was the lack of available or reliable data on Project ECHO and its ability to meet learning objectives and address multiple substances through providers’ knowledge, self-efficacy, skill, and attitudes. Furthermore, self-reported data to assess knowledge and skills, and self-reported data in general, could present participant biases and is difficult to corroborate with outcomes. The use of internally designed survey instruments instead of using validated instruments presents as a limitation. In light of these limitations, future studies in this subject matter should include a larger data set. Additionally, future studies using a nested analysis approach might provide more insight into how the learning objective themes coincide with the various illicit and nonillicit substance types and would be a useful analysis to contribute to the knowledge base. Another recommendation for future studies in this subject matter should include a deeper analysis of attendance dose and exposure to didactic topics to better understand the impact on changes in learner outcomes. Future research with greater validity will contribute to the significant gaps in literature regarding this subject.

**Conclusions**

The purpose of this research study was to assess the ability of CSUDC ECHO to both address and meet 7 learning objectives (Textbox 2) and address multiple substances by analyzing (1) the frequency of exposure to the learning objective topics and substance types during case presentations and discussions and (2) participants’ knowledge, self-efficacy, skills, and attitudes related to the treatment of SUDs from pre- to postprogram. The results of this study indicate that CSUDC ECHO was able to both address and meet its learning objectives while addressing multiple substances, as demonstrated by improvements in learner knowledge, self-efficacy, and skills. All learning objective themes resulted in high frequencies and doses, appearing in a majority of case presentations throughout the series. These promising results suggest that Project ECHO is a potential tool to educate primary care providers, behavioral health providers, and care team members in a comprehensive approach to SUD assessment and treatment through complex case discussions combined with didactic learning for certain settings. As Project ECHO programs continue to be established globally and existing programs strengthen, further research examining the model’s ability to achieve positive learning outcomes and factors that may contribute to these outcomes (eg, frequency of topic dose) is needed to confirm the outcomes in larger population samples, additional topics of focus, and other geographical settings.

**Acknowledgments**

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Data Availability

The data sets generated and analyzed during this study are not publicly available due to a portion of the data being deemed as exempt by the institutional review board and the institutional review board approving a waiver of informed consent for the exempt data, as well as the sensitive nature of the data, but are available from the corresponding author on reasonable request.

Authors' Contributions

MK wrote this paper, reviewed this paper, designed the evaluation plan, and performed the qualitative and statistical analyses. AP wrote this paper, reviewed this paper, and assisted with the evaluation design and approval. RM wrote this paper, reviewed this paper, performed the literature review, and assisted with the evaluation design and approval. NRN wrote this paper, reviewed this paper, and performed the literature review. KA critically reviewed this paper.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Weitzman Extension for Community Healthcare Outcomes: Comprehensive Substance Use Disorder Care preseries survey instrument.
[DOCX File, 22 KB - mededu_v10i1e48135_app1.docx ]

Multimedia Appendix 2

Weitzman Extension for Community Healthcare Outcomes: Comprehensive Substance Use Disorder Care postseries survey instrument.
[DOCX File, 19 KB - mededu_v10i1e48135_app2.docx ]

References


15. Weitzman Institute. URL: https://www.weitzmaninstitute.org/education/weitzman-echo/ [accessed 2024-03-12]

Abbreviations
CFIR: Consolidated Framework for Implementation Research
CSUDC: Comprehensive Substance Use Disorder Care
ECHO: Extension for Community Healthcare Outcomes
IRB: institutional review board
MAT: medication-assisted treatment
OUD: opioid use disorder
SUD: substance use disorder
WI: Weitzman Institute

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Abstract

Background: Interoperability between health information systems is a fundamental requirement to guarantee the continuity of health care for the population. The Fast Healthcare Interoperability Resource (FHIR) is the standard that enables the design and development of interoperable systems with broad adoption worldwide. However, FHIR training curriculums need an easily administered web-based self-learning platform with modules to create scenarios and questions that the learner answers. This paper proposes a system for teaching FHIR that automatically evaluates the answers, providing the learner with continuous feedback and progress.

Objective: We are designing and developing a learning management system for creating, applying, deploying, and automatically assessing FHIR web-based courses.

Methods: The system requirements for teaching FHIR were collected through interviews with experts involved in academic and professional FHIR activities (universities and health institutions). The interviews were semistructured, recording and documenting each meeting. In addition, we used an ad hoc instrument to register and analyze all the needs to elicit the requirements. Finally, the information obtained was triangulated with the available evidence. This analysis was carried out with Atlas-ti software. For design purposes, the requirements were divided into functional and nonfunctional. The functional requirements were (1) a test and question manager, (2) an application programming interface (API) to orchestrate components, (3) a test evaluator that automatically evaluates the responses, and (4) a client application for students. Security and usability are essential nonfunctional requirements to design functional and secure interfaces. The software development methodology was based on the traditional spiral model. The end users of the proposed system are (1) the system administrator for all technical aspects of the server, (2) the teacher designing the courses, and (3) the students interested in learning FHIR.

Results: The main result described in this work is Huemul, a learning management system for training on FHIR, which includes the following components: (1) Huemul Admin: a web application to create users, tests, and questions and define scores; (2) Huemul API: module for communication between different software components (FHIR server, client, and engine); (3) Huemul Engine: component for answers evaluation to identify differences and validate the content; and (4) Huemul Client: the web application for users to show the test and questions. Huemul was successfully implemented with 416 students associated with the 10 active courses on the platform. In addition, the teachers have created 60 tests and 695 questions. Overall, the 416 students who completed their courses rated Huemul highly.

Conclusions: Huemul is the first platform that allows the creation of courses, tests, and questions that enable the automatic evaluation and feedback of FHIR operations. Huemul has been implemented in multiple FHIR teaching scenarios for health care professionals. Professionals trained on FHIR with Huemul are leading successful national and international initiatives.
interoperability; health information system; Health Level Seven International; HL7; Fast Healthcare Interoperability Resource; FHIR; certification; training; interoperable; e-learning; application programming interface; API

Introduction

A critical requirement for universal access to health is to have interconnected and interoperable health systems that guarantee effective and efficient access to quality data, strategic information, and tools for decision-making and people’s well-being [1]. One of the most relevant areas in medical informatics is the interoperability between health information systems. The interoperability eliminates duplication and errors in health data. For this reason, health informatics professionals must be educated about the benefits of interoperable systems. Therefore, strategic education on eHealth and interoperability standards is needed to enable health care professionals to make informed decisions [2].

The Fast Healthcare Interoperability Resource (FHIR) is an interoperability standard used in health information technology, introduced in 2011 by the Standard Developing Organization Health Level Seven International (HL7) [3]. FHIR is based on previous HL7 standards (HL7 versions 2 and 3 and Clinical Document Architecture) and combines their advantages with established modern web technologies such as a Representational State Transfer (REST) architecture [4], application programming interface (API), XML, JSON formats, and authorization tools (Open Authorization). The main idea behind FHIR was to build a set of resources and develop http-based REST APIs to access and use these resources. FHIR uses components called resources to access and perform operations on patient health data at the granular level [5,6].

The adoption of FHIR in health information systems by developers and companies has grown in recent years with multiple applications in various fields [5,7-9]. Thus, FHIR is positioned as an interoperability standard that is easy to understand by nontechnology professionals, with fast learning curves that minimize the development time of applications and new tools. In addition, its technological core is aligned with the latest architectures and web standards that allow the development of open APIs, which facilitates interoperability between systems [10].

Teaching and learning interoperability standards, particularly FHIR, within digital health education programs have been oriented more toward delivering content, presentations, and audiovisual material, considering the solution of practical problems separately [2]. Continuously emerging new technologies (synchronous and asynchronous) promise new and improved experiences for individual users but often bring new challenges [11].

The existing learning management systems (LMSs) are oriented to support cross-cutting activities (forums, chat, and content uploading) with content delivery (videos, documents, and links) [12] but not to evaluate REST operations for accessing and using resources. For the use of APIs, some platforms allow interaction with FHIR servers, such as Postman (Postman, Inc) or Insomnia (Kong Inc). However, they cannot create content, manage questions, automatically evaluate the response, or provide feedback but only act as an interface between the user and the FHIR server.

The configuration currently used to teach FHIR is to publish the contents in an LMS or website and, for practice, use tools such as Postman [13,14] without the possibility of having automatic feedback and correction of the activities. The results of the practical exercises must be uploaded as a document to the LMS, with written create, read, update, and delete (CRUD) operations and server response in plain text. The teacher must review them, which makes it challenging to implement workshops with many questions for large groups of students. Other websites offer the opportunity to learn FHIR with guides and theoretical content, such as Simplifier (Firely Corporation).

It should be noted that Simplifier is a platform for building FHIR implementation guides. It does not claim to be an LMS or to manage courses.

There is currently no LMS for training on FHIR that allows problem-oriented assessment and practice of web-based CRUD operations. Practice is essential to learn FHIR; therefore, a problem-oriented platform is necessary, allowing the creation and administration of practical courses (where a problem is presented) with different levels of complexity and for multiple professionals (clinicians, engineers, and technicians). In addition, each course should be associated with a set of exercises, which the students must answer with CRUD operations (eg, create a patient with the data given in the description or modify the patient information with the new phone number provided). The platform should automatically evaluate these answers, and feedback should be provided to guide each question’s achievement (or nonachievement). This would help generate an extensive repository of massive web-based training programs focused on specific problems, where students must practice as requested. The lack of such platforms has motivated the interoperability team of the National Center for Health Information System (CENS) [15] to design a tool capable of automatically teaching and evaluating FHIR.

In this sense, our goal was to develop an API that allows us to integrate and communicate a set of loosely coupled modules that enable teachers to manage FHIR training programs, designing courses, questions, and scenarios. In addition, learners can interact through a web client for self-learning sessions, where the API, in conjunction with an assessment engine, provides feedback for each attempt the learner makes. This undoubtedly streamlines the self-learning process and automates the correction of hundreds of CRUD operations and the submission of learner responses within a context that the platform delivers.
The design and development of a platform called Huemul support the creation of courses associated with multiple questions (which expect a CRUD operation as an answer), automate the evaluation of the responses, and provide automatic feedback to the students in each exercise. We have also created an administrator that allows us to create and manage courses, questions, and users.

**Methods**

**Study Design**

The e-learning system requirements for teaching FHIR were collected through interviews with experts involved in academic and professional activities (universities and health institutions). The interviews were semistructured, recording and documenting each meeting. In addition, we used an ad hoc instrument to register and analyze all the needs to elicit the requirements.

The CENS academic committee, formed by 5 senior biomedical informatics researchers (3 engineers: 2 biomedical and 1 informatics and 2 medical doctors), was the initial core of experts consulted. In another focus group, engineers from the interoperability area of CENS, experts in FHIR, were consulted. They presented their requirements and needs to automate both the deployment and evaluation of the different interoperability challenges organized by CENS, where the need to register, quantify, and evaluate the hundreds of requests sent by the participants to the server was a problem when assessing their tests. These interoperability events were part of Chile’s CENS human capital training program.

Both academics and CENS engineers were interviewed with the following questions: Do you think a platform for teaching HL7 FHIR is necessary? What functions should it have? What non-functional requirements do you think are essential for the platform? For more details, see Multimedia Appendix 1.

Finally, the students (engineers from health institutions) were consulted on the platform’s functionality, modules, and usability in the first application of the pilot. A small instrument with 5 questions on a Likert scale (scale of 1-5) was applied to assess the application and the proposed modules, considering the user interface, quality of feedback, response times, quality of the content, and the response console. In addition, 2 open-ended questions were asked about the advantages and disadvantages of the platform.

The focus group sessions were transcribed, the topics of interest were categorized (user profile, usability, perceptions of use, and design), the patterns present were identified and interpreted, and the information obtained was triangulated with the available evidence. This analysis was carried out with Atlas-ti software (Scientific Software Development GmbH). With this information, the final prototype and the website for its deployment were designed.

End users are classified according to the following profiles: (1) system administrator in charge of the deployment and administration of the modules, client, and all technical aspects of the server; (2) professor who designs the course and describes the clinical context and associated questions; and (3) students in charge of accessing the client to answer questions about the course they are enrolled in.

**Requirements**

The system design requirements were divided into functional and nonfunctional (Textbox 1). The system development aimed to support the functional requirements to run e-learning sessions for FHIR courses. Regarding the nonfunctional requirements, security and usability are essential to design functional and secure interfaces by considering technological aspects, learner interactions, and instructional design [16,17] (Table 1). For more details, see Multimedia Appendix 1.
Textbox 1. Functional requirements to design the system for teaching FHIR (Fast Healthcare Interoperability Resource).

1. Test and question manager:
   - Users’ management
   - FHIR create, read, update, and delete (CRUD)-oriented test management
   - FHIR CRUD operations
   - CRUD courses
   - Create and manage a database with questions, tests, and courses

   For an FHIR test (where the context and the problem are explained), examples of questions could be:
   - Create the patient with the information given in the description
   - Create a medical encounter
   - Modify the phone number and address of the doctor
   - Delete the patient

2. Application Programming Interface (API) for orchestrating components:
   - Users’ authentication management
   - Call up tests and questions
   - Validate user answers
   - Save user answers
   - Execute FHIR CRUD operation on the server

3. Test evaluator:
   - Evaluate answers
   - Compare questions and answers
   - Build resources with the HAPI FHIR library
   - Validate resources with standard

   The expected answer should be a CRUD operation for a FHIR test (where the context and the problem are explained). For example, for the creation of a patient, the student must complete the following:
   - Method for creating a FHIR resource (post)
   - [FHIR Endpoint]/patient (URL server and resource name)
   - Patient data (JSON format; patient information)

4. Client application:
   - Create responsive front end
   - Communicate using the Huemul API
   - Decoupled other components
Table 1. Tools, libraries, and relation with each software component.

<table>
<thead>
<tr>
<th>Development area and tools or libraries</th>
<th>Related component</th>
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<tbody>
<tr>
<td></td>
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</table>

<sup>a</sup>API: application programming interface.
<sup>b</sup>FHIR: Fast Healthcare Interoperability Resource.

Software Development Methodology

The development methodology was based on the traditional spiral model. The spiral development model starts with a small set of requirements and goes through each development iteration for that set of requirements. Then, the development team adds functionality for the additional requirement in ever-increasing spirals until the application is ready for the production phase [18].

Each iteration has objectives related to the evolution of the components to be developed:

1. Modeling and management: in the first iteration, a functional database model was generated with the objective that it can support the definition of models related to tests, users, questions, and courses and the creation of FHIR learning tests. In addition, an administration application (Huemul Admin) was created to maintain the generated models. Once the model was built, a REST API (Huemul API) was developed to consult the information.

2. Improvements to the data model and API: in the second iteration, improvements to the model were included with the analysis of the previous iterations, authentication and security features of the REST API, and the creation of a web client (Huemul Client) for the consumption and interaction of the REST API.

3. Response processing and evaluation: in the third iteration, models for response processing are included, an interface for sending responses to the web client is added, and an engine (Huemul Engine) for response evaluation is created. The administrator creates a test planning mechanism, setting start and end times.

4. Functional improvements and feedback: in the fourth iteration, modifications are introduced in the processing of answers, feedback in case of incorrect answers, and the enabling of a natural resource query interface.

Each developed component has a set of tools described in Table 1, the languages used are Python (Python Software Foundation) and Java (Oracle Corporation) in the backend, and all interaction between components involves using a REST API. In addition, the front end group has some traditional libraries for client development, as it uses another API to consume resources independently and does not restrict alternative clients.
Three full-time computer engineers and the leader of the CENS interoperability area worked on the platform to create the software. It took 6 months to develop the prototype and 1 month to make modifications during the pilot implementation.

**Ethical Considerations**

It should be noted that this research complied with ethical standards in accordance with the Declaration of Helsinki (updated in 2013).

**Results**

**Overview**

Huemul has 4 components that were designed and named considering the functional and nonfunctional requirements. Therefore, the following modules are necessary to develop a scalable and robust system:

1. **Huemul Admin**: web application to create users, tests, questions, and scores.
2. **Huemul API**: communication between different components of Huemul (FHIR server, client, and engine).
3. **Huemul Engine**: answers evaluation to identify differences and validate responses.
4. **Huemul Client**: web application for users to show the test and questions.

The architecture of the developed system allows for the separation into different layers. For example, the software was built under the Model-View-Controller architecture [19] to separate the views from the data model and the business logic (Figure 1). Furthermore, since usability is one of the most important nonfunctional requirements, views use web technologies, such as HTML5, JavaScript, and CSS3, to ensure access to different web browsers.

The front end can display the courses created and managed by the administration component, where the users can answer each question. In the business-oriented layer, Huemul API interconnects with the validation engine and communicates the user’s answers to this engine, which oversees validating and reviewing their structure and content. The API is Huemul’s communication core. Once a user’s response has been validated, it connects the operation with the backend (HAPI FHIR server) and communicates the result to the client.

**Figure 1.** The system architecture of Huemul with the components and their relations. API: application programming interface; FHIR: Fast Healthcare Interoperability Resource.

### Huemul Admin

The admin component was developed as a web application to create users, tests, and questions with associated test scores. This component is decoupled from the overall system architecture, providing independence and modularity. Figure 2 shows a set of screenshots with the main functionalities of the Huemul Admin component. It shows the questions created, associated FHIR servers, tests, users, and courses. Each mentioned element can be modified and associated with generating modular courses that are easy to administer.

It is essential when creating a course to situate the clinical scenario within a context (outpatient, emergency, inpatient, and home). This will help health professionals, who are learning about interoperability, to better design the necessary resources, and CRUD operations required to solve the problems presented.
Huemul API

The core of the communication is Huemul API. This API communicates the different components of Huemul (FHIR server, client, and evaluation engine), orchestrating the whole system. An essential task of the API is communicating between the client and the evaluation engine. The test evaluation process begins when the learner sends an answer through the Huemul client application until the response is received. Specifically, the steps are as follows (Figure 3):

1. Send a request from the client: the student sends the response through the client application.
2. Internal validation: the API performs basic validations of the request sent from the client. It validates the server URL, the headers, and the body of the JSON content.
3. Engine validation: performs a full validation by comparing the answer sent by the student with the expected answer configured when creating the question.
4. Evaluation response: once all the validations have been carried out, the result is delivered, either a successful or unsuccessful comparison.
5. FHIR request: once the expected response has been validated against the one sent, if the evaluation in the engine was successful, the student’s response is sent to the corresponding FHIR server to be saved.
6. FHIR response: the FHIR server receives the request, processes it, and assigns a destination variable to the resource to identify the student who sends the response and responds to the API.
7. Build success answer: if the response from the FHIR server is successful, the API constructs the response with the summary of the validation process, evaluation, and result from the FHIR server, which will be sent to the client application.
8. Response: the API sends the answer to the client application so that the result of its submission is displayed on the screen to the learner.
Huemul Engine

This component has the function of response evaluation, for which it evaluates 2 responses, the expected response and the user’s response. The processing comprises 3 subprocesses to finally have an evaluation result that allows us to assess if the answer is correct or to assess the percentage of completeness (Figure 4).

A FHIR request, by definition, contains the following elements to be assessed:

- Base URL of the FHIR server.
- Path of the resource or query to be made to the server.
- The header of the requested content is JSON or XML.
- The body of the resource is JSON or XML format if, in case, REST methods require a body; otherwise, the body will not have information for the request.

The methods accepted to create a question are POST, PUT, GET, and DELETE.

Huemul Client

Huemul provides a web client for users, allowing them to display the test and the questions, and is the interface with the platform. For example, on the screen for sending the answer, the question statement and essential information for answering (action, precondition, expected task, etc) are presented; there is also a button to visualize the description of the scenario, and below in notifications, the platform gives feedback to the user to improve and correct the answers (Figure 5). For more details, see Multimedia Appendix 2.

When the user enters a course, the client presents the complete scenario, including information relevant to the test. Below is a
list of the exercises to be answered; each activity has an associated answer button with different colors.

- Orange button: exercise active but still needs to be answered.
- Green button: exercise with the correct answer.
- Red button: exercise with the wrong answer.

Figure 5. Huemul Client with a test consisting of an explanation of the scenario and associated questions. FHIR: Fast Healthcare Interoperability Resource.

Initial Evaluation of Huemul Use

In early 2020, we conducted a pilot project in which we invited 20 health care professionals from different national institutions (10 systems development, 3 physicians, 4 computer scientists, and 3 nurses). They were students in a pilot course that presented a clinical situation and had to answer the questions through CRUD operations with HL7 FHIR. Once the course was completed, we gave them 5 questions. The questions had 5 scores according to the Likert scale for quality: 1=very poor, 2=poor, 3=fair, 4=good, and 5=excellent.

Each question focused on evaluating aspects related to the following five dimensions:

1. End-user interface: the platform is accessible and attractive for students.
2. Quality of response: feedback provided by the platform was helpful.
3. Response times: platform response times are adequate.
4. Quality of content: course description and questions are adequate.
5. Response console: response console is intuitive and easy to use.

In addition, we incorporated 2 open-ended questions that inquired about the advantages and disadvantages of the platform. The most rates of the dimensions scored on average above 4 (response times=4.9, quality of content=5, and response console=4.6). The only dimensions that did not cut above 4 on average were end-user interface and quality of feedback, with averages of 3.4 and 3.0, respectively.

This was consistent with the qualitative analysis of the open-ended questions, where students rated the content, questions, response times, and the working console positively. In general, they expressed the platform’s usefulness for self-study of FHIR. However, the usability was criticized...
Concerning the navigation between the questions and the test, the font and size of the text, and the lack of information to support formatting.

Currently, Huemul has the following usage statistics:

- Users: 416 students with one or more courses in the platform.
- Courses: 10 courses.
- Tests: 60 tests.
- Questions: 695 questions (431 used and 264 unused; 572 general questions that can be used by any teacher with a Huemul account and 123 private questions).
- Response rate: 1725 (1666 completed+59 incomplete).

During the last 3 years, including the COVID-19 pandemic, 416 students have answered the same questions to evaluate the platform (with the exact 5 dimensions applied in the 2020 pilot). The evaluation has been good, with slight improvements since the pilot in dimensions 1 and 2. The same open-ended questions were applied in each course. The general comments are good or excellent, with suggestions for improvements, mainly in usability issues. The main criticisms collected in the open questions coincide with the pilot’s answers, making comments for feedback too brief and needing more helpful information to solve the exercise. Another aspect that stands out is usability, color, and font size.

Each comment has helped us to improve, incorporating a graphic designer into the team and improving the navigability of Huemul. In addition, feedback was complemented with templates of the principal associated resources that allow students to learn in a more guided way.

The preliminary impact detected is the increase in interoperability projects associated with FHIR in Chile, where the project leaders are the professionals who participated in the CENS courses with Huemul. In addition, some professionals (clinicians and engineers) were incorporated into the government to work on national strategies linked to FHIR. Other participants were recruited for medical informatics departments in hospitals (both public and private), where they led projects with FHIR.

Discussion

Principal Findings

The Huemul FHIR learning platform was designed and developed with loosely coupled components to communicate through a central API orchestrating module communication. This design was fundamental when starting to plan, considering the development of an API rather than a platform. In addition, its decoupling allows the API to interact with different technologies and with other systems and software that students can use while maintaining the independence of the components.

Integrating information dispersed in different systems is a relevant problem in health informatics. Thus, health informatics professionals must strengthen interoperability by learning standards that allow proper use. Currently, the most promising interoperability standard is FHIR. It builds on the concepts of the previous HL7 standards. The main objective of FHIR is to facilitate the implementation of solutions in various contexts: mobile apps, cloud communications, telemedicine, and medical records data sharing, among many others. Therefore, one of its main strengths is its ease of use and better learning curve compared to previous standards; this allows doctors, nurses, and engineers to work together in designing interoperable health care informatics solutions.

To develop competencies in FHIR, Huemul has been fundamental for training professionals in Chile. The CENS [15], with its Health Information Systems (HIS) Reference Competency Model [20], has developed and used it to strengthen and generate competencies in interoperability and standards, especially with HL7 FHIR. The model proposed by CENS brings together consensual knowledge, skills, and attitudes as a reference that guides the training of excellence in biomedical informatics. Moreover, the model drives the design of undergraduate and postgraduate training curricula and establishes common training standards in the country and the region. In addition, it makes it possible to make it evident on what is expected of professionals and technicians in this sector and what is expected of them from the point of view of job opportunities or professional development.

In Chile and Latin America, there is a need for biomedical informatics professionals trained in interoperability and standards for sharing data between HIS [2]. Currently, the demand for professionals with these competencies has increased the digital gap in health and, consequently, has slowed down the changes needed to have a more connected health with robust standards, terminologies, and HIS. Huemul is available for training processes that require new ecosystems and models.

In this context, Huemul is a web application that creates users, tests, and questions to define scores and reviews them automatically in interoperability scenarios with HL7 FHIR. Huemul was the learning platform for Chile’s annual health interoperability meeting in 2020 and 2021 [21]. The interoperability meeting featured 4 sections of HL7 FHIR exercises (patient, diagnostic report, electronic medical prescription, and electronic health record), with 2 levels of complexity: introductory and intermediate. More than 100 participants each year performed hundreds of CRUD operations per exercise, which Huemul reviewed automatically. In addition, Huemul has been the official CENS platform for delivering HL7 FHIR training courses.

As a result, in the last 3 years, more than 400 technicians, engineers, and health professionals interested in learning FHIR from all over the country have been trained so far [20]. Moreover, the CENS academic team generated 10 courses with 60 associated tests. Huemul has made it possible to create a repository with more than 695 questions with different complexity levels. Each applied course has served as feedback, considering that we asked the students about the quality of our platform; considering all the dimensions exposed in the results, the users have a good evaluation of Huemul. We are still working on usability and feedback on the answers; we believe that we must improve and move forward, for example, to mobile devices and expand the content base and application areas.

Most trained professionals are leading interoperability projects with FHIR from the government, universities, and public or
private health institutions. CENS continues to support capacity building for both professionals and institutions. In this sense, Huemul is an effective tool to support practical activities, enabling the teaching of FHIR. We expect to continue advancing and complementing Huemul with new functionalities and modules in future work.

**Future Work**

Concerning future work, Huemul is currently in the process of redesigning for a 2.0 version that will allow us to incorporate new functionalities:

- Incorporate extensions, profiles, and extended Huemul for more search parameters. This would allow the number of questions, courses, and scenario options to be expanded as well as the complexity of the tests.

- Incorporate multiple choice and true and false questions to prepare for the HL7 FHIR certification examination. Incorporating content questions would give us a robust tool to prepare the CRUD operations in a clinical scenario and the theoretical context that will enable us to schedule examinations and certifications (eg, HL7 FHIR Proficiency examination).

- Create web-based courses with LMSs (for instance, Moodle) and Huemul. Integration with LMS platforms would extend the teaching ecosystem, incorporating content management systems, chat, forums, and all the tools with LMS.

- Incorporate other FHIR servers. Until now, Huemul has been working with HAPI FHIR, which is a complete implementation of the HL7 FHIR standard for health care interoperability in Java [22]. The advantage of having a decoupled system is the ease and modularity of its components. Huemul currently works with HAPI FHIR as a server; however, another server could be incorporated.

Another interesting aspect is evaluating and certifying interoperability levels in health information systems in a natural context [23]. Huemul could extend its applicability to other domains, for example, the assessment of HIS interoperability in hospitals, clinics, and all types of health institutions. Any modifications to its approach would be minimal, as its original 4-component structure would be maintained: Huemul Admin, Huemul API, Huemul Engine, and Huemul Client. The main changes should focus on the client-submitted request evaluation engine, broadening its focus from teaching HL7 FHIR to a more enterprise-based domain.

Considering a detailed systematic evaluation, the platform’s usability is interesting to investigate deeply. Therefore, a study design that allows the application of validated instruments and the collection of information from multiple profiles and professionals is proposed as future work.

**Conclusions**

Huemul is the first platform that allows the creation of courses, questions, and scenarios that enable the automatic evaluation and feedback of CRUD operations with HL7 FHIR. Huemul has been implemented and applied in multiple HL7 FHIR teaching scenarios for health care professionals. It has demonstrated its efficiency and effectiveness in courses and massive events, managing hundreds of users and evaluating thousands of answers in these 4 years of application.

Of the 416 students who were trained with Huemul, many are currently leading interoperability projects with HL7 FHIR, both in the government and the private sector, contributing to developing digital health and information systems in Chile.

**Acknowledgments**

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**Conflicts of Interest**

None declared.

**Multimedia Appendix 1**

Huemul functional requirements.

[DOCX File, 30 KB - mededu_v10i1e45413_app1.docx ]

**Multimedia Appendix 2**

User manual client.

[DOCX File, 2869 KB - mededu_v10i1e45413_app2.docx ]

**References**


Abbreviations

API: application programming interface
CENS: National Center for Health Information System
CRUD: create, read, update, and delete
FHIR: Fast Healthcare Interoperability Resource
HIS: Health Information Systems
HL7: Health Level Seven International
LMS: learning management system
REST: Representational State Transfer
The Effects of Immersive Virtual Reality–Assisted Experiential Learning on Enhancing Empathy in Undergraduate Health Care Students Toward Older Adults With Cognitive Impairment: Multiple-Methods Study

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Abstract

Background: Immersive virtual reality (IVR)–assisted experiential learning has the potential to foster empathy among undergraduate health care students toward older adults with cognitive impairment by facilitating a sense of embodiment. However, the extent of its effectiveness, including enhancing students’ learning experiences and achieving intended learning outcomes, remains underexplored.

Objective: This study aims to evaluate the impacts of IVR-assisted experiential learning on the empathy of undergraduate health care students toward older people with cognitive impairment as the primary outcome (objective 1) and on their learning experience (objective 2) and their attainment of learning outcomes as the secondary outcomes (objective 3).

Methods: A multiple-methods design was used, which included surveys, focus groups, and a review of the students’ group assignments. Survey data were summarized using descriptive statistics, whereas paired 2-tailed t tests were used to evaluate differences in empathy scores before and after the 2-hour IVR tutorial (objective 1). Focus groups were conducted to evaluate the impacts of IVR-assisted experiential learning on the empathy of undergraduate health care students toward older people with cognitive impairment (objective 1). Descriptive statistics obtained from surveys and thematic analyses of focus groups were used to explore the students’ learning experiences (objective 2). Thematic analysis of group assignments was conducted to identify learning outcomes (objective 3).

Results: A total of 367 undergraduate nursing and occupational therapy students were recruited via convenience sampling. There was a significant increase in the students’ empathy scores, measured using the Kiersma-Chen Empathy Scale, from 78.06 (SD 7.72) before to 81.17 (SD 8.93) after ($P<.001$). Students expressed high satisfaction with the IVR learning innovation, with a high satisfaction mean score of 20.68 (SD 2.55) and a high self-confidence mean score of 32.04 (SD 3.52) on the Student Satisfaction and Self-Confidence scale. Students exhibited a good sense of presence in the IVR learning environment, as reflected in the scores for adaptation (41.30, SD 6.03), interface quality (11.36, SD 3.70), involvement (62.00, SD 9.47), and sensory fidelity (31.47, SD 5.23) on the Presence Questionnaire version 2.0. In total, 3 major themes were identified from the focus groups, which involved 23 nursing students: enhanced sympathy toward older adults with cognitive impairment, improved engagement in IVR learning, and confidence in understanding the key concepts through the learning process. These themes supplement and align with the survey results. The analysis of the written assignments revealed that students attained the learning...
outcomes of understanding the challenges faced by older adults with cognitive impairment, the importance of providing person-centered care, and the need for an age-friendly society.

Conclusions: IVR-assisted experiential learning enhances students’ knowledge and empathy in caring for older adults with cognitive impairment. These findings suggest that IVR can be a valuable tool in professional health care education.

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KEYWORDS
immersive virtual reality; undergraduate health care education; empathy; cognitive impairment

Introduction

Background

Empathy is a cognitive ability that involves understanding other people’s experiences, concerns, and perspectives, along with a capacity to communicate this understanding and the motivation to help others [1,2]. Showing empathy to patients, such as through active listening and self-awareness, is associated with improved patient outcomes and satisfaction [3,4]. When health care professionals understand the needs of patients, patients may feel more secure in relating their concerns to health care professionals and raising issues that worry them [5].

Although the Association of American Medical Colleges identifies empathy as an essential learning objective in health care education [6], undergraduate health care students have been found to have negative attitudes toward older people, affecting their willingness to work in this specialty [7-10]. This is especially true for older adults with cognitive impairment, about whom undergraduate health care students may hold stereotypes and whom they might socially stigmatize, leading to concerns about a possible lack of attentiveness in the provision of care to this group [11].

Empathy has been found to be positively correlated with the attitude of undergraduate health care students toward older adults and their willingness to care for them [12,13]. The most common methods for cultivating empathy in students include experiential training, didactic training, skills training, and a mixed methods approach [14]. Experiential learning is cognitively stimulating and has an impact on the entire person. It allows students to acquire knowledge, skills, and attitudes cognitively, affectively, and behaviorally [15]. Undergraduate health care students can benefit from experiential learning by considering the perspectives of the patients and experiencing them firsthand [16]. Experiential learning allows undergraduate health care students to gain more insights into how to solve the problems that older adults with cognitive impairment may encounter [17]. It is usually challenging for undergraduate health care students to understand the needs of older adults with cognitive impairment as these older adults may not be able to clearly communicate their needs [18]. However, through experiential learning, students can gain hands-on experiences that can give them a deeper knowledge and understanding of the challenges that older adults with cognitive impairment may be encountering [19].

Despite being suitable for enhancing empathy in undergraduate health care students, the various forms of conventional experiential learning, including service learning, role-play, and simulation-based workshops, have limitations in terms of replicating realistic scenarios and patients in an authentic environment. In addition, in situations in which students may become distracted, instruction from supervisors is always required [20]. For example, in role-play, not all students can immerse themselves in the role of the patient [21], affecting their learning experience. However, a new type of experiential learning delivered via immersive virtual reality (IVR) provides students with an environment that encompasses them perceptually and gives them the feeling of being within it [22]. Owing to IVR’s capacity to stimulate different senses concurrently, it is highly efficient in immersing users and generating a strong sense of presence. It is becoming more common to use IVR in health care education. However, there is a scarcity of research on such IVR experiences in an educational context [23].

IVR provides students with a realistic but safe virtual clinical environment, allowing them to gain insights into patients’ perspectives through their eyes, voices, and emotions [24]. Buchman and Henderson [25] reported that undergraduate health care students had enhanced empathy and felt a sense of realism and authenticity in the IVR experience, with empathy being the clear theme arising from the focus group analysis. Undergraduate health care students have undoubtedly also reported positive experiences with receiving different types of experiential learning other than IVR [26]. However, the sense of presence and realism generated from IVR is not possible in conventional experiential learning. IVR-assisted experiential learning is also a highly customized learning method targeted at achieving specific learning outcomes [27]. By using IVR, teachers can put undergraduate health care students in situations that are tailored to their learning needs and outcomes, whereas this level of customization may be challenging to attain in conventional experiential learning, which invariably uses a one-size-fits-all approach. Nursing students have also been found to have a higher level of engagement when taking part in IVR learning compared with their engagement with conventional learning methods, and teachers have found IVR to be helpful in compensating for the limited clinical placements available for students in hospitals [28].

Previous studies have recognized the effectiveness of IVR-assisted experiential learning in improving empathy among undergraduate health care students [29]. The Cognitive Affective Model of Immersive Learning by Makransky and Petersen [30] suggests that the mental state of perceiving a virtual self as one’s actual self with a heightened sense of embodiment refers to the sensation of possessing a virtual body. Hence, using a first-person viewpoint with a virtual environment through IVR...
as a “perspective taking machine” could lead to a feeling of immersion and improve a participant’s level of embodiment, leading to an increase in empathy [31-33]. Scholars have also recommended that medical students participate in IVR experiential learning to improve their empathy before starting their clinical placement [34].

Despite previous studies, there has been little discussion on whether IVR-assisted experiential learning can enhance students’ attainment of learning outcomes such as understanding the special needs of older adults with cognitive impairment. Although there has been one study examining the improvement in the cognitive skills, such as communication competency, of multidisciplinary undergraduate and graduate health care students after an IVR simulation, its findings were based on the self-perceived evaluation of students [35]. This approach appears to lack a comparatively objective way of measuring learning outcomes, and the results of the study may be inconclusive as they may not reflect actual learning outcomes. To address this knowledge gap, it may be necessary to place more emphasis on comparatively objective assessments, such as teacher evaluations conducted according to preset assessment rubrics related to the learning outcomes.

**Objectives**

Therefore, this study aimed not only to evaluate the effects of IVR-assisted experiential learning on enhancing the empathy of undergraduate health care students toward older people with cognitive impairment (objective 1) but also to explore the students’ learning experiences, including “students’ satisfaction and self-confidence in learning” (objective 2), and their learning outcomes (objective 3) after attending the IVR-assisted experiential tutorial.

**Methods**

A multiple-methods design was used, which included a survey, focus groups, and student assignment reviews [36], to assess the effectiveness of the IVR-assisted experiential tutorial on students’ empathy and learning experiences and outcomes. This design produces more comprehensive findings than those obtained in single-method studies [37].

**Participants**

Convenience sampling was used to recruit participants for this study. Specifically, those invited to participate were undergraduate year-3 nursing students (n=267) who were taking the subject of gerontological nursing and year-3 occupational therapy (OT) students (n=100) who were taking the subject of human occupations. The nursing students were divided into 33 groups of 7 to 8 students each. They were invited to send a representative to participate in the focus groups. Ultimately, 23 group representatives participated in the focus groups. As a required learning activity, all students were obligated to attend the tutorial. However, they were given the option to join the study and complete surveys to share their learning experiences with the research team, of which 3 members (JYWL, PPKK, and KNKF) were subject lecturers. Only those who consented to join the study were included in the analysis and reporting of the results, and their anonymity was maintained in this paper.

**Design of the IVR-Assisted Experiential Tutorial**

**Overview**

To ensure that students had a solid grasp of the foundational knowledge in the subjects of gerontological nursing (for nursing students) and human occupations (for OT students), a 2-hour IVR-assisted experiential tutorial was arranged in week 7, halfway through the 13-week courses. Only the nursing students were mandated to complete and submit a group assignment within 2 weeks following the IVR tutorial.

The research team developed 2 IVR games that simulated experiences commonly encountered by older adults with cognitive impairment. The first IVR game simulated a scenario in which an individual with cognitive impairment gets lost in a community setting (Figure 1). The second IVR game simulated the distorted auditory and visual perceptions commonly experienced by older adults with delirium (Figure 2). These are common challenges faced on a daily basis by older adults with cognitive impairments. These 2 IVR games were used in the 2-hour IVR-assisted experiential tutorial. Each tutorial comprised students aged between 25 and 30 years who were divided into 7 to 8 subgroups. Each subgroup underwent concurrent IVR-assisted experiential learning.

**Figure 1.** Scenarios simulating getting lost when looking for a supermarket as experienced by individuals with cognitive impairment.
The intended learning outcomes of the IVR-assisted experiential learning tutorial were as follows: (1) students would gain insights into the lives of older adults with cognitive impairment and their problem-solving efforts when facing daily challenges and, thus, develop empathy toward this group of older adults, (2) students would apply the skills and knowledge that they learned about common situations to propose more inclusive solutions targeted at older adults with cognitive impairment, and (3) students would be able to develop age-friendly care plans to meet the whole-person needs of older adults with cognitive impairment.

On the basis of the experiential learning model suggested by Kolb [38], 4 stages were included in the tutorial to enhance the students’ learning experiences and outcomes.

Stage 1: Concrete Experience Through Experiential Learning

The students’ concrete experience was obtained by exposing them to 10 to 15 minutes of IVR environments through head-mounted devices. This involved creating a realistic and immersive virtual environment that simulated a real-world experience, allowing students to engage with the internet-based environment in a meaningful way. For example, students were required to complete some daily tasks (eg, finding a supermarket) in the virtual reality (VR) environment while overwhelmed by stimuli to mimic the experiences of older people with cognitive impairment or during delirium, such as encountering confusing noises and images played through a VR head-mounted device.

Stages 2 and 3: Reflective Observations and Abstract Conceptualizations Through Reflective and Integrative Learning During Debriefings

Debriefing is considered an important element in experiential-based learning that reinforces and helps consolidate learning [39]. Reflective observation involves reflecting on the experience and considering what happened during the IVR simulation. The subject lecturers guided the students to reflect on and discuss the thoughts, feelings, and emotions that they experienced during the IVR-assisted experiential learning. This reflective process can help students gain insights into their own behavior and thought patterns as well as identify areas for improvement [40].

Abstract conceptualization involves interpreting and integrating the IVR experience into existing knowledge and understanding [41]. Therefore, students were motivated to reflect on and make connections between their previous experiences with older people and the insights that they gained from the IVR games. Through this process, the students showed that they were acquiring a deeper understanding of the complexities and challenges that older people with cognitive impairment face in everyday life. At the same time, students experienced the frustration and vulnerability associated with these challenges while navigating the IVR environment. The students became aware of the need for empathy, good communication, compassion, a caring and respectful attitude, and patience when working with older people with different impairments. This reflective and integrative learning approach helped cultivate empathy among the students and gave them a deeper understanding of the needs of older people.

Stage 4: Active Experimentation by Applying the Learning in Practical Ways

Afterward, each subtutorial group in the nursing subject was required to submit a written group report to describe the strategies (a plan) for assisting older people with cognitive impairment to remain in society. The students were expected to relate the knowledge and experiences they had gained from IVR experiential learning to the proposed strategies. They shared their strategies with their teachers and fellow students on Blackboard (a web-based education platform; Anthology Inc). The lecturers evaluated the students’ performance on this assignment based on the predeveloped rubric. This exercise in active experimentation equipped the students with the skills that they would need to work with older people and develop their advocacy roles in practice.
Outcome Measures

Empathy Toward Older Adults (Objective 1)

Students’ empathy toward older adults (objective 1) was measured using the Kiersma-Chen Empathy Scale (KCES). The 15-item KCES was developed from the theoretical perspective of empathy, which includes cognitive (ie, the ability to understand and view the world from the perspective of other people) and affective (ie, the ability to connect with the experiences or feelings of others) aspects [42]. Each item in the KCES is rated on a 7-point Likert-type scale (1=strongly disagree; 7=strongly agree). The scores on the KCES range from 15 to 105, with higher scores indicating greater empathy toward older adults. The KCES has demonstrated good test-retest reliability, with an intraclass correlation coefficient of 0.78. It correlates positively with the Jefferson Scale of Physician Empathy [43] (r=0.52) and negatively with the cynicism subscale of the Maslach Burnout Inventory (r=-0.24) [44], providing evidence of its construct validity [42]. Students were asked to complete this web-based questionnaire 1 week before the VR-assisted experiential tutorial and return the posttest questionnaire within 1 week after the tutorial.

Learning Experience (Objective 2)

The students’ experiences in learning (objective 2) with IVR-assisted experiential learning were evaluated through a posttutorial web-based survey and a focus group interview. The Student Satisfaction and Self-Confidence scale was administered after the completion of the IVR experiential tutorial. This questionnaire contains 13 items with 2 subscales (ie, satisfaction and self-confidence). Each item is rated on a 5-point Likert scale ranging from 1 (strongly disagree with the statement) to 5 (strongly agree with the statement). The scores on the satisfaction with learning scale range from 5 to 25, and the self-confidence scores range from 8 to 40, with a higher score indicating greater satisfaction and self-confidence, respectively. Both scales had high internal reliability, with a Cronbach α of .94 and .87 for the satisfaction and self-confidence scales, respectively [45].

The Presence Questionnaire version 2.0 (PQ2) was also used to evaluate the students’ sense of presence in the IVR environments (ie, IVR fidelity; objective 2) [46,47] after the VR-assisted experiential tutorial class. The 29-item questionnaire includes 4 subscales: involvement (score range from 0 to 84), sensory fidelity (score range from 0 to 42), adaption or immersion (score range from 0 to 56), and interface quality (score range from 0 to 21), with higher scores indicating better or higher involvement, sensory fidelity, adaption or immersion, and interface quality. The students rated their experiences on a 7-point Likert scale from 1 (not at all) to 7 (completely). The PQ2 has been found to have high internal consistency, with a Cronbach α coefficient of .90, and correlate strongly with other measures of presence (r=0.78) [46].

A trained research assistant conducted 3 focus groups, with each group comprising 7 to 8 nursing students, to explore their learning experiences (objective 2) with IVR. They were asked questions such as the following: “What was your overall experience with IVR in your learning?” “How did IVR contribute to your understanding of the daily challenges of older people with cognitive impairment?” “Did you face any challenges or difficulties while using IVR for learning?” “How did IVR compare to other learning methods?” and “What suggestions do you have for improving the use of IVR in learning?” The interviews were audio recorded and then transcribed verbatim.

Learning Outcomes (Objective 3)

In this study, the impact on the students’ attainment of the learning outcomes (objective 3) referred to the students’ ability to show their understanding of the needs of older people with cognitive impairment (intended learning outcome 1) and their ability to apply this knowledge to identify inclusive strategies to help older people stay in the community (intended learning outcome 2). Only nursing students were required to complete a group assignment to describe the plan and strategies to develop age-friendly care plans to meet older adults’ needs (intended learning outcome 3). The Design of the IVR-Assisted Experiential Tutorial section provides details on the intended learning outcomes of the tutorial, and the Stage 4: Active Experimentation section provides details on the arrangement of the assignment. The group assignment was evaluated based on the assessment rubric by the lecturers of gerontological nursing (JYWL and PPKK), who were also members of the project team.

Data Analysis

The numerical data collected via the surveys were summarized as descriptive statistics using SPSS (version 27; IBM Corp) for the analysis. Simple frequencies, percentages, means, and SDs were calculated. For the pre- and posttest assessments, paired t-tests and confidence levels were calculated to test the differences before and after the tutorial. The level of significance was set at P<.05, and all tests were 2-tailed.

The text data collected through focus groups to identify the students’ learning experiences were analyzed using descriptive thematic analysis. To identify the students’ achievement of the learning outcomes, their written assignments were also analyzed using a descriptive thematic analysis. In contrast to other similar approaches, in thematic analysis, there is no commitment to a specific theoretical framework; therefore, a thematic analysis can be used between various theoretical frameworks. Thus, it is a more accessible and flexible form of analysis. What researchers do with the themes once they are uncovered will differ based on the aim of the research and the process of analysis [48]. In total, 2 researchers (JYWL and PPKK) read the students’ written assignments and independently identified codes from them. Codes with similar content were grouped together to form subthemes. The subthemes were then categorized into themes. Another researcher (KC) reviewed the codes, subthemes, and themes, and any discrepancies were resolved through discussion to achieve a consensus.

Ethical Considerations

This study was approved by the Human Subjects Ethics Application Review System of the Hong Kong Polytechnic University (HSEARS20200423001) and conducted between June 2021 and May 2022. It was carried out in accordance with
the Declaration of Helsinki. This included but was not limited to guaranteeing the anonymity of participants and obtaining the informed consent of the participating students. The participation of the students was voluntary, and their academic results were not affected by their decision to participate in the study.

Results

Overview

Of the 367 students who were enrolled in the 2 subjects, 93.7% (344/367) consented to join the study, of whom 75.6% (260/344) were nursing students and 24.4% (84/344) were OT students. They completed and returned the pre- and posttest surveys with an overall response rate of 93.7% (344/367). Most participating students were female (256/344, 74.4%), 23.3% (80/344) were male, and 2.3% (8/344) did not report their gender. Their ages ranged from 18 to 24 years.

We invited all 33 subgroups from the nursing subject to send 1 representative to join the focus groups. Eventually, 23 group representatives (a response rate of 23/33, 70%) participated in the focus groups, of whom 16 (70%) were female students. The participants were assigned to 1 of the 3 focus groups, with each group comprising 7 to 8 students to facilitate in-depth group discussions.

Empathy Toward Older Adults (Objective 1)

Participating students showed moderate empathy toward older people, as reflected by a KCES score of 78.06 (SD 7.72) out of 105 before the IVR-assisted experiential tutorial. After completing the tutorial, this score increased to 81.17 (SD 8.93). The results of the paired-sample 2-tailed t test showed a significant increase in the mean score from before to after the tutorial ($t_{304}=3.95; P<.001$; Table 1). A further subgroup analysis was conducted, and a significant difference was found in the results between the nursing and OT students in KCES scores. There was a significant improvement in KCES scores among the nursing students but a decreasing trend among the OT students (Multimedia Appendix 1).

Table 1. Changes in the Kiersma-Chen Empathy Scale (KCES) score before and after immersive virtual reality experiential learning (n=344)

<table>
<thead>
<tr>
<th>Question</th>
<th>Before, mean score (SD)</th>
<th>After, mean score (SD)</th>
<th>$t$ statistic</th>
<th>Mean difference (SD)</th>
<th>$t$ test (df)</th>
<th>$P$ value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. It is necessary for a health care practitioner to be able to comprehend someone else’s experiences.</td>
<td>5.80 (0.89)</td>
<td>5.83 (0.91)</td>
<td>0.03 (1.11)</td>
<td>0.46 (304)</td>
<td>.64</td>
<td></td>
</tr>
<tr>
<td>2. I am able to express my understanding of someone’s feelings.</td>
<td>5.38 (0.92)</td>
<td>5.61 (0.91)</td>
<td>0.23 (1.04)</td>
<td>3.91 (304)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>3. I am able to comprehend someone else’s experiences.</td>
<td>5.33 (0.85)</td>
<td>5.65 (0.88)</td>
<td>0.32 (1.06)</td>
<td>5.32 (304)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>4. I will not allow myself to be influenced by someone’s feelings when determining the best treatment*.</td>
<td>4.62 (1.27)</td>
<td>4.65 (1.43)</td>
<td>0.62 (2.28)</td>
<td>4.88 (304)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>5. It is necessary for a health care practitioner to be able to express an understanding of someone’s feelings.</td>
<td>5.77 (0.85)</td>
<td>5.85 (0.74)</td>
<td>0.79 (0.93)</td>
<td>1.48 (304)</td>
<td>.14</td>
<td></td>
</tr>
<tr>
<td>6. It is necessary for a health care practitioner to be able to value someone else’s point of view.</td>
<td>5.80 (0.88)</td>
<td>5.93 (0.82)</td>
<td>0.13 (1.04)</td>
<td>2.10 (304)</td>
<td>.04</td>
<td></td>
</tr>
<tr>
<td>7. I believe that caring is essential to building a strong relationship with patients.</td>
<td>6.06 (0.79)</td>
<td>6.03 (0.82)</td>
<td>0.03 (0.89)</td>
<td>0.58 (304)</td>
<td>.56</td>
<td></td>
</tr>
<tr>
<td>8. I am able to view the world from another person’s perspective.</td>
<td>5.34 (0.94)</td>
<td>5.69 (0.85)</td>
<td>0.35 (1.15)</td>
<td>5.26 (304)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>9. Considering someone’s feelings is not necessary to provide patient-centered care*.</td>
<td>3.15 (1.79)</td>
<td>3.78 (2.11)</td>
<td>0.64 (2.28)</td>
<td>4.88 (304)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>10. I am able to value someone else’s point of view.</td>
<td>5.43 (0.87)</td>
<td>5.70 (0.84)</td>
<td>0.27 (1.05)</td>
<td>4.52 (304)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>11. I have difficulty identifying with some else’s feelings*.</td>
<td>3.51 (1.43)</td>
<td>3.98 (1.66)</td>
<td>0.47 (1.88)</td>
<td>4.38 (304)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>12. To build a strong relationship with patients, it is essential for a health care practitioner to be caring.</td>
<td>5.81 (0.88)</td>
<td>5.93 (0.82)</td>
<td>0.12 (1.02)</td>
<td>2.03 (304)</td>
<td>.04</td>
<td></td>
</tr>
<tr>
<td>13. It is necessary for a health care practitioner to identify with someone else’s feelings.</td>
<td>5.73 (0.87)</td>
<td>5.94 (0.79)</td>
<td>0.20 (0.94)</td>
<td>3.77 (304)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>14. It is necessary for a health care practitioner to be able to view the world from another person’s perspective.</td>
<td>5.69 (0.87)</td>
<td>5.90 (0.84)</td>
<td>0.21 (0.92)</td>
<td>4.03 (304)</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>15. A health care practitioner should not be influenced by someone’s feelings when determining the best treatment*.</td>
<td>4.81 (1.36)</td>
<td>4.70 (1.60)</td>
<td>0.11 (1.59)</td>
<td>1.15 (304)</td>
<td>.25</td>
<td></td>
</tr>
<tr>
<td>Total KCES</td>
<td>78.06 (7.72)</td>
<td>81.17 (8.93)</td>
<td>3.11 (0.523)</td>
<td>3.95 (304)</td>
<td>&lt;.001</td>
<td></td>
</tr>
</tbody>
</table>

*Items with negative wordings are scored in reverse.
**Learning Experience (Objective 2)**

**Students' Satisfaction and Self-Confidence in Learning**

Students were satisfied with the current learning innovation, as reflected by a high satisfaction mean score of 20.68 (SD 2.55) out of 25. For example, 92.7% (319/344) of the students agreed or strongly agreed that IVR-assisted experiential learning was suitable for the way they learned (item 5). The same percentage of students agreed or strongly agreed that the IVR learning experience provided an alternative learning experience to promote their learning interests (item 2). A total of 91.6% (315/344) of the students agreed or strongly agreed that the IVR simulation was motivating and helped them learn better (item 4).

They also showed a high level of self-confidence in their IVR experiential learning, with a mean score of 32.04 (SD 3.52) out of 40. Approximately 85.5% (294/344) of the students agreed or strongly agreed that they were confident that they would obtain the necessary skills and knowledge through learning with the IVR simulation (items 6-8). A total of 95.1% (327/344) of the participants agreed or strongly agreed that students should take responsibility for their learning (items 10-11; Table 2).

**Table 2.** The findings of the Student Satisfaction and Self-Confidence scale (n=344).

<table>
<thead>
<tr>
<th>Item</th>
<th>Participants, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Strongly disagree (1)</td>
</tr>
<tr>
<td><strong>Satisfaction with the current learning subscale</strong></td>
<td></td>
</tr>
<tr>
<td>1. The teaching methods used in the IVR simulation were helpful and effective.</td>
<td>2 (0.6)</td>
</tr>
<tr>
<td>2. The IVR simulation provided me with a variety of learning materials and activities to promote my learning curriculum.</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>3. I enjoyed how my instructor taught the IVR simulation.</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>4. The teaching materials used in this IVR simulation were motivating and helped me to learn.</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>5. The way my instructor taught the IVR simulation was suitable to the way I learn.</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td><strong>Self-confidence in learning subscale</strong></td>
<td></td>
</tr>
<tr>
<td>6. I am confident that I am mastering the content of the IVR simulation activity that my instructor presented to me.</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>7. I am confident that this simulation covered critical content necessary for the mastery of the curriculum.</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>8. I am confident that I am developing the skills and obtaining the required knowledge from this simulation to perform necessary tasks in a clinical setting.</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>9. My instructors used helpful resources to teach the simulation.</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>10. It is my responsibility as the student to learn what I need to know from this IVR simulation activity.</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>11. I know how to get help when I do not understand the concepts covered in the simulation.</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>12. I know how to use simulation activities to learn critical aspects of these skills.</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>13. It is the instructor’s responsibility to tell me what I need to learn of the simulation activity content during class time.</td>
<td>1 (0.3)</td>
</tr>
</tbody>
</table>

*IVR: immersive virtual reality.*

**IVR Fidelity**

IVR fidelity was measured using the PQ2. The results showed that students developed a good sense of presence in the IVR learning environment, as seen in their scores on adaptation (mean 41.30, SD 6.03 out of 56), interface quality (mean 11.36, SD 3.70 out of 21), involvement (mean 62.0, SD 9.47 out of
84), and sensory fidelity (mean 31.47, SD 5.23 out of 42) (Table 3).

On the basis of the focus group discussions with the students about their experiences of experiential learning with IVR, 4 themes were identified: enhanced sympathetic feeling toward older adults with cognitive impairment, improved engagement in IVR learning, confidence in understanding key concepts in the IVR experiential learning process, and limitations of IVR technology.
Table 3. The findings of the Presence Questionnaire version 2.0 (n=344).

<table>
<thead>
<tr>
<th>Item</th>
<th>Participants, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td><strong>Involvement</strong></td>
<td></td>
</tr>
<tr>
<td>1. How much were you able to control events?</td>
<td>3 (0.9)</td>
</tr>
<tr>
<td>2. How responsive was the environment to actions that you initiated (or performed)?</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>3. How natural did your interactions with the IVR(^a) environment seem?</td>
<td>8 (2.3)</td>
</tr>
<tr>
<td>4. How much did the visual aspects of the IVR environment involve you?</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>6. How natural was the mechanism that controlled movement through the environment?</td>
<td>6 (1.7)</td>
</tr>
<tr>
<td>7. How compelling was your sense of objects moving through space?</td>
<td>2 (0.6)</td>
</tr>
<tr>
<td>8. How much did your experiences in the virtual environment seem to be consistent with your real-world experiences?</td>
<td>14 (4.1)</td>
</tr>
<tr>
<td>10. How completely were you able to actively survey or search the IVR environment using vision?</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>14. How compelling was your sense of moving around inside the virtual environment?</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td>17. How well could you move or manipulate objects in the virtual environment?</td>
<td>12 (3.5)</td>
</tr>
<tr>
<td>18. How involved were you in the virtual environment experience?</td>
<td>3 (0.9)</td>
</tr>
<tr>
<td>26. How easy was it to identify objects through physical interaction (eg, touching an object, walking over a surface, or bumping into a wall or object)?</td>
<td>10 (2.9)</td>
</tr>
<tr>
<td><strong>Sensory fidelity</strong></td>
<td></td>
</tr>
<tr>
<td>5. How much did the auditory aspects of the IVR environment involve you?</td>
<td>5 (1.5)</td>
</tr>
<tr>
<td>11. How well could you identify sounds?</td>
<td>3 (0.9)</td>
</tr>
<tr>
<td>12. How well could you localize sounds?</td>
<td>3 (0.9)</td>
</tr>
<tr>
<td>13. How well could you actively survey or search the virtual environment using touch?</td>
<td>10 (2.9)</td>
</tr>
<tr>
<td>15. How closely were you able to examine objects?</td>
<td>2 (0.6)</td>
</tr>
<tr>
<td>16. How well could you examine objects from multiple viewpoints?</td>
<td>1 (0.3)</td>
</tr>
<tr>
<td><strong>Adaption or immersion</strong></td>
<td></td>
</tr>
<tr>
<td>9. Were you able to anticipate what would happen next in response to the actions that you performed?</td>
<td>4 (1.2)</td>
</tr>
<tr>
<td>20. How quickly did you adjust to the virtual environment experience?</td>
<td>3 (0.9)</td>
</tr>
<tr>
<td>21. How proficient in moving and interacting with the virtual environment did you feel at the end of the experience?</td>
<td>2 (0.6)</td>
</tr>
<tr>
<td>24. How well could you concentrate on the assigned tasks or required activities rather than on the mechanisms used to perform those tasks or activities?</td>
<td>0 (0)</td>
</tr>
</tbody>
</table>
25. How completely were your senses engaged in this experience?  
27. Were there moments during the virtual environment experience when you felt completely focused on the task or environment?  
28. How easily did you adjust to the control devices used to interact with the virtual environment?  
29. Was the information provided through different senses in the virtual environment (eg, vision, hearing, touch) consistent?  

**Interface quality**  
19. How much delay did you experience between your actions and the expected outcomes?  
22. How much did the visual display quality interfere or distract you from performing assigned tasks or required activities?  
23. How much did the control devices interfere with the performance of assigned tasks or with other activities?  

Enhanced Sympathetic Feelings Toward Older Adults With Cognitive Impairment  
All participants in the focus group were impressed by the authenticity of the IVR games, which allowed them to experience the daily challenges faced by older people with cognitive impairment. One student remarked the following:  
*The IVR experience allowed me to see the world from the perspective of an older person with cognitive impairment who was getting lost. This experience helped me to better understand the confusion and disorientation that older people may face, which in turn helped me to be more empathetic and compassionate toward them.*  

Another student added the following:  
*This VR experience was so lifelike that it helped me to empathize with their (older people with cognitive impairment) situation and understand their needs better.*  

Improved Engagement in IVR Learning  
Most participants in the focus groups said that IVR helped them stay engaged and interested in the learning process, which could sometimes be challenging in traditional classroom settings. One student said the following:  
*With IVR, I was able to experience the daily challenges of older adults with cognitive impairment, which made the learning process more exciting and engaging than conventional teaching methods. With this firsthand experience, I am motivated to learn and identify strategies to help them (older adults) overcome those challenges.*  

Confidence in Understanding Key Concepts in the IVR Experiential Learning Process  
Students also showed confidence in their learning with IVR. They stated that learning with IVR improved their memory retention by providing a more realistic and memorable learning experience. One student commented the following:  
*The IVR game of delirium was a great way to simulate the condition and learn how to manage it (delirium in patients). It gave me the confidence to recognize and manage delirium in a real-life situation.*  

This sentiment was echoed by another student, who said the following:  
*The “get lost” game made me realize the importance of taking extra precautions to ensure the safety of older people with cognitive impairment. Overall, these experiences allowed me to develop a deeper understanding of the challenges associated with caring for them, which gives me more confidence in my ability to provide effective care to them.*  

Limitations of IVR Technology  
Although IVR offered a unique and engaging learning experience for students, technical issues such as equipment malfunctions and slow processing times could limit the effectiveness of the IVR learning experience. One student stated the following:  
*I encountered some technical issues during the IVR experience, which interrupted the flow of the scenario...*
and disrupted my immersion in the experience. It was frustrating, and I felt like I missed out on some important learning opportunities as a result.

Another student added the following:

The VR headset was heavy and its size needed to be adjusted continually to fit my head, making it difficult to fully immerse myself in the scenario. I found it challenging to stay focused and engaged during the entire experience.

### Learning Outcomes (Objective 3)

#### Overview

To understand the students’ attainment of the 3 learning outcomes after completing the IVR-assisted experiential tutorial, we conducted thematic analyses of the group written assignments. The analysis was based on 33 group assignments from the nursing students. In total, 3 themes were identified.

### Understanding the Challenges Faced by Older People With Cognitive Impairment

The analysis of the students’ written assignments indicated that they had developed a basic understanding of the challenges faced by older people with cognitive impairment. For example, one group report stated the following:

> The psychological well-being of older people would be negatively influenced due to their hallucinations. It is because restlessness and agitation would be provoked by the experiences of distorted images and sounds. The situations may happen at any time, which gives the older people much mental stress.

Another statement also said the following:

> Their quality of life would be seriously affected since their cognitive functions are impaired, lowering their independence in daily living. To prevent themselves from making mistakes, they (older adults) may withdraw from society or stop doing things that they used to do. Therefore, some older adults may suffer from depression and become socially isolated due to cognitive decline.

### Person-Centered Care

This care approach was mentioned consistently in group assignments. One report stated the following:

> Person-centered care is essential to ensure that older people with cognitive impairment receive care that is tailored to their unique needs and preferences.

“Effective communication,” “family involvement,” and “supportive care with patience” were 3 critical aspects of person-centered care that were frequently discussed in the assignments:

> Effective communication is a key component in person-centered care to ensure that this vulnerable group can express their needs and preferences so that the care can be tailored for them.

They also mentioned the need for family members to be included in the care planning and decision-making process. One group wrote the following:

> Family members play a critical role in providing support and care to older people with cognitive impairment. This is particularly the case during delirium.

> Their involvement can promote continuity of care and provide emotional support to their families with cognitive impairment, especially when they are in a distressing situation, such as delirium.

The need to be supportive was stated frequently in the written assignments. For example, one report stated the following:

> As nurses, we need to provide support to individuals with cognitive impairment to promote their independence and autonomy. In order to empower them to be able to continue living their life with dignity, we should give them various forms of support.

### Creation of an Age-Friendly Society

It was stated that this is an essential strategy to enable older people with cognitive impairment to stay in the community with dignity for as long as possible. In a written report, students recognized the need to reduce the stigma surrounding cognitive impairment and stated the following:

> We need to raise awareness and educate people about the common daily challenges faced by older people with cognitive impairment to eliminate negative stereotypes and improve social inclusion for them.

Students also became aware of the importance of social inclusion in creating an age-friendly society, stating the following:

> We need to create a supportive and inclusive environment that recognizes the unique needs of individuals with cognitive impairment.

They also suggested some concrete community-based services and support to enable this segment of the population to remain in their community for as long as possible. One group wrote the following:

> Community-based services, such as transportation, social activities, and assistive technologies, can help them to stay connected and engaged in their communities.

Another group echoed this with the following suggestion:

> Provide more community activities to enhance their interaction with the society, which can help the older adults expand their social circle to reduce the rate of deterioration of their cognitive function.

### Discussion

#### Principal Findings

The results suggest that IVR-assisted experiential learning is effective in enhancing empathy toward older people among undergraduate nursing and OT students, as reflected in their higher scores on the KCES after the IVR simulation. The
students reported a high level of satisfaction with the IVR learning experience, citing its suitability, ability to motivate, and innovativeness in the self-administered survey. In addition, the findings from the survey suggest that the students experienced a strong sense of presence in the IVR learning environment, enabling them to gain a deeper understanding of the challenges involved in caring for older adults with cognitive impairment. In total, 3 major themes were identified from the focus groups with 23 nursing students: enhanced sympathetic feelings toward older adults with cognitive impairment, improved engagement in IVR learning, and confidence in understanding the key concepts through the learning process.

The thematic findings supplement and are in line with the results from the survey. The analysis of the written assignments showed that the students attained the learning outcomes of understanding the challenges faced by older people with cognitive impairment, the importance of providing person-centered care, and the need to create an age-friendly society.

These findings are consistent with those of previous studies that demonstrated the effectiveness of IVR as a mode of experiential learning to enhance the empathy of students toward older adults [49,50]. However, previous studies have mainly measured changes in students’ level of empathy using questionnaires without exploring the underlying reasons.

Empathy Toward Older Adults and Learning Experience

Our survey findings for objectives 1 and 2 are consistent with the insights gained from the focus groups. For example, the PQ2 scores indicated that the students felt a strong sense of presence in the IVR environment, which was also reflected in their comments during the focus groups. Participants in the focus groups mentioned that the authentic IVR games allowed them to better understand and empathize with the daily challenges faced by older people with cognitive impairment, which may have contributed to the significant increase in empathy toward older adults reflected in the KCES scores. Furthermore, both the surveys and focus groups revealed that students were satisfied with the IVR-assisted experiential learning and felt confident in their ability to understand the key concepts through this approach. These consistent findings across multiple data sources provide strong evidence to suggest the effectiveness of IVR-assisted learning in enhancing students’ empathy and understanding of key concepts as well as their satisfaction with the IVR teaching approach. Compared with conventional teaching methods, IVR creates a sense of presence and provides an excellent medium for experiencing alternative points of view, allowing undergraduate health care students to virtually “step into the shoes of older adults” [23]. The hands-on experiences provided by IVR enable students to gain a deeper understanding and knowledge of the challenges that older adults with cognitive impairment may encounter [19].

The findings of this study suggest that IVR can promote positive learning experiences, including increased satisfaction, self-confidence, self-assessed competency, self-efficacy, and enjoyment among undergraduate health care students [51]. This evidence is consistent with the positive learning experiences identified in this study based on both quantitative and qualitative data. In addition, IVR facilitates a constructivist approach to education that emphasizes active participation in the learning process rather than the passive receipt of information [52]. That was why, in the focus groups, students stated that they experienced improved engagement with this innovative learning approach. It provides active and constructivist learning and increases students’ engagement in their learning, leading to an increase in the frequency of authentic learning experiences. Being engaged encourages students to become aware of learning concepts such as empathy and other soft skills needed to care for older adults.

The subgroup analysis revealed a notable enhancement in KCES scores among nursing students in contrast to a declining trend among OT students. As the aim of this study was not to draw comparisons between these 2 student groups but rather to evaluate overall empathy levels among nursing and OT students, we are unable to explain the reasons for these differences. This discrepancy could potentially be attributed to the non–discipline-specific design of the intervention, which may have been more beneficial to nursing students than to OT students.

Learning Outcomes

Apart from enhancing empathetic experiences, an analysis of the students’ group assignments in this study revealed 3 major themes related to their learning outcomes [53]. These findings indicate that the students improved their understanding of the challenges faced by older people with cognitive impairment. Consequently, nursing students recognized the importance of person-centered care for this population, including effective communication, family involvement, and supportive care. Finally, the students highlighted the need to create an age-friendly society by reducing stigma, promoting social inclusion, and providing community-based services and support.

Implications

By improving empathy levels through IVR experiential learning, students become more capable of comprehending needs and experiences from the perspective of the patients. The empathetic response of the students can provide insights into how newly acquired knowledge of the lived experiences of older adults with cognitive impairment can be used to enhance the quality of life of these older adults [54]. In this way, students will be better equipped to develop individualized care plans tailored to the specific needs of patients [55]. IVR experiential learning also inspires students to adopt a holistic approach when providing care to older people with cognitive impairment, recognizing the significance of social and environmental factors in their care plans [56].

Limitations and Challenges of IVR Learning

Although IVR-assisted experiential learning has shown positive results in enhancing health care education, it is important to acknowledge the limitations and challenges associated with adopting this technology in teaching. Technical issues such as equipment malfunctions and slow processing times could result in missed learning opportunities, as noted by some students during the focus group discussions. Similar technical issues mentioned in previous studies disrupted the flow of scenarios...
and limited the effectiveness of the IVR learning experience [57,58]. These technical limitations must be addressed to ensure that IVR can be used effectively for teaching. Other main challenges that we experienced include the cost of implementing and maintaining the IVR technology, including hardware and software [50]. Another challenge is the need for technical support to develop and maintain IVR simulations, which requires collaboration between educators and technologists [59]. This may be prohibitive for some educational institutions to undertake.

Study Limitations

This study had several limitations that should be considered when interpreting the results. First, without a control group for comparison, it is unclear whether the positive outcomes identified from the surveys were based solely on this teaching innovation or because of the Hawthorn effect or the effect of novelty. However, the qualitative analyses were aligned with the survey findings, providing a more comprehensive understanding of this teaching innovation. Second, the use of the self-report method may have induced expectation bias. However, anonymity was adopted when conducting the questionnaires, which may have helped minimize bias. In addition, the objective evaluation of the students’ assignments strengthened the study by providing an independent measure of their attainment of the intended learning outcomes. Third, the students’ attainment of the learning outcomes was analyzed through a group assignment; thus, we could not differentiate between individual students in terms of performance. Fourth, the study population was restricted to one undergraduate nursing and OT cohort enrolled in a single university, thereby limiting the generalizability of the findings. Fifth, we were unable to confirm the reason behind the significant difference in empathy levels between nursing and OT students as it was beyond the scope of this study. Therefore, future studies are needed to explore the specific types of IVR teaching content suitable for enhancing empathetic feelings in undergraduate students from different health care professions. Sixth, we could not confirm the transferability of the knowledge obtained through IVR-assisted experiential learning to actual clinical practice.

Future Directions

To address the limitations of our study, we recommend conducting a randomized controlled trial with a control group in the future to evaluate the effects of IVR-assisted experiential tutorials on students’ empathy, learning experiences, and outcomes. In addition, individual assignments should be used to assess students’ attainment of the intended learning outcomes and explore factors that could affect their performance. Such a study design would allow for a more robust evaluation of the effectiveness of IVR-assisted learning and provide deeper insights into the mechanisms underlying this approach. Moreover, future studies may be needed to determine whether the designs of related interventions have to be discipline specific to enhance empathy and understanding toward older adults with cognitive impairment among students of different health care disciplines. Further observational studies in clinical areas should also be considered to explore the transferability of knowledge to clinical practice regarding IVR-assisted experiential learning.

Conclusions

In conclusion, the findings of this study suggest that IVR-assisted experiential learning appears to have the potential to promote empathy and enhance the learning outcomes of undergraduate health care students regarding the care of older adults with cognitive impairment. Through immersive simulations, students were able to gain a deeper understanding of the challenges faced by this population and the importance of person-centered care. The findings also highlight the need to create age-friendly societies that reduce stigma, promote social inclusion, and provide community-based services and support. However, the challenges and limitations associated with the use of IVR for health care education must be addressed, such as technical issues, cost, and the need for technical support.

Acknowledgments

The authors sincerely thank the students and teachers who participated in this study. They also thank Ms Jay Wong, the research assistant, for her excellent work in ensuring that this project ran smoothly. This study was funded by a Large-Scale Collaborative Teaching Development Grant (2019-2022) from the Learning and Teaching Committee and matching funds from the School of Nursing (.53.XX.49LP), Hong Kong Polytechnic University.

Data Availability

The data sets are not publicly available owing to pending further analysis of the data. The virtual reality scenarios used in this study were just a part of the scenarios present in the complete virtual reality training system. As we may need to conduct further comparisons, we regret not being able to disclose the data sets.

Authors' Contributions

All the authors were involved in the design of the virtual reality (VR) games and the study. JYWL contributed to the conceptualization of the study. JYWL, DSKC, PPKK, KNKF, and TM implemented the VR games in their subjects. JYWL was responsible for data collection, data analysis, and quality control of the study. JYWL and PYM wrote the original draft of the manuscript. All coauthors commented on and rewrote the manuscript. All the authors have read and approved the final version of the manuscript.
Conflicts of Interest
None declared.

Multimedia Appendix 1
The findings on the between-group changes in Kiersma-Chen Empathy Scale scores across the time points between nursing and occupational therapy students.

References


Abbreviations

IVR: immersive virtual reality
KCES: Kiersma-Chen Empathy Scale
OT: occupational therapy
PQ2: Presence Questionnaire version 2.0
VR: virtual reality

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Development and Implementation of a Safety Incident Report System for Health Care Discipline Students During Clinical Internships: Observational Study

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Abstract

Background: Patient safety is a fundamental aspect of health care practice across global health systems. Safe practices, which include incident reporting systems, have proven valuable in preventing the recurrence of safety incidents. However, the accessibility of this tool for health care discipline students is not consistent, limiting their acquisition of competencies. In addition, there is no tool to familiarize students with analyzing safety incidents. Gamification has emerged as an effective strategy in health care education.

Objective: This study aims to develop an incident reporting system tailored to the specific needs of health care discipline students, named Safety Incident Report System for Students. Secondary objectives included studying the performance of different groups of students in the use of the platform and training them on the correct procedures for reporting.

Methods: This was an observational study carried out in 3 phases. Phase 1 consisted of the development of the web-based platform and the incident registration form. For this purpose, systems already developed and in use in Spain were taken as a basis. During phase 2, a total of 223 students in medicine and nursing with clinical internships from universities in Argentina, Brazil, Colombia, Ecuador, and Spain received an introductory seminar and were given access to the platform. Phase 3 ran in parallel and involved evaluation and feedback of the reports received as well as the opportunity to submit the students’ opinion on the process. Descriptive statistics were obtained to gain information about the incidents, and mean comparisons by groups were performed to analyze the scores obtained.

Results: The final form was divided into 9 sections and consisted of 48 questions that allowed for introducing data about the incident, its causes, and proposals for an improvement plan. The platform included a personal dashboard displaying submitted reports, average scores, progression, and score rankings. A total of 105 students participated, submitting 147 reports. Incidents were mainly reported in the hospital setting, with complications of care (87/346, 25.1%) and effects of medication or medical products (82/346, 23.7%) being predominant. The most repeated causes were related confusion, oversight, or distractions (49/147, 33.3%) and absence of process verification (44/147, 29.9%). Statistically significant differences were observed between the mean...
final scores received by country ($P<.001$) and sex ($P=.006$) but not by studies ($P=.47$). Overall, participants rated the experience of using the Safety Incident Report System for Students positively.

**Conclusions:** This study presents an initial adaptation of reporting systems to suit the needs of students, introducing a guided and inspiring framework that has garnered positive acceptance among students. Through this endeavor, a pathway toward a safety culture within the faculty is established. A long-term follow-up would be desirable to check the real benefits of using the tool during education.

**Trial Registration:** Trial Registration: ClinicalTrials.gov NCT05350345; https://clinicaltrials.gov/study/NCT05350345

**KEYWORDS**
reporting systems; education; medical; nursing; undergraduate; patient safety

**Introduction**

**Background**

Patient safety is an objective of health care practice in the health systems of all countries. However, the complexity and uncertainty that accompany health care make this a practice not without risks. The World Health Organization leads the World Alliance for Patient Safety with the purpose of implementing safe practices and other actions with which to generate a safer environment in all health centers [1].

The information available regarding safety incidents focuses primarily on adverse events (AEs), which are incidents that result in harm to a patient. Slightly more than half of these AEs could have been prevented [2]. The results of research studies show that, in high-income countries, approximately 10% of patients admitted to hospitals experience an AE [3]. In primary and outpatient care, approximately 3% to 10% of patients experience an AE over the course of a year [4]. In 80% of cases, the damages are avoidable. In low- and middle-income countries, there are higher rates of AEs due to deficiencies in infrastructure, facilities, and accessibility [2]. So-called safe practices aim to reduce these figures and have proliferated across all countries [5]. Among them, incident reporting systems (IRSs) have emerged as a valuable tool to prevent safety incidents stemming from the same cause from recurring [2].

Studies indicate that up to 30% of students are involved in an AE during an academic year [6]. Moreover, during their internships, students observe decisions and procedures that may lead to errors or cause harm (AEs) to patients [7]. While access to IRSs is widespread in all health care systems, students of health care disciplines are often not adequately trained on how to use and benefit from these tools to create safer environments for patients. This lack of training restricts students’ acquisition of crucial competencies in several ways.

The familiarization of students with incident reporting addresses a significant educational practice gap. First, the absence of IRS exposure hinders students’ ability to understand what an incident report is, how to complete it, the extent of the information required, and how it functions to promote safer environments. This exposition to IRSs not only enhances their capability to effectively report incidents in future real-world contexts but also helps reduce the initial reluctance toward reporting. Second, reporting unsafe events can enhance practice and prevent future safety incidents. This active learning helps students identify and avoid recurring incidents by raising awareness of their causes. Third, providing students with access to IRSs raises awareness among future professionals of the critical importance of patient safety. It serves as a vital learning resource and offers an opportunity to change attitudes and foster the development of a proactive safety culture [8].

Despite this, the interventions designed and validated to achieve the goal of promoting incident reporting among health care discipline students are scarce [9]. There are also no tools to introduce these students to the analysis of the remote and immediate causes of safety incidents and the identification of barriers to prevent them from recurring. However, there are digital tools that are starting to be used to increase patient safety, particularly those based on gamification [10,11].

The effectiveness of gamification in health care education has been analyzed in several studies [12,13], showing improvements in knowledge, skills, satisfaction, behavior change, and attitudes compared to control groups. However, the usefulness of engaging health care discipline students in patient safety has not been assessed.

**Objectives**

The primary objective of this study was to develop a patient safety IRS tailored to the needs of health care discipline students. The secondary objectives were to study the performance of different groups of students in the use of the platform and train them on the correct procedures for reporting.

**Methods**

**Study Design**

This was an observational study developed in 3 phases (Figure 1), in which safety incident reports made by final-year students in medicine and nursing during their clinical internships were analyzed. The students were enrolled in universities from Argentina, Brazil, Colombia, Ecuador, and Spain once they had gained experience from their clinical placements. All these universities are members of the European Researchers’ Network Working on Second Victims Consortium, with the Latin American ones as third-party or observer countries and Spain as the promoter of the network.
In the participating countries, medical studies are typically completed over 6 years, with the last 3 years progressively incorporating more clinical practice. However, nursing studies exhibit greater variability and can range from 4 to 6 years in duration. In these programs, the final year is usually dedicated to clinical practice. Nursing curricula also show more diversity in their content, with some programs focusing more on hospital-based activities whereas others emphasize community health practice. Nonetheless, due to international guidelines on required competencies and clinical practice hours, these programs are standardized to ensure consistency in training.

In countries such as Argentina, Brazil, Chile, Ecuador, and Spain, medical and nursing programs follow this general structure but with some national variations. For example, in Spain, medical students undergo a rigorous 6-year program with a strong emphasis on clinical rotations in the later years. Nursing programs in Spain typically last 4 years, with the final year focused on intensive clinical practice. In Brazil and Argentina, similar patterns are observed, although the specifics of the curriculum and clinical exposure may differ slightly due to local health care needs and educational frameworks. As in other places, teaching patient safety is limited, representing one of the gaps highlighted in various studies [14].

This study is reported according to the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines for cross-sectional studies ([15]; see Multimedia Appendix 1).

Phase 1: Development of the Web-Based Platform and Incident Registration Form

This phase consisted of the development of the web-based platform and the incident registration form, named Safety Incident Report System for Students (SAFEST).

To design the content for the incident registration form, various existing systems at different levels were used as references. The existing systems in health care centers require users to be part of the center’s staff, making them inaccessible to other groups, including students. In addition, while these systems collect the reporter’s assessment of potential causes, they do not advance to propose alternatives for preventing future safety incidents. This aspect of our educational initiative is crucial to influencing students’ attitudes toward safety reporting. Due to these limitations, the available safety systems in the health care facilities were not suitable for student practice and, therefore, deemed inappropriate for our purposes. Consequently, we decided to design a new system that closely mimics the systems that students will encounter in their professional practice. This approach ensures that students receive relevant and practical training, enhancing their ability to effectively report and analyze safety incidents in the future.

A database was then constructed incorporating fields gathered from the Patient Safety Reporting and Learning System of the Spanish National Health System [16]; the Adverse Event Reporting and Registration System of the Valencia Health Agency [17]; and Based on Root Cause Analysis (BACRA) [18,19], a web-based application based on root cause analysis and failure mode and effects analysis.

One of the key features of SAFEST is that each section and registration field (eg, center type, care complications, damage type, or care received after the incident) offered an extensive range of response options in different formats (single-select drop-down menu or multiple-choice answer). This design facilitated the reporting task for the students as they rarely needed to use natural language to describe a situation. This approach aligns with the latest advancements in reporting systems, minimizing errors in subsequent coding while providing a comprehensive catalog of options. However, in some cases in which the preset options may limit the recording, students can add a qualitative description to complement the recording. For example, when describing the incident, the student should characterize the event according to the classic typification of its nature, that is, whether the origin of the incident was related to complications of care, care-related infection, effects of medication or medical devices, complications of a procedure, or other situations not covered by the previous categories (eg, unexpected death of the patient). All these categories are detailed in a list of possibilities in a
multiple-choice format. However, in all categories (including “Other”), the student may choose a final option as “Other,” in which case they should describe in words the situation in question. The first version of the database was created in Spanish.

From this database, common and specific aspects of each form were identified, and a preliminary draft of the proposal was developed accordingly. This draft underwent review by 3 subject matter experts from different Latin American countries, and the resulting changes and suggestions were incorporated to produce a high-quality form. This latest version of the tool was translated into English by EB and VRN, both of whom use the 2 languages regularly in the academic setting, ensuring the equivalence of the versions through back translation. The necessary modifications to ensure the adequacy of the system were made. Simultaneously, the visual identity and acronym for the platform were developed (Multimedia Appendix 2).

Phase 2: Introduction Seminar and Incident Reporting Execution

Overview

During this phase, students received an introductory seminar on patient safety and reporting and were given access to the platform. These introductory seminars were conducted by the responsible coordinators from the 5 universities (1 from each country; see Multimedia Appendix 3 for the educational materials used during the seminars). During these seminars, the project and the platform were presented, and attendees were given the opportunity to ask any questions they had.

The seminars contributed to the recruitment of participants based on voluntary participation without offering any academic grade advantages. To incentivize student engagement, they were provided with the opportunity to obtain a Miguel Hernández University nanocourse certificate. Moreover, the highest scores qualified for a draw with 4 new smartwatches as the prize, thus incorporating classic elements of gamification strategies. Of the smartwatches, 2 were assigned to the people with the highest and second-best scores and who had also submitted their feedback, whereas the other 2 were drawn among all reports with a score of >3.0 and who had also completed their feedback.

The specific instruction given to the students was to report any safety incidents that had occurred in their training health care center and of which they were aware, either because they had been involved or because they were witnesses. To introduce students to this exercise and standardize explanations and instructions on how to respond, concise use instructions were created along with video tutorials on navigating the website and submitting reports and a schematic diagram of the operation (Multimedia Appendix 4). The same presentation was used in all countries. In accordance with the academic calendars of the participating countries, the report submission period spanned from September 14, 2022, the day when the first seminar was held, to November 8, 2023.

Participants

Medicine (n=176) and nursing (n=47) students who had completed more than half of their educational program and were performing clinical internships were invited to participate. Recruitment was conducted by the professor in charge in each country with students in the corresponding academic years who met the selection criteria.

Study Size

According to existing literature, in pilot studies, if a problem exists with a 5% probability in a potential study participant, a sample size of 59 participants will almost certainly identify the problem with 95% confidence [20].

Phase 3: Assessment of Reports and Feedback on the Experience

Feedback

This phase ran in parallel to the previous one and involved external evaluation and feedback on the reports received that could prove useful for the students improvement in continuing to send reports. In total, 2 independent assessments were conducted for each incident report by members of the platform’s promoting team. As a final exercise, students who had submitted at least 1 report were invited 1 month after this activity was over to fill out a satisfaction questionnaire.

Data Sources

The information provided in this study stems from the firsthand experiences of each student.

Variables

The outcomes we aimed to assess were the students’ performance in reporting using the platform, which includes an estimation of potential causes to raise awareness of the inherent risks in health care activities, and their satisfaction with the experience.

To study their ability in reporting, a rubric (Table 1) was followed, in which the 2 reviewers independently rated the information provided about the incident, the analysis of immediate and latent causes, and the corrective or preventive plan proposed by the student using a scale of 1 to 5 points for each one, where the higher the score, the better the assessment. In addition, strengths and areas for improvement were included in the evaluation as an open-text field. The individual score from each evaluator was obtained by calculating the arithmetic mean of these 3 points. The final score for that report was the average of the 2 scores obtained from each evaluator.
Table 1. Rubric designed to assess the correctness of the reports made by students.

<table>
<thead>
<tr>
<th>Points</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>To what extent is the information complete and descriptive enough?</td>
</tr>
<tr>
<td>2 points</td>
<td>The provided information allows for the understanding of the events.</td>
</tr>
<tr>
<td>2 points</td>
<td>The information is consistent throughout the entire report.</td>
</tr>
<tr>
<td>1 point</td>
<td>All fields are properly filled out.</td>
</tr>
<tr>
<td></td>
<td>To what extent is the analysis of immediate and latent causes complete and adequate?</td>
</tr>
<tr>
<td>2 points</td>
<td>The provided information is comprehensive, and reasons with a high probability of influence are not overlooked.</td>
</tr>
<tr>
<td>2 points</td>
<td>The provided information offers sufficient details to envision the scenario of what happened.</td>
</tr>
<tr>
<td>1 point</td>
<td>The selected information is logical and does not appear to have been chosen merely for completion.</td>
</tr>
<tr>
<td></td>
<td>To what extent the corrective or preventive plan proposed is realistic and responds to the problem?</td>
</tr>
<tr>
<td>1 point</td>
<td>The plan has a corrective or preventive nature.</td>
</tr>
<tr>
<td>1 point</td>
<td>The proposed plan is realistic.</td>
</tr>
<tr>
<td>1 point</td>
<td>The proposed plan is understandable.</td>
</tr>
<tr>
<td>1 point</td>
<td>Details are addressed to implement the proposed plan.</td>
</tr>
<tr>
<td>1 point</td>
<td>Language and spelling are appropriate.</td>
</tr>
</tbody>
</table>

To analyze their satisfaction with the experience, they were asked to complete a questionnaire with 3 aspects to rate on a scale of 1 to 5, with 1 being not at all and 5 being very much: “Do you believe that after this experience you would be capable of generating reports accurately?” (question 1), “Has viewing the assessments and comments you received on your reports been beneficial for your learning?” (question 2), and “Have you felt confident in terms of the privacy and anonymity of your reports?” (question 3). In addition, they had a text field available to input any suggestions that could contribute to improving the platform (question 4).

The independent variables used included the country from which the report was made, the sex of the reporter, their ongoing studies, and the number of internship hours completed up to the moment of reporting. All these data were incorporated into the incident registration form itself.

**Bias**
When the form was sent to the partners for review, a language check was also requested to address any idiomatic barriers that may have existed to allow for cross-cultural conclusions of the study and avoid possible biases related to linguistic nuances. Cultural differences were also considered, ensuring that items were comparable across countries.

**Statistical Methods**
To gain a comprehensive understanding of the reported incidents, descriptive analyses were conducted. To obtain the results of the phase of assessment, various statistical analyses were conducted. Descriptive statistics were computed for each of the 3 dimensions under analysis as well as for the overall score, with stratification by country, sex, and educational background. The weighted Cohen $\kappa$ was computed to evaluate the agreement among the scores assigned by different pairs of evaluators for each dimension. Before proceeding with the analysis of the final scores of each report, the normality of the sample was assessed using $Q-Q$ plots and the Shapiro-Wilk normality test. The relationship between the number of internship hours and the final score was examined using the Spearman correlation coefficient. Finally, differences in scores among countries, sexes, and educational backgrounds were investigated using the nonparametric Kruskal-Wallis test and the Mann-Whitney $U$ test. The $P$ value significance was set at .05. Data analyses were performed using SPSS Statistics (version 28.0.0; IBM Corp).

**Ethical Considerations**
This study was authorized by the Research Ethics Committee of Sant Joan d’Alacant University Hospital (22/027) and registered on ClinicalTrials.gov (NCT05350345).

Informed consent for study participation was obtained at the time of registration on the platform, whereby individuals were required to select the corresponding checkbox with instructions provided regarding the process for revoking their participation. After reporting, the report was automatically encoded with a numerical identifier by the platform. Throughout the assessment process, participant sociodemographic data were concealed to ensure evaluator objectivity.

No form of financial compensation was provided for participation or recruitment.

**Results**

**Phase 1: Development of the Web-Based Platform and Incident Registration Form**
SAFEST [21] and the servers were located in Miguel Hernández of Elche University (Spain). Participation was allowed both individually and in groups of 2 to 3 students.

When accessing the page, users could find an explanatory text about the project, logos of collaborators, and buttons to access the platform or register. Upon initial access, the user was
required to provide consent to participate in the study. The platform was available in both Spanish and English. Once logged in, the dashboard was shown (Figure 2), where they could view the total of submitted reports, their average score, and the progression of their results, as well as their position in the score ranking at any time. In addition, they had access to previously submitted reports, as well as the button to access the incident registration form.

Figure 2. Appearance of the Safety Incident Report System for Students (SAFEST) platform dashboard.

The final form was divided into 9 sections: data of the reporting center, patient data, notifier data, incident data, description of the incident, damage assessment, factors influencing the incident, care received after the incident, and reflections.

In total, it consisted of 48 questions (distributed as depicted in Textbox 1) that allowed for obtaining the necessary information about the incident, conducting an analysis of the causes, and proposing corrective or preventive actions. The complete form can be found in Multimedia Appendix 5.
Textbox 1. Questions asked on the reporting form and types of responses.

<table>
<thead>
<tr>
<th>Data of the reporting center</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>● Center type (drop-down menu)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Patient data</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>● Patient’s age (drop-down menu)</td>
<td></td>
</tr>
<tr>
<td>● Patient’s sex (drop-down menu)</td>
<td></td>
</tr>
<tr>
<td>● Patient’s risk factors (multiple choice)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Notifier data</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>● Notifier’s sex (closed-ended question)</td>
<td></td>
</tr>
<tr>
<td>● Country from which the notification was made (drop-down menu)</td>
<td></td>
</tr>
<tr>
<td>● Studies in the course (drop-down menu)</td>
<td></td>
</tr>
<tr>
<td>● Institution (drop-down menu)</td>
<td></td>
</tr>
<tr>
<td>● Year (closed-ended question)</td>
<td></td>
</tr>
<tr>
<td>● Internship hours carried out so far in that department (open-ended question)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Incident data</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>● Date of the incident (date)</td>
<td></td>
</tr>
<tr>
<td>● Time of the incident (time)</td>
<td></td>
</tr>
<tr>
<td>● Date of the notification (date)</td>
<td></td>
</tr>
<tr>
<td>● Time of the notification (time)</td>
<td></td>
</tr>
<tr>
<td>● Where it took place (drop-down menu)</td>
<td></td>
</tr>
<tr>
<td>● Number of people related to the incident (open-ended question)</td>
<td></td>
</tr>
<tr>
<td>● Position or positions of the person or people involved (multiple choice)</td>
<td></td>
</tr>
<tr>
<td>● Frequency or probability of recurrence (drop-down menu)</td>
<td></td>
</tr>
<tr>
<td>● Participation in the incident (drop-down menu)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Description of the incident</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>● Care complications (multiple choice)</td>
<td></td>
</tr>
<tr>
<td>● Care-related infection (multiple choice)</td>
<td></td>
</tr>
<tr>
<td>● Effects of medication or medical products (multiple choice)</td>
<td></td>
</tr>
<tr>
<td>● Complications of a procedure (multiple choice)</td>
<td></td>
</tr>
<tr>
<td>● Other (multiple choice)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Damage assessment</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>● Damage type (drop-down menu)</td>
<td></td>
</tr>
<tr>
<td>● Severity (drop-down menu)</td>
<td></td>
</tr>
<tr>
<td>● Patient autonomy (drop-down menu)</td>
<td></td>
</tr>
<tr>
<td>● Estimation of the damage duration (drop-down menu)</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Factors that conditioned the incident</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>● Patient or family factors (multiple choice)</td>
<td></td>
</tr>
<tr>
<td>● Equipment and resource factors (multiple choice)</td>
<td></td>
</tr>
<tr>
<td>● Individual factors of the health care professional or professionals (multiple choice)</td>
<td></td>
</tr>
<tr>
<td>● Work environment factors (multiple choice)</td>
<td></td>
</tr>
<tr>
<td>● Oral and written communication between professionals factors (multiple choice)</td>
<td></td>
</tr>
</tbody>
</table>
- Patient communication factors (multiple choice)
- Teamwork and leadership factors (multiple choice)
- Task-related factors (multiple choice)
- Organizational and management factors (multiple choice)
- Other factors (open-ended question)

Care received after the incident
- Care received after the incident (multiple choice)

Reflections
- Has the center been notified? (drop-down menu)
- Could the incident have been prevented? (drop-down menu)
- How could it have been prevented? (open-ended question)
- How could the probability of occurrence or the severity of this event be reduced? (open-ended question)
- To what extent was all the information necessary to analyze the causes of the event available? (open-ended question)
- Have measures been put in place to prevent it from happening in the future? (drop-down menu)
- What measures have been put in place to prevent it from happening in the future? (open-ended question)
- Do you consider that the analysis could have been different if you had had access to another source of information? (open-ended question)
- Write here any other comments you may have (open-ended question)

To streamline the use of the system, selection questions and drop-down menus were used to report incidents. Both the Description of the incident and Factors that conditioned the incident blocks allowed for more than one option to be selected. Written input was only necessary in the Reflections part.

Phase 2: Introduction Seminar and Incident Reporting Execution

A total of 105 students from the 5 countries participated voluntarily and actively by submitting at least 1 report (participation rate: 105/223, 47.1%). By country, this corresponds to 16.2% (17/105) of students from Argentina, 12.4% (13/105) of students from Brazil, 10.5% (11/105) of students from Colombia, 32.4% (34/105) of students from Ecuador, and 28.6% (30/105) of students from Spain. Of the 105 participants, 35 (33.3%) were male, 68 (64.8%) were female, and 2 (1.9%) specified their sex as other. Only 1.9% (2/105) of them formed a team. Regarding their studies, 66.7% (70/105) were pursuing a degree in medicine, 28.6% (30/105) were enrolled in nursing studies, 1.9% (2/105) were part of the pediatric specialization program, and 1% (1/105) belonged to the orthopedics and traumatology specialization program.

A total of 147 reports were submitted as 14 users provided >1 report. Of the 147 received reports, 18 (12.2%) were from Argentina, 13 (8.8%) were from Brazil, 44 (29.9%) were from Colombia, 35 (23.8%) were from Ecuador, and 37 (25.2%) were from Spain.

Of the 147 safety incident reports, a substantial majority, specifically, 144 (98%) reports, occurred in a health care setting, with most occurring in a hospital context (n=132, 89.8%). Within this hospital-centric subset, most incidents were concentrated in hospitalization units (45/132, 34.1%). Other noteworthy locations included surgical block areas (21/132, 15.9%), emergency departments (17/132, 12.9%), support services (14/132, 10.6%), day hospitals (12/132, 9.1%), and intensive care units (10/132, 7.6%).

Regarding the nature of the incidents, Table 2 illustrates the frequency with which each major classification category was selected. On most occasions, events from different blocks were registered in the same report.

Table 2. Nature of the reported safety incidents (n=346).

<table>
<thead>
<tr>
<th>Type of incident</th>
<th>Reports, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Care complications</td>
<td>87 (25.1)</td>
</tr>
<tr>
<td>Effects of medication or medical products</td>
<td>82 (23.7)</td>
</tr>
<tr>
<td>Complications of a procedure</td>
<td>67 (19.4)</td>
</tr>
<tr>
<td>Other</td>
<td>60 (17.3)</td>
</tr>
<tr>
<td>Care-related infection</td>
<td>50 (14.5)</td>
</tr>
</tbody>
</table>
Specifically, from the available list of the most common safety events included in SAFEST (drop-down list), students’ reports were related to “Worse evolutionary course of the main pathology” (27/147, 18.4%), “No harm” (24/147, 16.3%), “Ineffective analgesia-related pain” (19/147, 12.9%), “Falls and consequent fractures” (18/147, 12.2%), “Surgical site or traumatic wound infection” (15/147, 10.2%), “Contusion” (14/147, 9.5%), “Unexpected death” (14/147, 9.5%), “Headache” (13/147, 8.8%), and “Prescription error” (13/147, 8.8%).

The reported causes are shown in Table 3. According to the number of reports in which they appear, we established the following categories: “Patient or family factors” (112/147, 76.2% of reports), “Equipment and resource factors” (71/147, 48.3% of reports), “Individual factors of the healthcare professional(s)” (118/147, 80.3% of reports), “Work environment factors” (103/147, 70.1% of reports), “Oral and written communication between professionals factors” (76/147, 51.7% of reports), “Patient communication factors” (64/147, 43.5% of reports), “Teamwork and leadership factors” (93/147, 63.3% of reports), “Task-related factors” (91/147, 61.9% of reports), and “Organizational and management factors” (81/147, 55.1% of reports).
Table 3. Causes and contributing factors of the incidents grouped by category (n=147).

<table>
<thead>
<tr>
<th>Factor</th>
<th>Reports, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Patient or family factors</strong></td>
<td></td>
</tr>
<tr>
<td>Comorbidity or complexity of the condition</td>
<td>33 (22.4)</td>
</tr>
<tr>
<td>Low economic level</td>
<td>30 (20.4)</td>
</tr>
<tr>
<td>Noncooperative attitude (noncompliance)</td>
<td>35 (23.8)</td>
</tr>
<tr>
<td>Lack of family or support networks</td>
<td>40 (27.2)</td>
</tr>
<tr>
<td>Poor communication with relatives</td>
<td>18 (12.2)</td>
</tr>
<tr>
<td>Altered cognitive status</td>
<td>8 (5.4)</td>
</tr>
<tr>
<td>Does not provide correct or enough information</td>
<td>14 (9.5)</td>
</tr>
<tr>
<td>Recent surgery</td>
<td>15 (10.2)</td>
</tr>
<tr>
<td>Educational and social factors to consider</td>
<td>20 (13.6)</td>
</tr>
<tr>
<td>Other patient factors</td>
<td>18 (12.2)</td>
</tr>
<tr>
<td>Mental disorder</td>
<td>3 (2)</td>
</tr>
<tr>
<td><strong>Equipment and resource factors</strong></td>
<td></td>
</tr>
<tr>
<td>Improper storage or accessibility</td>
<td>19 (12.9)</td>
</tr>
<tr>
<td>Malfunctions</td>
<td>14 (9.5)</td>
</tr>
<tr>
<td>Equipment maintenance issues</td>
<td>12 (8.2)</td>
</tr>
<tr>
<td>Lack of alternative materials</td>
<td>11 (7.5)</td>
</tr>
<tr>
<td>Incorrect labeling</td>
<td>11 (7.5)</td>
</tr>
<tr>
<td>Equipment deficit (including nonsterile material)</td>
<td>10 (6.8)</td>
</tr>
<tr>
<td>Inadequate resource design (eg, bell)</td>
<td>10 (6.8)</td>
</tr>
<tr>
<td>Product or drug unavailability</td>
<td>10 (6.8)</td>
</tr>
<tr>
<td>Improper calibration</td>
<td>9 (6.1)</td>
</tr>
<tr>
<td>Nonstandard equipment</td>
<td>7 (4.8)</td>
</tr>
<tr>
<td>New equipment or resource</td>
<td>5 (3.4)</td>
</tr>
<tr>
<td>Failure to access or unavailability of the digital medical record</td>
<td>4 (2.7)</td>
</tr>
<tr>
<td>Expiration</td>
<td>2 (1.4)</td>
</tr>
<tr>
<td>Similar container or name</td>
<td>2 (1.4)</td>
</tr>
<tr>
<td><strong>Individual factors of the health care professional or professionals</strong></td>
<td></td>
</tr>
<tr>
<td>Confusion, oversight, or distractions</td>
<td>49 (33.3)</td>
</tr>
<tr>
<td>Overload or work pressure</td>
<td>37 (25.2)</td>
</tr>
<tr>
<td>Lack of knowledge of regulations or protocols of performance</td>
<td>25 (17)</td>
</tr>
<tr>
<td>Uncooperative attitude</td>
<td>24 (16.3)</td>
</tr>
<tr>
<td>Inadequate or insufficient anamnesis, examination, or tests</td>
<td>23 (15.6)</td>
</tr>
<tr>
<td>Medication error (prescription or dispensing)</td>
<td>21 (14.3)</td>
</tr>
<tr>
<td>Inadequate or insufficient knowledge or skills</td>
<td>20 (13.6)</td>
</tr>
<tr>
<td>Low motivation</td>
<td>15 (10.2)</td>
</tr>
<tr>
<td>Diagnostic error</td>
<td>13 (8.8)</td>
</tr>
<tr>
<td>Inadequate or insufficient training</td>
<td>13 (8.8)</td>
</tr>
<tr>
<td>Not verifying the treatment that the patient is currently taking</td>
<td>12 (8.2)</td>
</tr>
<tr>
<td>Little experience in the workplace</td>
<td>10 (6.8)</td>
</tr>
<tr>
<td>Inadequate timetable</td>
<td>8 (5.4)</td>
</tr>
<tr>
<td>Inappropriate interpretation of analytical or test results</td>
<td>5 (3.4)</td>
</tr>
<tr>
<td>Factor</td>
<td>Reports, n (%)</td>
</tr>
<tr>
<td>----------------------------------------------------</td>
<td>----------------</td>
</tr>
<tr>
<td><strong>Work environment factors</strong></td>
<td></td>
</tr>
<tr>
<td>Distractions in the environment</td>
<td>38 (25.9)</td>
</tr>
<tr>
<td>Shift-related fatigue</td>
<td>36 (24.5)</td>
</tr>
<tr>
<td>High care pressure</td>
<td>29 (19.7)</td>
</tr>
<tr>
<td>Inadequate environment—cleaning, beds, or space</td>
<td>26 (17.7)</td>
</tr>
<tr>
<td>Inadequate environment—noise, light, or temperature</td>
<td>19 (12.9)</td>
</tr>
<tr>
<td>Performance of outside tasks</td>
<td>14 (9.5)</td>
</tr>
<tr>
<td>Excessive staff turnover or inexperience</td>
<td>12 (8.2)</td>
</tr>
<tr>
<td>Inadequate staff-to-patient ratio</td>
<td>11 (7.5)</td>
</tr>
<tr>
<td>Security and access to restricted areas</td>
<td>2 (1.4)</td>
</tr>
<tr>
<td><strong>Oral and written communication between professionals factors</strong></td>
<td></td>
</tr>
<tr>
<td>The information does not reach the entire team</td>
<td>30 (20.4)</td>
</tr>
<tr>
<td>Ambiguous verbal indications</td>
<td>23 (15.6)</td>
</tr>
<tr>
<td>Insufficient or inadequate records</td>
<td>20 (13.6)</td>
</tr>
<tr>
<td>Using an inappropriate channel</td>
<td>19 (12.9)</td>
</tr>
<tr>
<td>Inappropriate body language</td>
<td>15 (10.2)</td>
</tr>
<tr>
<td>Incorrect use of language</td>
<td>11 (7.5)</td>
</tr>
<tr>
<td><strong>Patient communication factors</strong></td>
<td></td>
</tr>
<tr>
<td>Insufficient or inadequate records</td>
<td>23 (15.6)</td>
</tr>
<tr>
<td>Ambiguous verbal indications</td>
<td>17 (11.6)</td>
</tr>
<tr>
<td>Using an inappropriate channel</td>
<td>16 (10.9)</td>
</tr>
<tr>
<td>Incorrect use of language</td>
<td>14 (9.5)</td>
</tr>
<tr>
<td>Inappropriate body language</td>
<td>12 (8.2)</td>
</tr>
<tr>
<td>Language barrier</td>
<td>6 (4.1)</td>
</tr>
<tr>
<td><strong>Teamwork and leadership factors</strong></td>
<td></td>
</tr>
<tr>
<td>Lack of coordination in the team</td>
<td>40 (27.2)</td>
</tr>
<tr>
<td>Inadequate supervision</td>
<td>40 (27.2)</td>
</tr>
<tr>
<td>Low risk awareness</td>
<td>31 (21.1)</td>
</tr>
<tr>
<td>Inaccurate assignment of tasks</td>
<td>20 (13.6)</td>
</tr>
<tr>
<td>Conflict between team members</td>
<td>12 (8.2)</td>
</tr>
<tr>
<td>No effective leadership</td>
<td>9 (6.1)</td>
</tr>
<tr>
<td><strong>Task-related factors</strong></td>
<td></td>
</tr>
<tr>
<td>Absence of process verification</td>
<td>44 (29.9)</td>
</tr>
<tr>
<td>Unknown protocol or noncompliance</td>
<td>30 (20.4)</td>
</tr>
<tr>
<td>Absence of guidelines or protocols</td>
<td>19 (12.9)</td>
</tr>
<tr>
<td>Inadequate or outdated protocol</td>
<td>18 (12.2)</td>
</tr>
<tr>
<td>Too complex task</td>
<td>7 (4.8)</td>
</tr>
<tr>
<td><strong>Organizational and management factors</strong></td>
<td></td>
</tr>
<tr>
<td>Absence of evaluation systems</td>
<td>16 (10.9)</td>
</tr>
<tr>
<td>Error in health information</td>
<td>16 (10.9)</td>
</tr>
<tr>
<td>Nonexistent or inadequate risk management</td>
<td>16 (10.9)</td>
</tr>
<tr>
<td>Error in medical documentation</td>
<td>12 (8.2)</td>
</tr>
<tr>
<td>Insufficient organizational structure</td>
<td>12 (8.2)</td>
</tr>
</tbody>
</table>
When asked about whether the event had been reported at the center, in 41.5% (61/147) of the reports the answer was “Yes”; in 34.7% (51/147) of the reports, the answer was “I don’t know”; and, in 23.8% (35/147) of the reports, the answer was “No.” Finally, 93.9% (138/147) of the reported events were classified as preventable compared to 6.1% (9/147) that were categorized as nonpreventable.

### Phase 3: Assessment of Reports and Feedback on the Experience

Considering the 147 reports received, the mean final score obtained was 3.40 (SD 0.92) out of 5, and 111 (75.5%) reports had a final score of ≥3.0. For each of the 3 aspects studied, an average score of 3.38 (SD 1.29) was obtained for the section on giving information about the incident, an average score of 3.54 (SD 1.21) was obtained for the analysis of causes, and an average score of 3.30 (SD 1.30) was obtained for the proposal of a corrective or preventive plan. Table 4 shows the means of the final scores segregated by category.

#### Table 4. Mean final scores segregated by country, sex, and studies.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Values, mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Country</strong></td>
<td></td>
</tr>
<tr>
<td>Argentina</td>
<td>3.66 (0.89)</td>
</tr>
<tr>
<td>Brazil</td>
<td>3.65 (0.75)</td>
</tr>
<tr>
<td>Colombia</td>
<td>3.28 (0.88)</td>
</tr>
<tr>
<td>Ecuador</td>
<td>2.81 (0.88)</td>
</tr>
<tr>
<td>Spain</td>
<td>3.89 (0.73)</td>
</tr>
<tr>
<td><strong>Sex</strong></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>3.06 (0.99)</td>
</tr>
<tr>
<td>Female</td>
<td>3.64 (0.84)</td>
</tr>
<tr>
<td>Team</td>
<td>3.46 (0.60)</td>
</tr>
<tr>
<td>Other</td>
<td>3.58 (0.42)</td>
</tr>
<tr>
<td><strong>Studies</strong></td>
<td></td>
</tr>
<tr>
<td>Medicine</td>
<td>3.34 (0.95)</td>
</tr>
<tr>
<td>Nursing</td>
<td>3.66 (0.82)</td>
</tr>
<tr>
<td>Pediatric specialization</td>
<td>3.25 (0.92)</td>
</tr>
<tr>
<td>Radiology and diagnostic imaging specialization</td>
<td>3.55 (0.59)</td>
</tr>
<tr>
<td>Orthopedics and traumatology specialization</td>
<td>2.75 (1.30)</td>
</tr>
</tbody>
</table>

Significant differences were found in the final scores based on country ($P<.001$) and sex ($P=.006$). However, no significant results were obtained when comparing scores based on studies ($P=.47$). Similarly, when focusing on the 2 main groups (medicine and nursing), there were no significant differences ($P=.11$). Comparisons by groups for the significant variables are presented in Tables 5 and 6.
Table 5. *P* values for final score mean comparisons (country).

<table>
<thead>
<tr>
<th>Country</th>
<th>Argentina</th>
<th>Brazil</th>
<th>Colombia</th>
<th>Ecuador</th>
<th>Spain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Argentina</td>
<td></td>
<td>.40</td>
<td></td>
<td>.004</td>
<td>.40</td>
</tr>
<tr>
<td>Brazil</td>
<td>.92</td>
<td></td>
<td>.15</td>
<td>.004</td>
<td>.36</td>
</tr>
<tr>
<td>Colombia</td>
<td>.15</td>
<td>.19</td>
<td></td>
<td>.01</td>
<td>.003</td>
</tr>
<tr>
<td>Ecuador</td>
<td>.004</td>
<td>.004</td>
<td>.01</td>
<td></td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Spain</td>
<td>.40</td>
<td>.36</td>
<td>.003</td>
<td>&lt;.001</td>
<td></td>
</tr>
</tbody>
</table>

*Not applicable.

Table 6. *P* values for final score mean comparisons (sex).

<table>
<thead>
<tr>
<th>Sex</th>
<th>Male</th>
<th>Female</th>
<th>Other</th>
<th>Team</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td></td>
<td>.001</td>
<td>.44</td>
<td>.25</td>
</tr>
<tr>
<td>Female</td>
<td>.001</td>
<td></td>
<td>.82</td>
<td>.33</td>
</tr>
<tr>
<td>Other</td>
<td>.44</td>
<td>.82</td>
<td></td>
<td>.69</td>
</tr>
<tr>
<td>Team</td>
<td>.25</td>
<td>.33</td>
<td>.69</td>
<td></td>
</tr>
</tbody>
</table>

*Not applicable.

Regarding the internship hours carried out in that department, no correlation was found with the score obtained on each report (–0.079; *P*=.18). Finally, the interrater agreement analyses revealed consistency between each pair of evaluators across all cases (Table 7).

Table 7. Weighted Cohen κ values obtained for each pair of evaluators.

<table>
<thead>
<tr>
<th></th>
<th>Pair 1</th>
<th></th>
<th>Pair 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cohen κ</td>
<td><em>P</em> value</td>
<td>Cohen κ</td>
<td><em>P</em> value</td>
</tr>
<tr>
<td>Complete and descriptive information</td>
<td>0.324</td>
<td>&lt;.001</td>
<td>0.304</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Analysis of immediate and latent causes</td>
<td>0.420</td>
<td>&lt;.001</td>
<td>0.195</td>
<td>.009</td>
</tr>
<tr>
<td>Corrective or preventive plan</td>
<td>0.344</td>
<td>&lt;.001</td>
<td>0.258</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

A total of 15 students participated in discussing the experience through the satisfaction questionnaire, providing an average rating of 4.06 (SD 1.00) for question 1, an average rating of 4.18 (SD 1.22) for question 2, and an average rating of 4.56 (SD 1.09) for question 3. Moreover, they provided the following feedback in the improvement suggestion section: “The platform has been very useful to me, and I suggest that similar projects continue to be conducted virtually to encourage widespread participation.” “It would be beneficial if the platform allows the upload of images as evidence for each incident,” and “Consider incorporating a text comment box, allowing individuals involved in the incident to narrate the events rather than solely selecting an option. This would prevent overlooking crucial details that might be of interest for subsequent management and error prevention.”

**Discussion**

**Principal Findings**

A platform named SAFEST was developed, allowing students to submit reports and receive feedback regarding provided information, causal analysis, and proposed improvements. The educational practice simulates the environment they will encounter in their professional practice regarding the reporting of safety incidents. Students from 5 countries participated in this initiative, sending reports in which most incidents occurred within hospital settings and involved complications related to care and medication.

The identified causes of safety events reported by students using SAFEST included confusion, oversight, or distractions and absence of process verification. Across all countries, the average score exceeded 2.5, although significant differences in average scores among some countries are observed. Overall, the experience was highly regarded.

This paper delves into a comprehensive portrayal of the SAFEST platform, focusing on its inception, development, and implementation. The SAFEST platform stands as a pivotal reporting system strategically crafted to initiate health care discipline students into the realm of identifying and reporting current safety lapses within health care environments. In addition, this paper describes the perception that medical and nursing students had regarding incidents impacting patient safety, their attributed causes, and potential preventive or corrective measures. This reflection on what they identified as incidents can provide professors with feedback for planning their teaching.
The platform and designed materials allowed medical and nursing students to be introduced to safety incident reporting. SAFEST recreated the natural context in which reporting occurs, providing students with an experience close to reality but facilitating the process by allowing for step-by-step guided reporting. The IRS form follows the same structure and covers the same fields as those available for health care professionals as it was developed based on 3 existing systems. However, there are differences in terms of approach or responsibility. Students report situations that they observe or are involved in but are not the authors of. In addition, they encounter disparities regarding the accessibility of information for cause analysis as they do not have full access to the patient’s medical history. The gathered information is not disseminated, nor does it bring consequences for the involved parties. This type of active learning can also facilitate a better understanding of the impact of safety incidents and their causes. By doing this, students can grasp the basic concepts of fostering a proactive safety culture for patients. Once in clinical settings as professionals, they will be able to overcome the natural barrier hindering reporting through their participation in SAFEST. They will also have gained experience in analyzing both the immediate and remote causes of safety incidents and identifying preventive or corrective measures. These types of educational interventions prompt reflection on how errors occur in clinical practice, aiding in distinguishing between honest mistakes and intentional errors. If specific patient safety content is taught during regular classes while conducting the reporting practice, one can expect a greater impact of this practice on instrumental and attitudinal competencies. This aspect should be verified in the future.

Notably, the existing literature predominantly reflects studies conducted within the field of nursing [7,8,22], leaving a noteworthy void in the examination of reporting mechanisms across broader health sciences education. Breaking away from this convention, our research introduces a groundbreaking element not only by incorporating medical students into its purview but also by providing a system that can be extended to other disciplines that develop their practices in the clinical field. Moreover, the provision of feedback helps students learn and improve their skills. Similarly, the integration of a gamified environment adds an element of engagement and motivation to the learning process. By incorporating elements of game design such as rewards and progression systems, the learning experience is transformed into a user-friendly practice.

Reporting systems constitute one of the fundamental tools for creating increasingly safe environments for patients [2]. It has been demonstrated that they also have a positive impact on the safety culture within health care institutions. However, students in health care disciplines typically become familiar with this tool once they are in health care settings either as residents or professionals. Simulation, as portrayed in this case, stands as one of the most used approaches in teaching-learning methods [23]. The approach of this exercise ensures active student engagement in reporting. The feedback provided to the students facilitated the enhancement of their proficiency and enabled them to report accurately. This aspect has been highlighted as significant in other studies [24].

The data from this study suggest that introducing a practice on how to report and why it is important was well received by the participants in this academic exercise, resulting in reports of suitable quality. Previous studies [25] have suggested that students demonstrate enhanced proficiency in detecting and analyzing incidents when they are not involved in them. Therefore, incorporating a reporting exercise during their internship period would contribute to cultivating a patient safety culture among students. This approach facilitates experiential learning, enabling students to comprehend the intricacies of incidents, empowering them to identify and mitigate such occurrences in their future professional endeavors.

The incident reporting by students has 2 strengths: the firsthand experience in clinical risk management within a health care institution and the provision of specific information that can contribute to enhancing comprehensive patient safety education among students. When delving into the results obtained in terms of scores, we found congruence with the results of other studies [25] in that the analysis of causes emerged as the strongest aspect, whereas the proposal of an improvement plan proved to be the weakest. This is particularly evident in cases in which patient safety content was integrated into the curriculum, where greater familiarity with patient safety was correlated with higher-quality reporting. The variations in the scores obtained can be explained by the curricular differences between each country. The Argentinean university involved offers 2 subjects on patient safety during the 5 years of the degree. It also has a patient safety program in which theoretical, simulation, and practical modules on patient safety (international goals and risk management) are offered so that students receive training throughout their degree, from first to fifth year, in all subjects that involve field practice. In contrast, the Ecuadorian university involves lacks any specific courses on the subject during the 6 years. Spanish students receive specific lectures on patient safety in 4 subjects starting in the second year before entering the internship in the sixth year. One of these subjects also incorporates specific topics on AEs and their communication. In the Colombian university involved, there is no specific subject in the curriculum dedicated to this matter in the first 5 years of study. However, before engaging in clinical internships in the final year, students are required to complete a course on clinical management and health, which delves into introductory topics related to patient safety. In the case of the Brazilian university, the term “patient safety” is explicitly referenced in the curriculum of 6 subjects, spread out from the second to the fourth year of studies. Moreover, in another 17 subjects, while there may not be an explicit mention, faculty members address the subject matter throughout the duration of the academic term.

Similarly, female students achieved higher scores in the evaluation of their reports. Nevertheless, there is no existing literature to substantiate this observation, prompting the need to consider the influence of other factors that could account for it. In our case, these outcomes might be influenced by the sample distribution as reports submitted by male students were predominantly concentrated in Colombia (23/147, 15.6%) and Ecuador (21/147, 14.3%), the 2 countries exhibiting the lowest mean scores. Therefore, these differences might not be explained solely by sex but rather by the background in patient safety.
In this study, 47.1% (105/223) of students participated submitting at least one report. This percentage contrasted with the findings of other studies, which reported participation rates of approximately 12% [26]. This increase opens the door to a more in-depth exploration of the factors that may be influencing this elevated level of student participation. One potential line of inquiry focuses on student motivation and how it may be linked to the design or implementation of the reporting system. Examining the effectiveness of strategies used to encourage participation could shed light on the dynamics that lead to more active engagement by students in this particular context.

It is not surprising that many incidents took place in hospitals. First, students from both disciplines undertook most of their practical training in this environment, and this clinical exposure increases the likelihood of witnessing or being involved in safety incidents. Moreover, hospitals typically handle more complex and critical cases compared to other health care settings as well as conducting a greater quantity and variety of procedures. However, this figure may be influenced by the students’ risk perception. It is plausible that primary care settings are perceived as less prone to safety incidents, leading students to pay less attention to their surroundings in such environments. In analogous studies, the most frequently reported type of incident was associated with medication administration [7]. However, in our case, what emerged most frequently throughout the reports were incidents related to caregiving. This outcome is likely related to the information more readily accessible to students, explaining why they witness fewer medication errors than expected during their practice [22].

During their clinical placements in health care settings, students frequently witness safety incidents of different severities, triggering conflicting emotions—from fear of speaking up to guilt for remaining silent. Studies suggest that approximately 4 out of every 10 students in training admit to having made at least one medical error during their training period [27]. Most of these errors involve lapses in clinical judgment (7 out of 10 cases). The primary causes of these errors have been associated with deficiencies in supervision and in the students’ own technical competencies [28]. They often feel that the causes of these events are not adequately addressed. Once the practice session ends, they are left without information on whether the incident was reported, whether its causes were analyzed, or whether any subsequent actions were taken, all of which they might be unaware of. The attitudes and coping strategies of nursing students following the recognition of a medical error have been explored [29-31]. On the basis of our understanding, students who become implicated in an AE or near-miss situation tend to manifest symptoms aligned with the experience of second victims [27,32]. Familiarizing themselves with reporting and analyzing incident causes offers them a new perspective that we can also expect to aid them emotionally.

Finally, following the suggestions provided by the students and, thus, incorporating user-centered design principles, we found it highly beneficial to incorporate a text box for a brief narrative of the events. We believe that the optimal approach would involve presenting a comprehensive set of options to encourage reflection, prompting individuals to consider aspects they might not have otherwise. Subsequently, a field will be provided for participants to describe the unfolding of events in their own words. This aligns with the findings of King et al [33], who advocate for a balanced approach in future patient reporting systems, integrating closed-ended questions for cause analysis and classification alongside open-ended narratives to accommodate patients’ potential limitations in understanding terminology.

Implications of Findings

By providing a guided process, students are aided in considering a variety of factors that could pose potential risks, ranging from material resource deficiencies to patient attitudes or workload overload. Moreover, they learn to analyze different variables, weigh consequences, and make informed decisions based on available information. Consequently, students acquire skills and experience that they are expected to be able to apply in similar situations in the future. Similarly, by increasing awareness of risks and sources of mistakes and empowering students to identify them, the likelihood of involvement in dangerous or problematic situations is expected to be reduced [34], thereby contributing to the creation of safer environments.

The apprehension surrounding potential negative outcomes of reporting has been present since the initial implementation of reporting systems in Australia in 1993 [35]. Introducing students from health-related disciplines to the reporting process, emphasizing the understanding of why, how, and for what purpose they should contribute, aims to foster a safety culture among the forthcoming generations of health care professionals. Encouraging students to view errors as valuable learning opportunities rather than indicators of incompetence is highly necessary. Embracing mistakes as integral components of the learning process can foster a growth mindset where challenges become stepping stones to improvement. This positive approach not only cultivates resilience but also promotes a more constructive and proactive attitude toward learning.

Since digital systems offer a more enduring record-keeping mechanism and facilitate a higher volume of reports than their paper counterparts [9], approaches such as this one can increase the correctness and impact on the future rate of reporting. In addition, this educational practice should help overcome the initial reluctance that discourages reporting safety incidents. To know and have used an incident reporting tool, describing a safety incident and reflecting on its potential causes and the measures that could actively and thoughtfully prevent it, should have an impact on attitudes toward reporting [36,37].

Future Research

Several scales have been developed to assess students’ knowledge and the information they receive, aiming to model their safety culture. Among these, the scales proposed by Flin et al [29] and Mira et al [38] are remarkable. However, we need to identify which mechanisms are most effective in integrating curriculum content that matches the students’ knowledge levels and attitudes, fostering a cross-disciplinary education in patient safety.

In addition, although the students scored 4.0 out of 5 regarding the fact that after this experience, they would be capable of making reports properly, a follow-up over time is required to
really verify the benefits brought by this experience. Furthermore, it would be interesting to consider the use of this tool in students of earlier courses, provided they undergo some period of their training in clinical settings, to analyze its utility in earlier stages of education. This would also facilitate the development of longitudinal studies to monitor the impact in terms of reporting.

Limitations
The aim of this experience was not to detect the safety incidents themselves but rather to train students to make correct reports in their future professional practice. Thus, the frequencies and features described in this paper did not necessarily represent the actual safety incidents occurring and what students could witness in their countries.

Recognizing an error is not straightforward. Students in training may consider it risky for their future to report an incident, leading to a restriction in the information they provide to the system. If they end up working in an environment where psychological safety is at risk, despite actively participating in this educational practice, they might choose silence, and fear of potential negative consequences could undo what was gained from this practice. The same can happen with other organizational factors that may hinder and make reporting difficult for the group of professionals in a center. This practice does not prevent this from happening in some contexts.

It cannot be guaranteed that the reports accurately reflect incidents that actually occurred. A convenience sample was used, which restricts the generalizability of the results. The medical and nursing curricula in the different participating countries were not identical. Although participation in the study was offered in the context of subjects related to patient safety, it was not possible to control for students’ baseline knowledge of incident reporting. These differences may have influenced the quality of the reports. It will be necessary to delve into the safety culture in the course of subjects with patient safety content in training programs. The constant technological evolution requires timely updating of the proposal, adapting it to possible technological solutions. Student involvement should be facilitated by the participation of academics in the project. However, the project schedule may be affected by the academic obligations of this group (eg, exams, vacations, and internship periods).

With this exercise, students become familiar with a fundamental tool in patient safety that they will encounter at the beginning of their professional careers and often approach with some hesitation, particularly in the countries where the study was conducted. However, the reports are based on observations made during their placements, and the analysis of the proposed improvement plan was conducted without accessing all the clinical information necessary for a precise analysis of root and immediate causes. In this case, the remote causes could not be determined during the exercise.

The sample size and the study’s cross-sectional nature did not allow for assessing the impact of evaluators’ feedback on students’ learning and the quality of their subsequent reports. In the future, longitudinal studies with repeated measures over time would make it possible to establish the effect of feedback.

Finally, we would have liked to establish a user-centered platform from the outset. However, due to the lack of previous information from students regarding the subject matter, it was not feasible to conduct a consultation to determine which elements to consider. We have endeavored to compensate for this by incorporating the feedback provided subsequently.

Conclusions
In Europe, only a handful of medical or nursing schools have incorporated curriculum plans addressing patient safety [14]. Studies examining the nature of patient safety training received by students in health care disciplines are limited [39,40]. Faculties and schools might consider these reflections and data, incorporating reporting as a practical exercise into their curriculum. This study presents an initial adaptation of reporting systems to suit the needs of students, introducing a guided and inspiring framework that has garnered positive acceptance and evaluation among students. Through this endeavor, a pathway toward a safety culture within the faculty is established.

Acknowledgments
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Data Availability
The data sets generated during and analyzed during this study are available from the corresponding author on reasonable request.
Authors' Contributions

All the authors meet the International Committee of Medical Journal Editors criteria for authorship. JJM, IC, MG, and CF were responsible for the design of the study. IC and EGH were responsible for obtaining ethics approval and registration in ClinicalTrials.gov. IC and MG conducted the review and compilation of the existing tools, and JJM and EGH drafted the first version of the form. PCS, JMD, and MMM reviewed the form and made the necessary clarifications. EB and VRN translated the contents into English, and finally, all authors approved the final form. Regarding the platform, CF developed the acronym and visual identity; EGH, IC, MG, and VRN prepared the instructional and introductory materials; and JJM, PCS, JMD, MMM, and EB were in charge of the recruitment and introductory seminar in each country. Finally, EGH, IC, and MG carried out the evaluation and feedback of the reports, and CPE performed the statistical analysis and interpretation of the results. JJM and EGH developed the first version of the manuscript. All authors revised the paper critically for important intellectual content and read and approved the final version of the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1
STROBE checklist for cross-sectional studies.
[PDF File (Adobe PDF File), 210 KB - mededu_v10i1e56879_app1.pdf ]

Multimedia Appendix 2
Acronym and visual identity developed for the platform.
[PDF File (Adobe PDF File), 5499 KB - mededu_v10i1e56879_app2.pdf ]

Multimedia Appendix 3
Educational materials used during the seminars.
[PDF File (Adobe PDF File), 905 KB - mededu_v10i1e56879_app3.pdf ]

Multimedia Appendix 4
Schematic diagram of the Safety Incident Report System for Students platform operation.
[PDF File (Adobe PDF File), 81 KB - mededu_v10i1e56879_app4.pdf ]

Multimedia Appendix 5
Safety Incident Report System for Students reporting form.
[DOCX File, 98 KB - mededu_v10i1e56879_app5.docx ]

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21. Safety incident reporting system for students during their clinical internship. safest. URL: https://calite.umh.es/valoracion/en/ [accessed 2024-04-29]


Abbreviations

AE: adverse event
BACRA: Based on Root Cause Analysis
IRS: incident reporting system
SAFEST: Safety Incident Report System for Students
STROBE: Strengthening the Reporting of Observational Studies in Epidemiology

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Global Trends in mHealth and Medical Education Research: Bibliometrics and Knowledge Graph Analysis

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Abstract

Background: Mobile health (mHealth) is an emerging mobile communication and networking technology for health care systems. The integration of mHealth in medical education is growing extremely rapidly, bringing new changes to the field. However, no study has analyzed the publication and research trends occurring in both mHealth and medical education.

Objective: The aim of this study was to summarize the current application and development trends of mHealth in medical education by searching and analyzing published articles related to both mHealth and medical education.

Methods: The literature related to mHealth and medical education published from 2003 to 2023 was searched in the Web of Science core database, and 790 articles were screened according to the search strategy. The HistCite Pro 2.0 tool was used to analyze bibliometric indicators. VOSviewer, Pajek64, and SCImago Graphica software were used to visualize research trends and identify hot spots in the field.

Results: In the past two decades, the number of published papers on mHealth in medical education has gradually increased, from only 3 papers in 2003 to 130 in 2022; this increase became particularly evident in 2007. The global citation score was determined to be 10,600, with an average of 13.42 citations per article. The local citation score was 96. The United States is the country with the most widespread application of mHealth in medical education, and most of the institutions conducting in-depth research in this field are also located in the United States, closely followed by China and the United Kingdom. Based on current trends, global coauthorship and research exchange will likely continue to expand. Among the research journals publishing in this joint field, journals published by JMIR Publications have an absolute advantage. A total of 105 keywords were identified, which were divided into five categories pointing to different research directions.

Conclusions: Under the influence of COVID-19, along with the popularization of smartphones and modern communication technology, the field of combining mHealth and medical education has become a more popular research direction. The concept and application of digital health will be promoted in future developments of medical education.

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KEYWORDS
mHealth; mobile health; medical education; bibliometric; knowledge map; VOSviewer

Introduction

The rapid development of information and communication technologies in recent years has enabled greater connections to the mobile internet to access any information desired at any time and place, providing favorable conditions for the development of mobile health (mHealth). mHealth offers a full range of health care and medical education services, transcending geographical, time, language, and even organizational barriers [1,2].

mHealth was first defined as “unwired e-med” by Laxminarayan and Istepanian [3] in 2000. In 2003, mHealth was defined as an emerging mobile communication and networking technology for health care systems [4]. mHealth can provide diagnostic and treatment support services through mobile communication devices such as mobile phones, iPads, and personal digital assistants. An mHealth system and its associated app functions have a significant impact on typical health care, clinical data collection, record maintenance, health care information awareness, detection and prevention systems, drug counterfeiting, and theft. Thus, mHealth services have a powerful impact on all health services, including hospitals, care centers, and acute care, and are designed to significantly improve the lives of patients, especially older adults, individuals with physical disabilities, and patients with chronic conditions [4].
Currently, medical resources are extremely unevenly distributed among populations. In many developing countries, medical services have not yet been updated to incorporate current technological capabilities and the level of medical education often lags far behind that of developed countries. The integration and development of mHealth and medical education can help to address this situation. Through mHealth, doctors can provide basic health care and concepts to people living in areas where health services are lacking, and researchers who are experts in the field can share their clinical experience and theoretical knowledge with their peers through mobile communication technologies such as mobile phones. Thus, the widespread adoption of mHealth can not only rapidly raise the level of medical services in a region but can also help to somewhat reduce the gap in health services between different regions of the world and promote the progress of the global health care industry. From the perspective of medical education, medical students have traditionally only been able to acquire theoretical knowledge in the classroom and obtain hands-on experience through clinical practice. With the development and promotion of various medical-related mobile apps, medical education is no longer limited to face-to-face interactions, and more advanced and quality teaching resources can be disseminated through mobile software and other digital means. The combination of mHealth and medical education has provided more access to educational resources for medical students and physician groups at different levels [4].

Bibliometric analysis is a quantitative analysis method combining mathematics and statistics that focuses on the bibliometric characteristics of a research field to help researchers better understand the development trends in the field for guiding more in-depth research [5-7]. As research on mHealth continues to deepen, there have been an increasing number of articles published in the field. However, to date, there has been no bibliometric analysis of research related to the applications of mHealth in medical education. Therefore, in this study, we summarized the literature related to mHealth and medical education to help deepen our understanding of mHealth and identify future directions for its in-depth research in the context of developing medical education.

Methods

Ethical Considerations

All of the data collected and analyzed in this study were obtained from online public databases and did not involve any human or animal; thus, ethical approval was not required.

Data Sources

The Web of Science (WoS) literature database was selected to search, export, and analyze the relevant literature linking mHealth and medical education. Although the concept of mHealth was first proposed in 2000, since it was only officially defined in 2003, we set the start date for the search to 2003 [3,4,8]. We searched the WoS platform on April 2, 2023, selecting the WoS Core Collection, which contains articles included in the SCI (Science Citation Index)-EXPANDED, SSCI (Social Science Citation Index), AHCI (Arts & Humanities Citation Index), CPCI-S (Conference Proceedings Citation Index-Science), CPCI-SSH (Conference Proceedings Citation Index-Social Science & Humanities), BKCI-S (Book Citation Index-Science), BKCI-SSH (Book Citation Index-Social Science & Humanities), ESCI (Emerging Sources Citation Index), CCR (Current Chemical Reactions)-EXPANDED, and IC (Index Chemicus) databases.

Search Strategy

The search in the WoS Core Collection was performed in advanced search mode and the search option was set to “exact search.” The search terms included a combination of “mHealth,” “mobile health,” and “medical education” as follows: “TS=((mobile health) OR (mHealth)) AND [medical education].” The time span was from January 1, 2003, to March 31, 2023; the document type was limited to “Articles”; and English was selected as the only language of publication. The first output of the articles retrieved was obtained according to this strategy without setting any other inclusion criteria.

Data Analysis and Visualization

The literature retrieved based on the search strategy outlined above was exported in both plain-text (txt) and tab-delimited (txt) file formats. Descriptive statistics were obtained using HistCite Pro 2.1 [9]. Microsoft Excel 2021 was used to summarize the results from the HistCite Pro 2.1 analysis quantitatively and present the data graphically. VOSviewer (version 1.6.17) was used for cocitation correlation analysis and knowledge mapping [10]. VOSviewer (version 1.6.17) [11] and Pajek64 (version 5.16) were used jointly to analyze the current state of research and time trends. Visualization of country/region coauthorship trends was achieved using the combined powerful mapping capabilities of VOSviewer (version 1.6.17) and SCImago Graphica (version 1.0.34).

VOSviewer Software Settings

We used VOSviewer to perform a keyword co-occurrence analysis on the exported documents, setting the unit of analysis to “all keywords” and the counting method to “full counting”; the minimum number of occurrences was set to 10. For the overlay visualization, we utilized Pajek software for classification assistance. In the national and regional coauthorship trends analysis, we set the minimum number of coauthors for each country to 5 in VOSviewer. In the cocited references analysis, we set the minimum number of citations to 10. In the cocited journal sources analysis, we set the minimum cocitation count to 35. In the cocited authors analysis, we set the minimum number of citations to 20.

Results

Search Results and Publication Trends

A total of 790 publications related to mHealth and medical education were retrieved based on the search strategy outlined in the Methods, which were analyzed by HistCite Pro 2.1. The local citation score (LCS) and global citation score (GCS) were calculated by the HistCite Pro software based on the information provided in the documents. The LCS refers to the number of times a document is cited within a given topic, reflecting the extent of recognition of research findings within the peer
community. The GCS represents the number of times a document is cited across all fields globally, serving as a significant indicator of the interdisciplinary and cross-domain impact of research outcomes. The GCS for the 790 articles was 10,600, with an average of 13.42 citations per article, and the LCS was 96.

Figure 1 shows the number of mHealth and medical education–related publications and the associated changes in the LCS over time. In the last two decades, especially since 2007, the annual number of publications has been steadily increasing year by year. Since 2020, the annual number of publications has exceeded 100, rising to 130 in 2022. However, data for 2023 only include publications from the first 3 months and are thus incomplete, making it difficult to determine the publication trend for that year. In terms of the LCS, the highest value was 15 in 2016, indicating a significant reference value for research in mHealth and medical education in that year. Additionally, there were peaks in the LCS detected in 2008 (7), 2013 (14), 2014 (14), and 2016 (15), indicating that studies in these years had large contributions to the research published in this field in the subsequent years. However, due to limitations of the search time frame, articles submitted in 2022 and 2023 may still be under review and not yet been published (and therefore not yet cited), resulting in an incomplete calculation of LCS values for the past 3 years.

Figure 1. Annual trend in the number of publications and local citation score (LCS) in the field of mobile health and medical education from 2003 to 2023.
Contributions of Countries and Institutions

We analyzed the top countries and institutions that have published research related to mHealth and medical education. Figure 2A shows the top 10 countries in terms of publication volume, with each country publishing over 20 articles. The United States ranked first with a total of 318 articles, accounting for 40.25% of the total publication volume, representing a contribution far greater than that of other countries. China (n=70) and the United Kingdom (n=62) ranked second and third, respectively. The top 5 countries with respect to the LCS are presented in Figure 2B, with the LCS for the United States reaching 47, which was much higher than that for any other country. Figure 2C lists the top 5 countries in terms of the article H-index, with the United States again ranking first with an H-index of 32; followed by the United Kingdom (17) in second; and China, Canada, and Australia tying for third with an H-index of 14 each. Therefore, the United States leads in both the quantity and quality of publications related to mHealth and medical education, while China and the United Kingdom also rank in the top three for all indicators.

Figure 2. Ranking of top publishing countries and institutions in the field of mobile health and medical education. (A) The top 10 countries with the largest number of publications and their proportions. (B) The top 5 countries with the largest LCS and their proportions. (C) The top 5 countries with the largest H-index values. (D) Institutions with more than 10 publications. (E) The top 6 institutions with the largest LCS. (F) The top 5 institutions with the largest H-index values. Hlth Bur Gansu Prov: Health Bureau of Gansu Province; LCS: local citation score; MCPHS: Massachusetts College of Pharmacy and Health Sciences; Minist Hlth: Ministry of Health; Peoples R China: People’s Republic of China.
We subsequently analyzed the institutions that published the retrieved articles in this field. Figure 2D shows the institutions with more than 10 publications on the topic, with The University of Sydney ranking first with 18 articles, followed by The University of Toronto (n=16), and Harvard Medical School and Johns Hopkins University tied for third place with 15 relevant publications each. In terms of the LCS, The University of Pennsylvania ranked first with a score of 10 (Figure 2E). Figure 2F compares the top 5 institutions in terms of the H-index, with The University of Pennsylvania and The University of Sydney having the highest H-index of 9 each. Thus, overall, the world's leading universities such as The University of Pennsylvania and The University of Sydney are producing relatively advanced research in mHealth and medical education, and this institutional-based analysis is largely consistent with the country-based analysis.

**Journal of Publication and Authors**

A total of 420 journals were involved in publishing mHealth and medical education–related articles according to statistics compiled with HistCite Pro 2.1. *JMIR mHealth and uHealth* ranked first with 67 related publications, *Journal of Medical Internet Research* ranked second with 35 articles, and *JMIR Formative Research* and *BMJ Open* ranked third with 19 articles each. Among the journals with more than 10 publications, five are from JMIR Publications (Figure 3A). In terms of the H-index, *JMIR mHealth and uHealth* again ranked first with an H-index of 20, *Journal of Medical Internet Research* ranked second (15), and *Telemedicine and e-Health* ranked third (9) (Figure 3B). This finding demonstrates the comprehensiveness and authority of the JMIR Publications journal series in the field of mHealth and medical education.

The authors with the highest number of publications published 5 articles each, and since most of these authors are repeated coauthors, this field appears to be dominated by a relatively small set of researchers. Table 1 lists the authors with more than 4 articles published along with their LCS and GCS; among them, Littman-Quinn R, Aungst TD, and Kovarik CL are at the top of the list in terms of both the quantity and quality of publications.
Figure 3. Contributions of journals to the field of mobile health and medical education. (A) Journals with more than 10 publications. (B) Top 5 journals with the largest H-index values.
### Authors with more than 4 publications and their associated local citation score (LCS) and global citation score (GCS).

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### Keyword Co-Occurrence and Research Trends

We used VOSviewer to conduct keyword co-occurrence analysis on the exported 790 documents. A total of 3288 keywords were extracted, with 105 keywords meeting the threshold. The 105 keywords were then plotted using VOSviewer for density, network, and overlay visualization.

**Figure 4** shows the density visualization of the 105 keywords, revealing that the majority of research in this field revolves around mHealth or education, which, to a certain extent, verifies the objectivity and scientificity of our search strategy and analysis.

**Figure 5A** shows a network visualization of the 105 keywords. A color node can roughly represent a research direction and a larger node area typically indicates a more popular keyword. The software divided all keywords into 5 categories. The red cluster consists of 34 keywords, primarily focusing on clinical medical education (including the keywords “education” and “medical education”), demonstrating that the application of mobile medical software (ie, mobile apps) in medical education and knowledge is widely studied. The green cluster comprises 33 keywords, mainly focusing on the management and development of mobile medical devices and software as well as their application in different age groups through the internet and mobile apps (including the keywords “internet,” “mobile app,” “management,” “outcomes,” “adults,” “children,” and “adolescents”). The blue cluster includes 21 keywords, emphasizing the promotion and education of mHealth in public health and epidemiology (including the keywords “public health,” “medical informatics,” “health education,” “epidemiology,” “HIV,” and “COVID-19”). The yellow cluster contains 16 keywords, primarily investigating the association of mHealth with smartphones, applications in remote diagnosis and treatment, and its role in digital medicine (including the keywords “mHealth,” “smartphone,” “mobile phone,” “telehealth,” “telemedicine,” and “digital health”). As the purple cluster contains only one keyword, “qualitative research,” this serves as a link between various research areas owing to its vague directionality.

**Figure 5B** presents an overlay visualization of the 109 keywords highlighted in research related to the field of mHealth and medical education. According to the color legend, over time, the main keywords in this research area have gradually shifted from the purple (prior to 2017) to yellow (after 2020) category. This indicates that initially, this field was limited to the understanding and learning of mobile information (including the keywords “information,” “mobile,” and “mobile learning”). With the development and popularity of the internet and mobile devices, their use in medical education began to be promoted (including the keywords “internet,” “mobile devices,” “mobile technology,” and “medical education”). Further, with the development of mobile phones and mobile software, the application of mHealth in medical education is no longer limited to the teaching of professional knowledge to students but is also oriented toward the general public and the promotion of educational medical health concepts among different groups of people (represented by most keywords in the teal-colored small-sized nodes).

In recent years, mHealth has increasingly shifted into the research spotlight with the continuous support of smartphones and a greater inclination toward public health, along with the implementation of inclusive medical services and health communication (yellow small-sized nodes). In the future, increased promotion and use of mHealth care may push digital health (highlighted as “digital health” in yellow in Figure 5, referring to the application of digital technologies such as the Internet of Things, artificial intelligence, and big data in health management) to a focused area of research.
Figure 4. Density visualization of the top 105 keywords. The higher the keyword density, the redder its surrounding color.
National and Regional Coauthorship Trends

Different countries and regions tend to collaborate on the same research topics rather than working in isolation. VOSviewer identified 37 countries with coauthorship relationships. As shown in Figure 6A, the red clusters (12 countries) have the strongest coauthorship relationships, with the United States (as the country with the highest number of publications) having the most significant coauthorship relationships. We then exported the results of the VOSviewer analysis to SCImago Graphica for further analysis of country coauthorship correlations in a world map (Figure 6B), which provides a clearer visual representation of the strong coauthorship links between countries on all continents, mainly comprising European countries. This map also shows that researchers working in different countries have a large breadth of interactions, even communicating with each other across continents.
Cocitation Analysis

Cocited References

Cocited references are an important indicator of the extent to which a particular field is linked to different researchers or research areas. A total of 25,986 cited references were considered valid in VOSviewer, with a total of 28 articles meeting the minimum threshold. These 28 references were divided into three interconnected clusters (Figure 7A), with 11 articles in the red cluster, 9 articles in the green cluster, and 8 articles in the blue cluster. The article “Smartphone and medical related app use among medical students and junior doctors in the United Kingdom (UK): a regional survey” by Payne and colleagues [12], published in *BMC Medical Informatics and Decision Making* [12], showed the highest cocitation frequency, with 28 citations.
Figure 7. Cocitation analysis. (A) Network map of cocited references. (B) Network map of cocited journal sources. (C) Network map of cocited authors.

Cocited Journal Sources
The analysis of cocited journal sources demonstrates the extent to which research in the fields of mHealth and medical education is published in journals that have previously published relevant literature on these topics. A total of 83 journal sources met the minimum threshold (Figure 7B), with the *Journal of Medical Internet Research* having the most cited articles at 898. The 83 journals were divided into six clusters, including 23 journals in the red cluster, 15 in the green cluster, 14 in the blue cluster, 13 in the yellow cluster, 11 in the purple cluster, and 7 in the cyan cluster.

Cocited Authors
The number of cocited authors serves as an important indicator for bibliometrics analysis, highlighting the closeness of scholarly relationships and research directions among scholars. In VOSviewer, 22 authors met the minimum threshold of 20,821 citations. According to the network of cocited authors (Figure 7C), a larger area of a color node indicates more citations. The World Health Organization (WHO) had the highest number of citations, reaching 160, reflecting its authority in the field of mHealth combined with medical education. Although each of the four colors represents a different research focus for different authors, the different clusters are not absolutely isolated from each other.
Discussion

Principal Results

In this study, we conducted a search of the literature in the WoS Core Collection and obtained 790 relevant articles on mHealth and medical education published from 2003 to 2023 according to the search strategy. In the past two decades, especially since 2007, the number of published papers in this combined field has gradually increased, reaching 130 published papers in 2022. The GCS is 10,600, with an average of 13.42 citations per article, and the LCS is 96. The United States stands out as the country with the greatest application of mHealth in medical education, and most of the institutions with in-depth research in this field are also located in the United States. The depth of research in China and the United Kingdom followed closely behind. Based on current trends, global coauthorship and research exchange will continue to expand. Among the journals publishing research on this topic, JMIR Publications journals have an absolute advantage in this joint field. The 105 keywords identified were divided into five categories pointing to different research directions.

An important indicator of research trends in a field is the number of relevant articles published each year. The results of this analysis show a general upward trend in research in mHealth and medical education, a field that has received a great deal of attention in recent years. As of 2020, research in this joint field can be divided into two phases: the nascent phase and the stable growth phase. The nascent phase spans from the introduction of mHealth in 2003 to 2007 when the model of combining mHealth and medical education was first proposed and associated research was in its infancy, as represented by the small number of relevant articles published in this period. The period from 2007 to 2020 represents a phase of steady growth, with a gradual increase in the number of relevant research articles. In terms of the LCS, there were four peaks detected in 2008, 2013, 2014, and 2016, respectively. Considering the annual publication volume over the entire period of mHealth research, it can be inferred that the research achievements in 2008 played a crucial role in the development of mHealth applications in medical education.

From Figure 5B, it can be seen that the main keywords representing the direction of mHealth before 2017 were “health care,” “internet,” and “information”; however, after 2019, the main keywords changed to “mobile phone,” “mHealth,” and “education,” indicating that the direction of mHealth development has been changing in recent years. This may be due to the popularity of smartphones, development of mobile software, spread of the internet, and rapid development of communication technology. mHealth has evolved from an initial focus on understanding and learning about mobile information and health care information to a combination of mHealth and mobile devices for research and medical education. On January 9, 2007, Steve Jobs, as the Chief Operating Officer of Apple, presented the iPhone 2G and its operating system iOS to the world. This event triggered the rapid development of smartphones and associated apps, as well as the emergence of new mobile platforms. Likely due to these breakthroughs in smartphones and mobile-related technologies, mHealth began to enter the minds of researchers, attracting the attention of scientists worldwide, and thus the number of annual publications related to mHealth began to rise steadily. In addition, the rapid development of communication technology, increasing popularity of smartphones, and development of mobile software provided a suitable platform for medical schools, hospitals, and research institutions in different regions to collaborate and communicate with each other.

On March 11, 2020, the WHO announced COVID-19 as a global pandemic caused by SARS-CoV-2, which affected the daily lives of billions of people [13-15]. The COVID-19 pandemic not only posed a serious challenge to global medical care systems [16] but also limited access to learning and education, with most students having to access knowledge via the internet using communication devices such as mobile phones, iPads, and computers at home. This led to the rapid development of online teaching and learning software, and ultimately accelerated the integration of mHealth and medical education. Consequently, the number of mHealth-related research articles exceeded 100 in 2020 and rose to 130 in 2022. The development and application of 5G mobile technology and the rapid development of online teaching–related software collectively contributed to the deeper integration of mHealth and medical education [17]. Analysis of keyword clusters (Figures 4 and 5A) showed that mHealth research in the last two decades can be roughly divided into four clusters: a clinical education–related cluster, an mHealth equipment and software–related cluster, a health care and public health mission cluster, and a telemedicine cluster. The development of the discipline requires mutual cooperation with other fields. Promoting the integration and development of mHealth and medical education is extremely important to improve the health care conditions in less developed areas such as developing countries and to promote the common development of the world’s health care standards, which is in line with the WHO’s aim to improve the health of people around the world as much as possible.

The high number of citations in this joint field is somewhat indicative of the quality of the research cited. The study by Payne et al [12] received a particularly high number of citations, indicating its significant impact on medical education and mHealth. This study found that medical students and physician groups enjoy acquiring theoretical knowledge through an mHealth teaching model, which is consistent with the overall findings of this bibliometric analysis. In terms of researchers, the WHO has the highest number of cited articles in the field of mHealth combined with medical education, which not only reflects the authority of the organization but also shows the importance the WHO attaches to mHealth combined with medical education. The top three cited journals for mHealth and medical education research are *Journal of Medical Internet Research* (impact factor 4.948, Q1), *Journal of Medical Internet Research* (impact factor 7.077, Q1), and *BMJ Open* (impact factor 3.007, Q2). According to their impact factors obtained from Journal Citation Reports 2022 [18], these three journals are considered Q1 and Q2 journals, indicating their strong contributions to their respective fields. The co-citation analysis demonstrated the authority of *Journal of Medical Internet Research* in the field.
of mHealth and medical education research, with an annual volume of 318 articles, an LCS of 47, and an H-index of 32. Although the United States is clearly the world leader in mHealth and medical education, making a significant contribution to the field, academic exchanges between different countries are also ongoing.

Limitations
There are limitations of our study that should be acknowledged. First, data completeness may be inadequate; although the WoS database has the most complete coverage of articles, our literature search was limited to the English language, which may have resulted in the omission of some key information for some countries where research was published in other languages. In addition, the search strategy was limited to the string “TS:=(mobile health OR (mHealth)) AND [medical education]” and therefore may not have been sufficiently comprehensive.

Conclusion
Bibliometric analysis indicates that mHealth-related research has been growing at an accelerating rate over the last two decades. In the area of combining mHealth and medical education, the WHO is playing an important leadership role, with many researchers following suit. With the influence of COVID-19, the spread of smartphones, and constant developments in modern communication technologies, the field of combining mHealth and medical education is becoming increasingly popular, and the concept and application of digital health will be promoted in the future drive for medical education.

Acknowledgments
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Data Availability
The data sets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Authors' Contributions
YH designed the study and analyzed the data. YH and ZX wrote the manuscript. JL and ZM prepared the figures and tables. CH reviewed and revised the manuscript. DX and CH supervised the research and thus made equal contributions to the work. All authors approved the final manuscript.

Conflicts of Interest
None declared.

References


Abbreviations

AHCI: Arts & Humanities Citation Index
BKCI-S: Book Citation Index-Science
BKCI-SSH: Book Citation Index-Social Science & Humanities
CCHR: Current Chemical Reactions
CPCI-S: Conference Proceedings Citation Index-Science
CPCI-SSH: Conference Proceedings Citation Index-Social Science & Humanities
ESCI: Emerging Sources Citation Index
GCS: global citation score
IC: Index Chemicus
LCS: local citation score
mHealth: mobile health
SCI: Science Citation Index
WHO: World Health Organization
WoS: Web of Science

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Development of Web-Based Education Modules to Improve Carer Engagement in Cancer Care: Design and User Experience Evaluation of the e-Triadic Oncology (eTRIO) Modules for Clinicians, Patients, and Carers

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Abstract

Background: Carers often assume key roles in cancer care. However, many carers report feeling disempowered and ill-equipped to support patients. Our group published evidence-based guidelines (the Triadic Oncology [TRIO] Guidelines) to improve oncology clinician engagement with carers and the management of challenging situations involving carers.

Objective: To facilitate implementation of the TRIO Guidelines in clinical practice, we aimed to develop, iteratively refine, and conduct user testing of a suite of evidence-based and interactive web-based education modules for oncology clinicians.
(e-Triadic Oncology [eTRIO]), patients with cancer, and carers (eTRIO for Patients and Carers [eTRIO - pc]). These were designed to improve carer involvement, communication, and shared decision-making in the cancer management setting.

**Methods:** The eTRIO education modules were based on extensive research, including systematic reviews, qualitative interviews, and consultation analyses. Guided by the person-based approach, module content and design were reviewed by an expert advisory group comprising academic and clinical experts (n=13) and consumers (n=5); content and design were continuously and iteratively refined. User experience testing (including “think-aloud” interviews and administration of the System Usability Scale [SUS]) of the modules was completed by additional clinicians (n=5), patients (n=3), and carers (n=3).

**Results:** The final clinician module comprises 14 sections, requires approximately 1.5 to 2 hours to complete, and covers topics such as carer-inclusive communication and practices; supporting carer needs; and managing carer dominance, anger, and conflicting patient-carer wishes. The usability of the module was rated by 5 clinicians, with a mean SUS score of 75 (SD 5.3), which is interpreted as good. Clinicians often desired information in a concise format, divided into small “snackable” sections that could be easily recommended if they were interrupted. The carer module features 11 sections; requires approximately 1.5 hours to complete; and includes topics such as the importance of carers, carer roles during consultations, and advocating for the patient. The patient module is an adaptation of the relevant carer module sections, comprising 7 sections and requiring 1 hour to complete. The average SUS score as rated by 6 patients and carers was 78 (SD 16.2), which is interpreted as good. Interactive activities, clinical vignette videos, and reflective learning exercises are incorporated into all modules. Patient and carer consumer advisers advocated for empathetic content and tone throughout their modules, with an easy-to-read and navigable module interface.

**Conclusions:** The eTRIO suite of modules were rigorously developed using a person-based design methodology to meet the unique information needs and learning requirements of clinicians, patients, and carers, with the goal of improving effective and supportive carer involvement in cancer consultations and cancer care.

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**KEYWORDS**
family carers; patient education; health professional education; web-based intervention; mobile phone

**Introduction**

**Background**

Carers (including but not limited to spouses, partners, adult children, siblings, parents, or friends [11]) of adults with cancer assume many responsibilities in supporting and caring for their loved one [2]. Carers can experience many challenges in this demanding role and often report high distress [3,4], poor physical health, low quality of life, and unmet needs [5,6]. As carer burden increases, carers may neglect their own needs, which can also impact their ability to support and care for their loved one [7,8].

While issues faced by carers are well recognized by health care professionals [9], many clinicians report that they do not know how to appropriately engage with carers or address their unique challenges [9,10]. Oncologists have reported a lack of education about communicating with carers [10], and suboptimal carer-clinician communication is common [11]. Some carers report being overlooked in medical consultations and feeling disempowered and unprepared in their caregiving role [12]. Clinician inclusion and support of carers have been reported as highly valued by both carers and patients [12].

Improving carer engagement and support needs to be addressed from multiple perspectives. Not only are clinicians uncertain about how to include carers in consultations [9] but also many carers often lack confidence and skills in caregiving [12,13], and some patients are unsure about what role their carer should assume in medical consultations and decision-making [14]. Therefore, interventions targeting all members of the clinician-patient-carer trio are needed.

Web-based delivery of education offers efficacy, efficiency, ability to undertake training in discrete periods, lower cost, flexibility, and greater reach than traditional face-to-face formats [15]. A systematic review of web-based health education by George et al [16] found web-based training for health professionals to be as effective as or better than face-to-face formats on outcomes such as knowledge, skills, and attitudes. Web-based communication skills interventions have been found to be effective in improving self-rated clinician confidence, communication skills, and knowledge among cancer clinicians [15]. For example, a web-based module developed by our group to educate nurses about managing conflict involving patients and carers (the Triadic Oncology [TRIO]–Conflict module) was found to improve cancer nurses’ attitudes and confidence in interacting with carers [17].

Patients and carers can also benefit from web-based resources and educational tools [18]. A systematic review of digital psychosocial interventions for patients with cancer and carers found web-based interventions to be both feasible and acceptable [19]. Digital interventions for carers have been shown to improve carer outcomes, knowledge, and skills, with the additional benefit of being accessible from home, thus minimizing the demands on carers’ time [20]. For example, a web-based psychosocial intervention for patients with cancer, Stress-Aktiv-Mindern (STREAM), has demonstrated beneficial patient outcomes including reduced stress and improved quality of life [21]. Similarly, the psychoeducational platform, Comprehensive Health Enhancement Support System (CHESS), has demonstrated favorable outcomes among carers such as significant reduction in negative mood and carer burden [22]. These beneficial effects were comparable to those of traditional psychoeducational interventions [23,24]. While STREAM and
CHESS demonstrate the efficacy of web-based patient and carer support, their focus is on psychosocial support. To date, there have been no web-based education modules dedicated to empowering and upskilling patients and carers in carer-relevant communication and engagement with cancer clinicians and in carer participation in cancer treatment decision-making. Therefore, we aimed to develop and evaluate a web-based learning tool to address these needs.

Interventions to support cancer carers are often difficult to implement in clinical practice and face barriers to implementation including problems with design, feasibility, acceptability, and cost [25]. One way to improve the acceptability and sustainability of an intervention is to use a co-design approach with the target population as stakeholders, to ensure that the program targets user needs and preferences. The person-based approach [26] ensures that intervention development is grounded in the perspectives and psychosocial context of end users via iterative, qualitative research with relevant stakeholders. This approach has been effectively used in the development of web-based health care interventions [27,28].

Objectives

This paper describes the development, iterative refinement, and user testing of evidence-based and interactive web-based interventions designed to improve engagement and communication with carers in cancer care. We have published the study protocol for a randomized controlled trial to test the efficacy of the e-Triadic Oncology (eTRIO) modules elsewhere [29]. However, necessary amendments to the planned randomized controlled trial due to the COVID-19 pandemic were made after publication of the protocol. The evaluation approach was revised to hybrid effectiveness and implementation studies using a pre-post, single-arm intervention design.

In this paper, we have reported about the development of web-based education modules for all 3 relevant stakeholder groups, including oncology health professionals and patients with cancer and carers (eTRIO for patients and carers [eTRIO-pc]).

Methods

Overview

The person-based co-design approach by Yardley et al [26] underpinned the module design. Development and user experience testing of the clinician (eTRIO) and patient-carer (eTRIO-pc) modules was undertaken in multiple cyclical phases of data collection, analysis, and integration, in a process of iterative refinement [30]. Consistent with the approach by Yardley et al [26], this involved (1) planning: development of module content based on evidence, qualitative interviews with stakeholders, and input from our expert advisory group; (2) design: iterative review and refinement based on advisory group feedback; and (3) development and evaluation of acceptability and feasibility: formal heuristic evaluation, System Usability Scale (SUS) questionnaire, and think-aloud review of the eTRIO modules by stakeholders (Figures 1 and 2). The final phase of implementation and trialing is currently being conducted in a separate pre-post evaluation study, which will be reported elsewhere.
Figure 1. e-Triadic Oncology (eTRIO; clinician) module development process. SUS: System Usability Scale.

Figure 2. e-Triadic Oncology for patients and carers (eTRIO-pc) module development process. CCNSW: Cancer Council New South Wales; SUS: System Usability Scale.
Phase 1: Development of eTRIO and eTRIO-pc Module Content

Development of the eTRIO Clinician Module

The content of the modules was informed by our extensive Triadic Oncology (TRIO) research program, which includes a systematic review of carer involvement in consultations [31]; qualitative interviews with oncology clinicians, patients, and carers [9,14,32]; quantitative and qualitative analyses of audiotaped oncology consultations [11]; a conceptual framework of carer involvement in medical decisions [33]; and carer communication guidelines for clinicians (TRIO Guidelines) developed via a Delphi consensus process [34,35]. Key clinician training needs, strategies, and behaviors relevant to the module were ascertained through this extensive research program.

On the basis of this prior research, we developed an initial draft of the eTRIO content. The draft module comprised 14 study sections (1 introductory section and 13 strategy areas covered in the TRIO Guidelines [34,35]). A clinician expert advisory group was formed to provide feedback about the module content, comprising medical oncologists (3/13, 23%), oncology nurses (2/13, 15%), psychologists (2/13, 15%), a radiation oncologist (1/13, 8%), an oncology surgeon (1/13, 8%), and the research team comprising psycho-oncologists (4/13, 31%). Each member of the clinician expert advisory group reviewed a text-based draft of the module content and provided written feedback about each module section, including interactive activities, reflective exercises, and wording of strategies. Multiple teleconferences were conducted, where group members provided feedback about the content and structure of each section. Major changes were discussed with the group until consensus was reached. Feedback from the advisory group was collated, and the module content was iteratively refined.

Development of the eTRIO-pc Patient-Carer Module

The eTRIO-pc module content was drafted based on a review of current web-based guidance for carers about involvement in medical consultations [18], qualitative studies of patients and carers [9,14,32], and analyses of audiotaped consultations [11]. A meeting with the staff at a leading nongovernment cancer support and advocacy organization (n=5) was also conducted to inform the content of the eTRIO-pc initial draft. The staff members were asked to describe the key content that should be included in the eTRIO-pc module, based on their experience in supporting patients and carers via a telephone information and support service.

Consumer advisers (3/5, 60% cancer carers and 2/5, 40% patients with cancer) also provided iterative feedback about the module content during a half-day workshop and via email. Consumer advisers were asked to comment about whether the module content was understandable, the relevance of the module content and feasibility of the suggested strategies, the language, and tone of the module. All feedback from the Cancer Council New South Wales support staff and consumer advisers was collated and discussed with the project team until consensus was reached through revisions.

After the development and iterative revision of the module content was complete, video vignettes modeling key carer communication skills were developed to supplement the written content. Video vignettes have been demonstrated as an effective educational tool for patients and carers and can improve accessibility for those with low literacy [36,37]. We engaged a professional medical education and communication production company to develop a script covering key learning areas for carers, as determined by the consumer advisory groups. The script was iteratively reviewed by the research team, consumer advisers, and a physician to ensure that the videos aligned with the TRIO communication guidelines [34,35] and were clinically relevant and feasible.

Phase 2: Iterative Design, Review, and Refinement of eTRIO and eTRIO-pc Web-Based Modules

Design and Refinement of the eTRIO Clinician Module

As shown in Figure 1, phase 2 involved consumer input and refinement of the modules. To translate the text-based content into an interactive web-based educational module, we studied the best practice principles for the delivery of e-learning to health professionals [16,38-40]. This included a review by de Leeuw et al [38] about e-learning features targeted at postgraduate medical students and health professionals completing ongoing professional development, which identified 6 domains of important elements for e-learning quality (preparation, design, communication, content, assessment, and maintenance). Informed by a previous review [38], we developed a base design and catalog of potential design features.

A prototype web platform was developed by a professional web development company. In 2 sessions conducted via Zoom (Zoom Video Communications), the clinician advisory group completed a walk-through of the module and provided comprehensive feedback. Their verbal and written feedback was collated and integrated into a revised web-based module.

Design and Refinement of the eTRIO-pc Patient-Carer Module

Similarly, as displayed in Figure 2, phase 2 involved the conversion of the text-based module content for patients and carers into an interactive web-based platform. We conducted a review of the content and design features of other available evidence-based web-based platforms for carers [18], drew on the evidence base surrounding education for carers [41-43], and received input from the consumer advisory group. To inform the website design, we reviewed the publicly available web-based resources for carers.

The final design features of eTRIO and eTRIO-pc were implemented by a professional web development company and included interactive activities, video vignettes, and text-based content. The clinician and consumer advisory groups were given access to the draft module, and its content and format were revised based on their extensive feedback. An expert in human-centered IT design was involved in all stages of development of the clinician and patient-carer modules.
Phase 3: Heuristic Evaluation and “Think Aloud” User Experience Evaluation of eTRIO and eTRIO-pc Web-Based Modules

As shown in Figures 1 and 2, phase 3 involved usability evaluations of the developed web-based module. We conducted a heuristic evaluation to discover technical and usability issues [44]. The modules were examined by the researchers to identify problems that did not comply with the usability principles recognized by Nielsen [45], which include consistency and standards, error prevention, and aesthetic and minimalist design. The severity and prevalence of the issues were ranked from 1 to 5, with a high rank indicating that the problem was a priority to fix, and the web platform was updated accordingly.

Usability and user experience testing for the penultimate versions of eTRIO and eTRIO-pc were conducted using think-aloud methodology with 11 participants, including clinicians, patients, and carers, all of whom were naïve to the TRIO Guidelines and modules. Think aloud is an effective evaluation method in which participants are provided with an interface and asked to verbalize their thoughts as they work through it [46,47]. Potential participants were identified through the research team’s professional networks and via social media advertisements.

The consenting participants completed a demographic questionnaire and a 4-item self-report measure of health literacy [48]. Participants were provided access to the relevant eTRIO module and asked to speak aloud their thoughts and impressions as they were completing the module (think-aloud). These sessions were conducted face to face or via videoconferencing. After working through the module, participants completed the SUS [49]. Think-aloud evaluations were audio recorded and transcribed verbatim. Transcripts were qualitatively analyzed using thematic analysis [50], which involved familiarization with the transcripts, coding of salient initial ideas as codes, identification of patterns in the codes to generate themes and subthemes, and iterative review of the themes and subthemes to ensure a coherent and comprehensive thematic structure. This process was conducted collaboratively and through iterative discussion by RLP, PB, ZB, MB, and IJ. Themes were related to the following: usability and technical issues, positive aspects of design and function, attitudes toward the content of the program, and perspectives about the impact or implementation of the program. All transcripts were analyzed based on the established thematic framework and were grounded in illustrative quotations. Subsequently, the modules were iteratively refined based on this feedback.

Ethical Considerations

Ethics approval was obtained from the University of Sydney Human Research Ethics Committee (protocol 2015/468). Participants provided informed consent and were given the opportunity to opt out at any point in time. Participant data were deidentified. Participants were provided a gift card worth Aus $20 (US $13.22) as compensation for their time.

Results

This section describes the clinician, patient, and carer feedback; iterative revisions made; and lessons learned in the design and development of the eTRIO and eTRIO-pc modules.

Phase 1: Development of eTRIO and eTRIO-pc Module Content

**eTRIO Clinician Module**

The clinician advisory group members (n=13) emphasized the importance of the module being concise. They suggested more content for the introductory section such as including a broad and inclusive definition for “carers,” content about culturally diverse carers, and more information about the legal and ethical aspects of involving carers. Clinicians also suggested the inclusion of self-reflections about one’s own attitudes and potential biases toward carers. Additional suggestions included addressing the diversity of settings in which family or carer interactions can occur (eg, outside traditional outpatient consultations such as at the patient’s bedside or via the telephone). Several clinicians stressed the importance of including clear learning outcomes and summaries for each of the 14 sections.

**eTRIO-pc Patient-Carer Module**

Cancer support staff (n=5) suggested a clear definition of the role of carers, tailoring based on the cultural backgrounds of patients and carers, and consideration of power imbalances that may exist in patient-carer relationships. They emphasized checking in on patient and carer emotions such as grief and distress, suggested that modules could include opportunities for self-reflection, and highlighted the need to include information about available support for carers.

The overall impression of the consumer advisory group (n=5) was that the language and tone of the draft module was very formal and academic; they wanted the tone to be more “personal,” “empathetic,” and “softer” and the language to be less prescriptive. They suggested additional strategies for patients with newly diagnosed cancer and carers, such as making notes during medical consultations, and suggested including quotes and stories from actual carers to illustrate examples.

Phase 2: Iterative Design, Review, and Refinement of eTRIO and eTRIO-pc Web-Based Modules

**Overview**

Table 1 describes the results from phase 2 using the e-learning design features by de Leeuw et al [38] applied to the eTRIO and eTRIO-pc modules.
### Table 1. e-Learning design features identified by de Leeuw et al, as applied to the e-Triadic Oncology (eTRIO) and e-Triadic Oncology for patients and carers (eTRIO-pc) modules.

<table>
<thead>
<tr>
<th>Elements of e-learning</th>
<th>Description</th>
<th>Use in eTRIO and eTRIO-pc</th>
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<tbody>
<tr>
<td><strong>Preparation</strong></td>
<td>Identifying the needs of the target audience</td>
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<td></td>
<td>Th research team conducted an extensive program of previous studies on the needs of carers</td>
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<tr>
<td></td>
<td>Stakeholder input, feedback, and evaluation</td>
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<tr>
<td><strong>Design</strong></td>
<td>Including elements of accessibility, reliability, user-friendly navigation, and visual appeal</td>
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<td></td>
<td>Web-based program, simple layout, and designed for easy use</td>
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<td></td>
<td>Font, color, size, and layout are optimized for accessibility</td>
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<td>User progress is saved when users log out</td>
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<tr>
<td></td>
<td>Website is designed and tested on various software and hardware</td>
<td></td>
</tr>
<tr>
<td><strong>Communication</strong></td>
<td>Communication with users and program facilitators</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Landing page introduces users to the learning objectives and goals (ie, communication skills and strategies, understanding carer roles, and benefits of carer involvement in cancer care)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Clear information about program use and navigation is included</td>
<td></td>
</tr>
<tr>
<td><strong>Content</strong></td>
<td>Including words, images, videos, interactive activities, summaries, and so on</td>
<td></td>
</tr>
<tr>
<td></td>
<td>All modules include multimedia content such as several clinical vignette videos, audios, text, images, and interactive features. Interactive activities were designed, including the following:</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• eTRIO (clinician): sorting and drag-and-drop activities, true-or-false exercises, open-text written responses, click-to-expand sections, and identifying behaviors in a vignette video</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• eTRIO-pc (patient-carer): resources that can be individually tailored (eg, assembling a caregiving team, building a question prompt list, and checklist for patients and carers to discuss carer role), click-to-expand sections, and open-text written responses</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Downloadable summaries are provided to allow access after completing or outside the module</td>
<td></td>
</tr>
<tr>
<td><strong>Assessment</strong></td>
<td>Assessing learning and acquiring feedback</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Each section of each module contains clear learning objectives, displayed on the first page of each section. For example, section 9 of eTRIO (clinician), related to the use of interpreters, states the following: “In this section you will explore reasons why patients/carers might resist professional language interpreters, and understand strategies to overcome these issues. You will learn practical strategies to engage and use formal interpretation services.”</td>
<td></td>
</tr>
<tr>
<td></td>
<td>All modules include assessment activities to facilitate learning and reflection:</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• eTRIO (clinician): self-reflection and assessment of own attitudes and practices, true-or-false assessment of content with correct answers and explanations, multiple choice questions asking users to reflect about how they would navigate a clinical scenario, and open-ended responses</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• eTRIO-pc (patient-carer): self-assessment of emotions, opportunities to reflect about own preferences and attitudes and to plan future actions or behaviors, and open-text reflections about video vignettes modeling key skills</td>
<td></td>
</tr>
<tr>
<td><strong>Maintenance</strong></td>
<td>Providing long-term access and updating information and links</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Website is regularly maintained and updated</td>
<td></td>
</tr>
<tr>
<td></td>
<td>All users will have access to the program after completion of the training</td>
<td></td>
</tr>
</tbody>
</table>

### eTRIO Clinician Module

During the transformation of content to a web-based module, features of e-learning [38] were applied as described in Table 1. The design features of other web-based clinician training modules were examined, revealing display, navigation, and interactive activity styles (eg, minimal use of text, prominent navigation buttons, and clickable and expandable content). Our team worked closely with graphic and web designers to develop a consistent color scheme and intuitive navigation system and aimed to minimize visual noise on each page. The refined content and design features were transformed into a web-based web platform.

All members of the clinician advisory group (13/13, 100%) commented that there was excessive content and that there would not be clinician appetite for web-based training that extended beyond 2 hours in total. The content was subsequently condensed, with the core content displayed with the option of more extensive content, which could be expanded for clinicians interested in deeper learning regarding an issue.

The final eTRIO clinician module comprises 14 sections (submodules), of which clinicians must complete a minimum of 8. The sections range between 3 and 15 minutes in duration. The following 4 sections were deemed to be mandatory by the clinician advisory group, based on their critical relevance to all clinicians: section 1—introduction, section 4—building rapport
with carers, section 7—supporting carers’ emotional and informational needs, and section 10—managing conflicting patient-carer treatment preferences. Clinicians could select additional 4 sections based on their interest and preference. The eTRIO module requires approximately 1.5 to 2 hours to complete, as determined by multiple stakeholders working through the content and documenting the amount of time each section required to complete.

**eTRIO-pc Patient-Carer Module**

Consistent with the principles of computer-based teaching for adult learners by Lau [51], the web-based eTRIO-pc module was created by transforming the written content into interactive, engaging learning activities. Our review of carer resources demonstrated several useful stylistic, formatting, and usability features, for example, the use of bullet points to convey written information, 1-page displays eliminating the need to scroll, and use of simple navigation buttons. These features and principles of web-based education were collated and discussed with the team’s academic IT expert and web developers to select and finalize the most appropriate features to be included. The resultant module prototype included video vignettes that could easily be played and paused, interactive activities such as “drag-and-drop” and “click to reveal” exercises, and type-your-response activities (Multimedia Appendix 1). We maintained consistency in design and formatting across the clinician, patient, and carer modules.

We sent the prototype to the members of the consumer advisory group (n=5), and they provided written feedback via email and offered additional personal quotes that could be included in the module to personalize the content. They re-emphasized the need for content that was empathetic and offered practical advice. The final eTRIO-pc modules contain 7 sections for patients and 11 sections for carers and requires approximately 1 to 1.5 hours to complete.

**Phase 3: “Think Aloud” Usability Evaluation of eTRIO and eTRIO-pc Web-Based Modules**

**Heuristic Evaluation**

Using the heuristic evaluation method [44], we identified 37 usability issues across the draft eTRIO and eTRIO-pc modules, and each was rated for severity. The main areas of the identified problems were as follows: (1) inconsistency of icons and redundancy in buttons (5/37, 14% of the issues; eg, inconsistent use of star and book icons to indicate the bookmark function), (2) buttons and interactions were not working (16/37, 43% of the issues; eg, nothing happens when the print button is clicked), (3) layout problems (6/37, 16% of the issues; eg, text is not aligned with the textbox), and (4) presentation of content (10/37, 27% of the issues; eg, color selection in the bar-slider activity may be confusing) [52]. Following this evaluation, problems with high severity and prevalence were prioritized, and all issues that could be corrected were fixed before conducting the think-aloud user evaluations.

**Think-Aloud User Experience Evaluations**

Overall, 11 individuals (n=5, 45% health professionals; n=3, 27% patients; and n=3, 27% carers) participated in the think-aloud evaluations in individual sessions lasting between 40 and 60 minutes. Participant characteristics are displayed in Table 2.
Table 2. Characteristics of participants of the think-aloud evaluations.

<table>
<thead>
<tr>
<th>Participant category and characteristics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Health professionals (n=5)</strong></td>
<td></td>
</tr>
<tr>
<td>Age (y), mean (SD; range)</td>
<td>47 (10.3; 35-58)</td>
</tr>
<tr>
<td>Sex, n (%)</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>4 (80)</td>
</tr>
<tr>
<td>Male</td>
<td>1 (20)</td>
</tr>
<tr>
<td>Profession, n (%)</td>
<td></td>
</tr>
<tr>
<td>Physician</td>
<td>2 (40)</td>
</tr>
<tr>
<td>Nurse</td>
<td>3 (60)</td>
</tr>
<tr>
<td>Clinical expertise, n (%)</td>
<td></td>
</tr>
<tr>
<td>Oncology</td>
<td>2 (40)</td>
</tr>
<tr>
<td>Palliative care</td>
<td>2 (40)</td>
</tr>
<tr>
<td>Geriatrics</td>
<td>1 (20)</td>
</tr>
<tr>
<td>Experience (years), mean (SD; range)</td>
<td>22 (9.8; 12-37)</td>
</tr>
<tr>
<td><strong>Patients (n=3)</strong></td>
<td></td>
</tr>
<tr>
<td>Age (y), mean (SD; range)</td>
<td>65 (13.7; 50-77)</td>
</tr>
<tr>
<td>Sex (female), n (%)</td>
<td>3 (100)</td>
</tr>
<tr>
<td>Diagnosis, n (%)</td>
<td></td>
</tr>
<tr>
<td>Kidney cancer</td>
<td>1 (33)</td>
</tr>
<tr>
<td>Colorectal cancer</td>
<td>1 (33)</td>
</tr>
<tr>
<td>Non-Hodgkins lymphoma</td>
<td>1 (33)</td>
</tr>
<tr>
<td>Cancer stage, n (%)</td>
<td></td>
</tr>
<tr>
<td>Local</td>
<td>2 (67)</td>
</tr>
<tr>
<td>Advanced</td>
<td>1 (33)</td>
</tr>
<tr>
<td>Health literacy, n (%)</td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>1 (33)</td>
</tr>
<tr>
<td>Medium</td>
<td>1 (33)</td>
</tr>
<tr>
<td>High</td>
<td>1 (33)</td>
</tr>
<tr>
<td><strong>Carers (n=3)</strong></td>
<td></td>
</tr>
<tr>
<td>Age (y), mean (SD; range)</td>
<td>65 (8.7; 58-75)</td>
</tr>
<tr>
<td>Sex, n (%)</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>2 (67)</td>
</tr>
<tr>
<td>Male</td>
<td>1 (33)</td>
</tr>
<tr>
<td>Relationship with care recipient, n (%)</td>
<td></td>
</tr>
<tr>
<td>Spouse or partner</td>
<td>2 (67)</td>
</tr>
<tr>
<td>Mother</td>
<td>1 (33)</td>
</tr>
<tr>
<td>Diagnosis of care recipient, n (%)</td>
<td></td>
</tr>
<tr>
<td>Lung cancer</td>
<td>1 (33)</td>
</tr>
<tr>
<td>Multiple myeloma</td>
<td>1 (33)</td>
</tr>
<tr>
<td>Non-Hodgkins lymphoma</td>
<td>1 (33)</td>
</tr>
<tr>
<td>Cancer stage of care recipient, n (%)</td>
<td></td>
</tr>
<tr>
<td>Local</td>
<td>1 (33)</td>
</tr>
<tr>
<td>Advanced</td>
<td>2 (67)</td>
</tr>
</tbody>
</table>
Participant category and characteristics | Values
---|---
**Health literacy, n (%)**
Medium | 1 (33)
High | 2 (67)

**eTRIO Clinician Module**

The usability of the module was rated by 5 clinicians, with a mean SUS score of 75 (range 68-80), which is interpreted as good [49]. All clinicians gave high ratings to their ability to use the module independently without technical assistance. Clinicians identified technical and navigation issues, which were subsequently rectified (such as the side scroll bar not appearing, text appearing outside the text bubble, and a sliding bar not working responsively). For some, the use of specific web browsers corrected these issues. Clinicians described the overall navigation through the module as “straightforward.” Formatting issues with font size and background color were highlighted. Clinicians commented that the ability to easily navigate back to certain sections to “refer back to later” was valued.

Content analysis of think-aloud evaluations revealed 7 categories related to clinicians’ attitudes toward the design and formatting of eTRIO. Clinicians appreciated that the modules could be completed in small “snackable” periods in any order, that they could keep track of what sections were completed (**trackable**), and that they were able to refer back to any module at any time. Clinicians enjoyed the “clickable” activities where they interacted with the content. Despite attempts to make the sections as short as possible (average 5-10 min/section), a few clinicians still perceived them as “too long,” with some stating that the videos were “slow” at times. They highlighted a preference for material that is brief, uses simple language, is easy to digest, and “skimmable.” A few clinicians reported “glossing over” or “tuning out” when sections were perceived as very long. They suggested simplifying the language and formatting the text to highlight important information (eg, use of bullet points and bold and italic style). Revisions were made to the text to further improve conciseness, including rephrasing the core content, moving some content to the expandable ‘additional information’ section, and greater use of bullet points and bold text. Where possible, videos were edited to remove nonessential scenes. Most participants appreciated that the content and activities were relevant and “relatable” to them as clinicians, that claims were “supported” by evidence, and that the activities and media were “diverse” and varied to facilitate engagement and interest. Illustrative quotes are provided in Table 3.
Table 3. Illustrative quotes from think-aloud evaluations by clinicians.

<table>
<thead>
<tr>
<th>Usability and content feature</th>
<th>Description</th>
<th>Illustrative quotes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snackable</td>
<td>Ability to complete the module in small segments</td>
<td>“So, you’re saying you don’t have to do it all in one go...oh, I think that’s really important because you do get called away and the phone is ringing...because I know even with our mandatory online training in the past, you just [had to] forfeit [all progress] if you couldn’t finish.” [Nurse 2]</td>
</tr>
<tr>
<td>Trackable</td>
<td>Ability to know what has been completed and refer to the content later</td>
<td>“It’s nice to have things you can refer back to because this might trigger things that make you think oh yeah, I did read about that.” [Physician 2]</td>
</tr>
<tr>
<td>Clickable</td>
<td>Importance of interactive content</td>
<td>“I like this section - it’s really good. I like that activity. I’ve never done one of those before - that’s really good. [Interactive activity clicking points of rapport building throughout a video vignette]. You definitely engage a thousand percent more with the activities.” [Physician 2]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>“I think [the activities] are quite good because at least you are giving people a little bit more of themselves...I think it’s good to have that interaction rather than just reading...that gets a bit boring. And then, that you ask people to actually write something is good.” [Nurse 2]</td>
</tr>
<tr>
<td>Skimmable</td>
<td>Importance of simple, concise language</td>
<td>“After reading articles all day I don’t want to read something that has too much jargon in it...Go back and simplify the language...when I read something apart from patients notes, I skim it. So, it’s got to be something that I can get the message with a glance.” [Physician 1]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>“Uhm why I am I finding it difficult to understand? I think it could be worded more simply.” [Physician 2]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>“Yeah. I hate the time pressure...It’s so built into our working day, it’s like get on, get it done, that you gloss over so much. I actually didn’t realize before doing this how much I gloss over...I probably would watch [the video] to the end but there’s a part of me thinking yeah it’s going on a little bit.” [Physician 2]</td>
</tr>
<tr>
<td>Relatable</td>
<td>Relevance of content to the user</td>
<td>“Yeah, I like that there is the suggestions of things to say. That makes it really relatable - I think those are good.” [Physician 2]</td>
</tr>
<tr>
<td>Supported</td>
<td>Evidence-based content</td>
<td>“I like scenarios...Just sort of triggers you to think a little bit more rather than just reading through something. I think the scenario allows me to put it into practice or put it into place a little bit more.” [Nurse 3]</td>
</tr>
<tr>
<td>Diverse</td>
<td>Importance of variety in media and activities</td>
<td>“Oh a video, that’s interesting, it’s sort of mixing it up, it’s nice to have the different things.” [Physician 2]</td>
</tr>
</tbody>
</table>

**eTRIO-pc Patient and Carer Module**

The average SUS score as rated by 6 patients and carers was 78 (SD 16.2; range 55-97.5), which is interpreted as good [49]. Patients and carers were generally happy with the content and usability of the eTRIO-pc module. They commented that the content was relatable and were pleased by the emphasis placed on carers. Overall, they found the web platform easy to navigate and enjoyed the interactive activities; however, 1 (17%) of the 6 patients found the interface to be “overwhelming.” A major critique of the formatting and layout was that the pages were “too busy” and contained excessive information. Illustrative quotes are provided in Table 4.

The final eTRIO and eTRIO-pc modules were updated based on this feedback. All technical and navigation issues were addressed by the web developers.

For both modules, the text was condensed and reformatted with the use of bold and italic style to highlight the important points and allow for easier reading and a more streamlined user interface.
Table 4. Illustrative quotes from think-aloud evaluations by patients and carers.

<table>
<thead>
<tr>
<th>Usability and content feature</th>
<th>Description</th>
<th>Illustrative quotes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Snackable</td>
<td>Ability to complete the module in small segments</td>
<td>“Looking at this dashboard I like it that it tells you how long each part is going to take just so you know in advance. You’re busy and maybe you just have time to do half of it and then you can sort of plan how you’re going to tackle it.” [Carer 1]</td>
</tr>
<tr>
<td>Clickable</td>
<td>Importance of interactive content</td>
<td>“Some of the activities like the questions, I really liked. The ones where you wrote down what you thought the carer might do for you if you then use it as a communication tool, really good as well.” [Patient 1]</td>
</tr>
<tr>
<td>Usable</td>
<td>Ease of navigation</td>
<td>“I think [navigation] is pretty easy and straightforward. I think anybody who’s used to doing online training, modules and so on will probably find it really easy.” [Carer 1]</td>
</tr>
<tr>
<td>Relatable</td>
<td>Relevance of content to the user</td>
<td>“I think this is a very useful slide. When we went in to our first meeting we were just there, me and my son did this.” [Carer 1]</td>
</tr>
<tr>
<td>Visually simple</td>
<td>Cleanliness of layout, formatting, and images</td>
<td>“I think you are making this page very busy with text and it’s a bit confronting.” [Carer 2]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>“It is pretty text-heavy and I guess that I am more of a visual learner so it might be nice to have some more pictures, icons, to make it a little bit more visually appealing.” [Patient 1]</td>
</tr>
</tbody>
</table>

**Final Web Platform Design and Content Summary**

The eTRIO modules reflect the reported informational needs of health professionals, patients with cancer, and carers. A full description of the module content has been published elsewhere [29]. The eTRIO modules have been rigorously designed to be easy to use, require minimal time commitment, and be flexible in terms of when and how the platform can be used. The modules are optimized for use on a computer but can also be used on a smartphone or tablet. Some notable features include the following: navigation buttons and a progress bar along the bottom of the page, expandable content for those who want deeper information about a specific topic, and downloadable summaries and lists. Notable interactive activities include the following: testing of knowledge through true-or-false exercises, identifying specific behaviors in a short video vignette, and building a question prompt list. Refer to Table 5 for descriptions and images of key features; full explanations of the interactive activities are provided in Multimedia Appendices 1 and 2.

Table 5. Key features of the e-Triadic Oncology (eTRIO) modules.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Description</th>
<th>Images</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interactive activities</td>
<td>Includes self-reflection, knowledge tests, and free-text responses</td>
<td><img src="x" alt="Image" /></td>
</tr>
<tr>
<td>Learning outcomes</td>
<td>The eTRIO clinician module features sign-posted learning outcomes at the beginning of each section</td>
<td><img src="x" alt="Image" /></td>
</tr>
<tr>
<td>Downloadable content</td>
<td>Includes materials and personalized checklists for patients and carers and downloadable summaries for clinicians</td>
<td><img src="x" alt="Image" /> and <img src="x" alt="Image" /></td>
</tr>
<tr>
<td>Video vignettes</td>
<td>Realistic scenarios modeling communication skills</td>
<td><img src="x" alt="Image" /></td>
</tr>
<tr>
<td>Intuitive navigation features</td>
<td>Navigation buttons are explained in the module’s introduction</td>
<td><img src="x" alt="Image" /></td>
</tr>
</tbody>
</table>
Discussion

Principal Findings

The web-based modules described in this paper represent a crucial step in the development and design of education for clinicians, patients, and carers that is evidence-based, practical, and interactive and can be easily disseminated. Drawing on the evidence for best practice web-based learning design [38,51], we sought input from a variety of stakeholders to develop a unique learning experience strongly informed by the needs of the target populations. Rigor was ensured via 3 stages of development in which module content and design were continually revised and refined. Overall, participants were positive about the content and interface. The final prototype was appraised as highly acceptable, relevant, and feasible among the small sample of users; however, more studies are needed to confirm this and to ascertain the effectiveness of the intervention. We are currently conducting a pre-post evaluation of these modules to explore their potential effectiveness in improving communication within the patient-carer-clinician trio.

Lessons Learned

Throughout the development and design of these modules, we observed the specific needs and preferences of end users. The person-based approach to developing eTRIO and eTRIO-pc was highly dynamic, and the modules underwent numerous iterations throughout all phases of the design process, which included the involvement of consumers and user-driven evaluations. While there are multiple approaches to developing health interventions, the benefits of the person-based approach include grounding the design in user contexts and lived experiences, integrating feedback based on the actual use of an intervention, and investigating user needs and perspectives beyond just the usability of the intervention [26]. The utility of the person-based approach has been extolled in recent studies [53-55] and is supported by the findings of this study. The eTRIO development process (Figures 1 and 2) provided the necessary building blocks to revise and refine the module for effective use in the real world. Consistent with other studies [56,57], we found that the collaborative co-design process led to positive evaluations of acceptability and usability and high levels of end-user satisfaction.

As highlighted in the person-based approach, the 3 user groups (clinicians, patient, and carers) demonstrated diverse learning preferences and needs. This was accommodated via tailoring the formatting or content to the strengths and contextual demands of different user groups and differentiating the content based on user needs. We found that clinicians had a strong desire for content that was written in simple, concise, and “sharp” language; could be “skim read”; and could be completed in brief, “snack-sized” sections. For example, clinicians in our advisory group often stressed that they lacked time and that training needed to be short, precise, and able to be stopped and restarted due to interruptions. On the other hand, the structure and time demands of training appeared to be less important to patients and carers. Instead, these groups emphasized the need for the module to be easy to use and navigate and for the content to be more conversational, empathetic, and in plain language (in contrast to the preferences of clinicians). Clinicians in our study valued the integration of academic literature and referencing, whereas some carers advocated for greater inclusion of carer experiences and quotes. The preferences of carers in our study are consistent with previous studies, which have similarly found that carers often prefer web-based education to have an empathetic and supportive tone, the web program to be easy to navigate, and the integration of other carers’ experiences into the content [58-60]. While several differences were identified between the clinician and carer user groups, there were also several similarities across all user groups in how the web-based modules should be structured and delivered. This is reflected in the evidence base, where health professionals, patients, and carers alike report that they prefer flexible, self-paced delivery of web-based programs that are interactive and include a variety of activities across media (visual, written, and auditory) [19,38]. These detailed insights are valuable in designing future training modules to facilitate their acceptability among users in each specific group.

The final interface used design principles to ensure engaging and interactive content. There is robust empirical evidence suggesting that interactivity in e-learning improves quality, efficacy, and learning outcomes [38,61]. For example, users of a web-based public health program had better learning outcomes when they used a gamified, interactive version featuring responsive design, learning challenges, visible progress, and rapid feedback compared to those using a minimally interactive, survey-based program [62]. Such interactivity was also demonstrated as important for users of the eTRIO modules. For example, in the initial design phases, when content was largely text based, the advisory committee members noted how dense the information appeared. While this was never intended to be the final format of the educational intervention, comments obtained from users in phase 1 highlighted the limitations of passive, didactic, text-heavy information. There is evidence suggesting that people do not learn effectively when information is given without any opportunity to reflect on, test, or demonstrate their knowledge and views [63]. Interactive activities, including assessments of learning and personal reflection activities, offer users the opportunity to reflect and reinforce their learning and become active participants in their education rather than passive consumers of information. Multimedia Appendices 1 and 2 display the engaging interactive activities that were acceptable to eTRIO users, which may be used in other web-based learning interventions and resources.

For both the clinician and patient-carer modules, we also incorporated a variety of media (text, audio, video, graphics, and images to cater to different learning styles and preferences. There is evidence suggesting that the use of multimedia may increase user satisfaction, acceptability, and engagement [64,65] and thus may improve adherence and broad implementation. The modules were designed such that users could navigate through them at their own pace and read, view, and explore the sections in a self-directed manner based on how they like to engage with and process content. For example, we found that users had mixed responses to the videos embedded in the training module. Some users commented that the videos were
very long and that they would mentally switch off or skip them. Others claimed to be “visual learners” and thoroughly enjoyed the opportunity to observe scenarios in this format, especially because the videos included interactive “trigger” questions such as “What would you do next?” where they were required to apply some of their learning to a scenario. This approach has been used in other web-based health interventions [66,67], which include complementary text, images, videos, audios, and interactive content to convey the educational content and cater to these diverse user preferences.

**Strengths and Limitations**

A thoughtful process of iterative design was conducted over a 2-year period, ultimately producing a suite of web-based interventions intended to improve communication between cancer clinicians, patients, and carers. However, important limitations should be noted. While extensive end-user feedback was collected through iterative feedback from clinician and consumer advisory groups, the sample size of participants (patients with cancer and carers) naive to the modules in phase 3 was small, and there was limited diversity among consumer advisers and participants. In addition, we did not measure the computer literacy of the participants, which may have impacted their views about the program’s usability. Thus, the attitudes and preferences of participants may not be reflective of the wider population. For example, we were unable to recruit a carer with low health literacy, and there was an overrepresentation of women. Further usability and acceptability testing is currently underway in a larger study with a more diverse sample of patients and carers. Recruitment of participants in phase 3 was conducted through professional networks and social media, and therefore, the participants may have had a strong interest web-based learning or carer communication, which could have biased their views. This study focused only on development and user testing, and therefore, no assessment of the effectiveness or uptake of the modules has been conducted. Larger evaluation studies of the modules are currently being conducted, which will provide insight into the utility of the eTRIO modules in improving carer-related communication and inclusion.

Finally, while most patients with cancer have a carer or support person, some patients do not. Further studies are required to better understand the needs of people without a carer, which is beyond the scope of this study.

**Future Directions**

The eTRIO and eTRIO-pc modules are now undergoing pre-post evaluation with additional qualitative learner feedback to inform the broad implementation and uptake of these educational resources.

**Conclusions**

By including and being receptive to the needs of our user groups throughout the design process, we were able to create interventions that end users are likely to be more engaged and satisfied with.

**Acknowledgments**

This study was supported by Cancer Australia and Cancer Council New South Wales Grant, through the Priority-Driven Collaborative Cancer Research Scheme (project 1146383).

**Conflicts of Interest**

None declared.

Multimedia Appendix 1
e-Triadic Oncology patient and carer module features.
[DOCX File, 1304 KB - mededu_v1011e50118_app1.docx ]

Multimedia Appendix 2
e-Triadic Oncology clinician module features.
[DOCX File, 1069 KB - mededu_v1011e50118_app2.docx ]

**References**


Abbreviations

CHESS: Comprehensive Health Enhancement Support System

eTRIO: e-Triadic Oncology
eTRIO-pc: e-Triadic Oncology for patients and carers

STREAM: Stress-Aktiv-Mindern

SUS: System Usability Scale

TRIO: Triadic Oncology

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Effectiveness of Blended Versus Traditional Refresher Training for Cardiopulmonary Resuscitation: Prospective Observational Study

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Abstract

Background: Generally, cardiopulmonary resuscitation (CPR) skills decline substantially over time. By combining web-based self-regulated learning with hands-on practice, blended training can be a time- and resource-efficient approach enabling individuals to acquire or refresh CPR skills at their convenience. However, few studies have evaluated the effectiveness of blended CPR refresher training compared with that of the traditional method.

Objective: This study investigated and compared the effectiveness of traditional and blended CPR training through 6-month and 12-month refresher sessions with CPR ability indicators.

Methods: This study recruited participants aged \(\geq 18\) years from the Automated External Defibrillator Donation Project. The participants were divided into 4 groups based on the format of the CPR training and refresher training received: (1) initial traditional training (a 30-minute instructor-led, hands-on session) and 6-month traditional refresher training (Traditional6 group), (2) initial traditional training and 6-month blended refresher training (an 18-minute e-learning module; Mixed6 group), (3) initial traditional training and 12-month blended refresher training (Mixed12 group), and (4) initial blended training and 6-month blended refresher training (Blended6 group). CPR knowledge and performance were evaluated immediately after initial training. For each group, following initial training but before refresher training, a learning effectiveness assessment was conducted at 12 and 24 months. CPR knowledge was assessed using a written test with 15 multiple-choice questions, and CPR performance was assessed through an examiner-rated skill test and objectively through manikin feedback. A generalized estimating equation model was used to analyze changes in CPR ability indicators.

Results: This study recruited 1163 participants (mean age 41.82, SD 11.6 years; n=725, 62.3% female), with 332 (28.5%), 270 (23.2%), 258 (22.2%), and 303 (26.1%) participants in the Mixed6, Traditional6, Mixed12, and Blended6 groups, respectively. No significant between-group difference was observed in knowledge acquisition after initial training (P=.23). All groups met the...
Sudden cardiac arrest is a severe condition, particularly when it occurs outside a medical facility, and the corresponding survival rates are very low. In Europe and North America, these survival rates range from 7% to 13%, whereas in Asia, they are even lower at 0.5% to 8.5% [1-3]. Furthermore, these survival rates vary significantly by location and demography. Some countries exhibit higher survival rates, ranging from 20% to 40%. In contrast, according to a database, the survival rate in Taiwan is 8% to 10% [3-6]. Therefore, survival after out-of-hospital cardiac arrest (OHCA) exhibits substantial variability across regions [7].

The survival status for OHCA is closely linked to the Chain of Survival of the American Heart Association (AHA), which emphasizes the early activation of emergency medical services (EMSs), early cardiopulmonary resuscitation (CPR), and early defibrillation as the first 3 critical links [8]. These 3 interventions can be administered in a prehospital setting, and achieving high-quality outcomes following these interventions is pivotal to enhancing OHCA survival rates. Owing to significant disparities in EMSs, bystander CPR rates, and public access to automated external defibrillators (AEDs) in different regions, OHCA survival rates exhibit corresponding variations [7]. However, through CPR training and dispatcher-assisted CPR, the global bystander CPR rate has improved from 20% in 2001 to 40% to 55% in 2023 [9-11]. In Taiwan, the government has implemented legally mandated continuous public CPR education and training programs aimed at improving the response of bystanders to sudden cardiac arrest [12]. This effort has resulted in significant increases in bystander CPR rates and the use of public AEDs [7,13]. Over a decade, 14% and 3.8% increases have been noted in the bystander CPR rate and the use rate of public AEDs, respectively [6,9,14].

Research has demonstrated a significant decline in CPR skills over time, especially regarding chest compression depth and rate [15]. Consequently, maintaining the public’s CPR skills and their motivation for learning CPR is challenging. In response to this challenge, the AHA recommended self-directed training for CPR during the COVID-19 pandemic [16]. Similarly, the European Resuscitation Council recognized blended training models as an alternative to traditional face-to-face teaching models [17,18]. Furthermore, previous studies have indicated that blended training is not inferior to traditional methods and offers advantages such as resource saving and time saving, making it an effective approach for CPR education [15]. By using blended training models, which combine web-based self-guided learning with hands-on practice, individuals can acquire or refresh their CPR skills at their own pace and convenience [15]. Such flexibility fosters increased levels of engagement and enhanced retention of CPR knowledge and thus ultimately enhances the public’s preparedness for treating sudden cardiac arrests. Therefore, blended approaches are valuable both during a pandemic and when in-person training cannot be conducted, ensuring widespread CPR education for a broad audience [19].

Limited research has been conducted regarding the effective implementation of relearning stimuli to maintain CPR skills within the framework of blended training. Therefore, the primary objective of this study was to provide relearning stimuli in a blended training setting after using both traditional and blended teaching methods; this study also investigated the effectiveness and most appropriate frequency of blended training. Finally, this study compared learners’ performance in 2 educational settings. We hypothesized that using the blended method with 6-month interventions would yield outcomes comparable to those achieved through the traditional method.

**Methods**

**Study Design, Setting, and Participants**

This study used a prospective observational design, and participants were recruited from the AED Donation Project, also called the Love GOGO program, implemented by Chang Gung Memorial Hospital, Taiwan. The Love GOGO program aims to establish an educational training system for CPR and build a comprehensive teaching database encompassing participants’ attributes, learning models, and CPR parameters. Individuals from government agencies, nonprofit organizations,
schools, and organizations required by current Taiwanese regulations to have AED facilities participate in this education and training program. These include transportation hubs, large long-distance vehicles, tourist spots, schools or large assembly places, large leisure places, large shopping malls, hotels, large public bathhouses, hot springs, and public service sectors such as police stations. These organizations voluntarily participated in the Love GOGO program and proactively contacted the research assistant (YTK) of this study. For this study, participants were enrolled in the Love GOGO program from January to December 2017. Based on our previous study, both traditional and blended teaching models showed a noticeable decline in skill retention after approximately 6 months [12,15]. In this study, mandatory retraining was administered every 6 months or 1 year (Figure 1), spanning a comprehensive training regimen conducted over 2 years. In the initial training phase, the participants were assigned to either traditional teaching or blended teaching modes. Learning effectiveness assessments were conducted every 12 months, with a retraining frequency of 6 or 12 months. Before refresher courses but following initial training, each group underwent evaluation at 12 and 24 months. The results of the 12-month learning effectiveness assessment were disclosed only at 24 months. The research assistants independently allocated training methodologies and the frequencies of subsequent follow-up assessments, using unit convenience and considering the practicalities of the study context. Those responsible for the execution of course training and assessments were not involved in the allocation process.

**Figure 1.** Schematic diagram illustrating the arrangement of four training courses: Mixed6, Traditional6, Mixed12 and Blended6.

The inclusion criteria are described as follows: (1) aged at least 18 years and (2) not having undergone any CPR training within the preceding 2 years. Individuals who had physical limitations preventing them from kneeling to perform CPR, who were pregnant, or who were unwilling to sign the informed consent form were excluded from this study. Before initial training, the research assistant divided the participants into groups, and their basic characteristics—namely age, sex, educational level, exercise habits, whether they were receiving CPR training for the first time, their most recent CPR training, and their basic life support (BLS) knowledge scores—were collected through a web-based survey. The assessment of CPR learning should encompass the status of both knowledge and skills. After initial training but before refresher training, we collected data regarding BLS knowledge, skill tests, and CPR quality at the scene at 12 and 24 months. The BLS knowledge and skill tests received approval from the Chairman of the Taiwan Society of Emergency Medicine and have also been published in previous studies [12,15] (Multimedia Appendices 1 and 2).

**Ethical Considerations**

This study was approved by the institutional review board of the Chang Gung Memorial Foundation (approvals: 201600149B0, 201900399B0, 202200559B0, CMRPG1M0081, and CMRPG1N0081), and this study was performed in accordance with relevant guidelines and regulatory requirements. The IGOGO database is anonymized or deidentified, and no type of compensation is provided to participants. Written informed consent was obtained from all the participants (Figure 2).
Sample Size

An appropriate sample size for this study was estimated based on a pilot study, in which the expected percentage of correct compression depth was 65.4 (SD 29.5) cm for traditional training. To achieve a statistical power of 90% by using a 2-tailed $t$ test with a significance level of $P<.05$, each group was required to have 225 participants. We planned to enroll at least 900 participants in total.

Interventions

The Love GOGO program offers 2 teaching models for CPR training: the traditional instructor-led, classroom-based model and the blended model. In the traditional model, participants undergo a 90-minute session, which includes a 60-minute CPR knowledge education session involving a CPR lecture and demonstration, an AED use demonstration, an introduction to relevant laws, and a 30-minute hands-on practice session focusing on compression-only CPR. The blended program, which was approved by the Chairman of the Taiwan Society of Emergency Medicine in 2016, combines an 18-minute e-learning module with a 30-minute hands-on session for compression-only CPR. The e-learning module comprises a video that covers essential knowledge related to CPR and AEDs, including knowledge related to cardiac arrest scenes, the technique of compression-only CPR, the benefits of using CPR and AEDs for OHCA treatment, CPR and AED use steps, and an introduction to relevant laws. In this study, the participants assigned to the blended program were granted access to the e-learning video 3 days before the hands-on session. After completing the e-learning module, the participants practiced their skills in a 30-minute instructor-led, hands-on session in a classroom setting. Both CPR training programs were conducted by AHA instructors who were also emergency physicians. For hands-on CPR practice, both groups used sensor-equipped manikins (Resusci Anne with QCPR, Laerdal Medical AS). The participant-to-manikin-to-instructor ratio per class was 6:3:1, involving 4 instructors and 6 examiners. The study team provided different certification learning stimuli (traditional and blended learning) at 2 frequencies: every 6 months (at 6, 12, 18, and 24 months) and every 12 months (at 12 and 24 months). To establish groups with unique frequencies, the research assistant (YTK) conducted allocation during the initial training phase. Therefore, the traditional teaching model was applied for initial training, and certification sessions for retraining occurring every 6 or 12 months were conducted using either the blended retraining model (18-minute e-learning module with self–hands-on practice for compression-only CPR) or the on-site retraining model (30-minute instructor-led, hands-on
session). These groups were called Mixed6 (initial traditional training and 6-month blended refresher training), Traditional6 (initial traditional training and 6-month traditional refresher training), and Mixed12 (initial traditional training and 12-month blended refresher training). For the Blended6 group, initial training was conducted using the blended teaching model, and for certification stimuli every 6 months, the blended retraining model was applied (Figure 1).

**Outcome Measures**

This study systematically assessed the participants’ CPR knowledge and performance at multiple time points. Initially, the CPR knowledge and performance of the participants were assessed immediately after training. Following initial training but before refresher training, subsequent evaluations of knowledge and performance were conducted at 12 and 24 months. CPR knowledge was examined through a written test comprising 15 multiple choice questions, with a maximum total score of 100. CPR performance was assessed through 2 methods: examiner-rated assessment and manikin feedback. Individual examiners meticulously assessed the participants’ ability to execute the BLS sequence, encompassing tasks from verifying scene safety to using an AED, with a maximum total score of 40. Objective assessment data regarding CPR quality—including compression depth, compression rate, and full chest recoil—were collected from manikin feedback. The assessment adhered to the 2015 AHA guidelines update for CPR and emergency cardiovascular care; high-quality CPR was characterized by the following three criteria: (1) achieving a compression depth of 5-6 cm, (2) maintaining a compression rate of 100-120 beats per minute (bpm), and (3) facilitating complete chest wall recoil of >80%. Notably, because of the focus on compression-only CPR, ventilation was excluded because it was therefore beyond the scope of the assessment in this study. The primary outcome measure was the comparison of high-quality CPR among the 4 groups. Secondary outcome measures were differences in the percentage of full chest recoil, the percentage of compressions delivered with adequate depth (5-6 cm), the percentage of compressions delivered at an adequate rate (100-120 bpm), written test scores, and examiner-rated skill test scores.

**Statistical Methods**

Descriptive statistics are expressed as mean (SD) for continuous variables and as counts and percentages for categorical variables. Linear regression analysis was conducted to determine any differences in the mean values of baseline characteristics among the groups, with adjustment for control variables—namely age, sex, educational level, exercise habits, whether CPR training was being received for the first time, most recent CPR training, and pretest BLS knowledge scores, which were based on the significance test result and which were proposed in previous research [12,15,20]. After allocation, differences in characteristics among groups were observed. To mitigate potential biases introduced by this allocation method, we applied multiple linear regression analyses and generalized estimating equation (GEE) to adjust for these variations when evaluating outcomes (Multimedia Appendices 3 and 4). The chi-square test was used to assess the differences in proportions among the groups, and the general linear model, such as analysis of covariance, was used to test differences among the groups. The control variables—namely age, sex, educational level, exercise habits, whether CPR training was being received for the first time, and pretest BLS knowledge scores—may have influenced skill retention and test scores. Therefore, the model was adjusted for these variables.

We conducted the assessments of the participant’s skill levels and BLS knowledge scores at multiple time points. Accordingly, we used a GEE to examine changes over time in CPR ability indicators among the groups. This allows us to comprehend the changes in CPR skills among trainees under different training methods, using a GEE model to analyze the change over time in CPR ability indicators among groups. The GEE analysis was adjusted for the control variables. To ensure fairness, statistical analysis was conducted using data obtained at time points specific to each group. That is, only data from the postinitial training (baseline), 12-month, and 24-month assessments were included in the analysis.

CPR performance is displayed by line charts, bar charts, and radar charts. In particular, we generated radar charts to illustrate the relative CPR performance in each session. The scores were converted using percent ranking, and the average score was then calculated to represent the performance of each skill for each training method. Statistical analysis was conducted using SPSS Statistics (version 26.0; IBM Corp) and STATA (MP 16.0; Stata Corp LLC).

**Results**

**Baseline Characteristics**

A total of 1163 participants were recruited for this study, and they were allocated to 4 training groups. The mean age of the participants was 41.82 (SD 11.6) years, and 62.3% (n=725) of participants were female. In this study, 332 (28.5%), 270 (23.2%), 258 (22.2%), and 303 (26.1%) participants were placed in the Mixed6, Traditional6, Mixed12, and Blended6 groups, respectively. Table 1 displays the baseline characteristics of these 4 training groups. As this study was observational rather than randomized, significant differences were observed among the 4 training groups in terms of age (P<.001), sex (P=.008), educational level (P=.006), and CPR training experience (P<.001; Table 1). Notably, the Traditional6 group had the highest average age (45.30, SD 11.39 years) and consisted of 68.9% (186/270) female participants. Additionally, this group had the highest proportion of individuals receiving CPR training for the first time (92/270, 34.1%). However, no statistically significant difference was observed in the BLS pretest knowledge score (P=.11), with an overall mean score of 67.96 (SD 15.08); this finding indicated similar baseline performance across the groups before BLS training.
Table 1. Baseline characteristics of the 4 training groups.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mixed6 (n=332)</th>
<th>Traditional6 (n=270)</th>
<th>Mixed12 (n=258)</th>
<th>Blended6 (n=303)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years), mean (SD)</td>
<td>40.78 (9.97)</td>
<td>45.30 (11.39)</td>
<td>40.72 (12.34)</td>
<td>40.78 (12.28)</td>
<td>&lt;.001a</td>
</tr>
<tr>
<td>Sex, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.008</td>
</tr>
<tr>
<td>Male</td>
<td>117 (35.2)</td>
<td>84 (31.1)</td>
<td>104 (40.3)</td>
<td>133 (43.9)</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>215 (64.8)</td>
<td>186 (68.9)</td>
<td>154 (59.7)</td>
<td>170 (56.1)</td>
<td></td>
</tr>
<tr>
<td>Education, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.006</td>
</tr>
<tr>
<td>Below high school</td>
<td>2 (0.6)</td>
<td>26 (9.6)</td>
<td>6 (2.3)</td>
<td>23 (7.6)</td>
<td></td>
</tr>
<tr>
<td>High school, college education, and above</td>
<td>330 (99.4)</td>
<td>244 (90.4)</td>
<td>252 (97.7)</td>
<td>280 (92.4)</td>
<td></td>
</tr>
<tr>
<td>Exercise habits, n (%)</td>
<td>142 (42.8)</td>
<td>116 (45.5)</td>
<td>123 (48.6)</td>
<td>120 (41.5)</td>
<td>.35</td>
</tr>
<tr>
<td>First time for CPRb training, n (%)</td>
<td>33 (9.9)</td>
<td>92 (34.1)</td>
<td>34 (13.2)</td>
<td>92 (30.4)</td>
<td>&lt;.006a</td>
</tr>
<tr>
<td>Last CPR training, n (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Within 2-3 years</td>
<td>122 (36.7)</td>
<td>62 (23)</td>
<td>138 (53.5)</td>
<td>73 (24.1)</td>
<td></td>
</tr>
<tr>
<td>Over 3 years</td>
<td>181 (54.5)</td>
<td>196 (72.6)</td>
<td>109 (42.3)</td>
<td>205 (67.7)</td>
<td></td>
</tr>
<tr>
<td>Not clear</td>
<td>29 (8.8)</td>
<td>12 (4.4)</td>
<td>14 (4.2)</td>
<td>25 (8.2)</td>
<td></td>
</tr>
<tr>
<td>BLS pretest knowledge scoreb, mean (SD)</td>
<td>67.78 (13.15)</td>
<td>67.96 (15.08)</td>
<td>70.57 (15.97)</td>
<td>68.17 (16.12)</td>
<td>.11</td>
</tr>
</tbody>
</table>

aItalic formatting indicates that there is a statistically significant difference in the P value.

bCPR: cardiopulmonary resuscitation.

cBLS: basic life support.

Posttraining Assessment

According to the results of the objective assessment after the first training session, significant differences were found among the 4 groups in skill tests (P=.002), average chest compression depth (P<.001), and average compression rate (P<.001; Table 2) after adjustment for the control variables in the multivariate analysis (Multimedia Appendix 5). In the multivariate analysis, higher skill test scores were associated with younger age (P=.003), higher educational level (P<.001), more previous CPR training experience (P=.04), and higher BLS pretest scores (P=.004). Furthermore, the average compression depth was significantly associated with age (P=.02) and sex (P<.001), and the average compression rate was significantly associated with educational level (P=.04) and CPR training experience (P=.02). Although the mean chest compression depths differed among the 4 groups, the proportion of participants achieving the correct chest compression depth did not differ on average (P=.11). For the overall performance assessment, the proportion of participants achieving high-quality CPR ranged from 27.4% (91/332) to 32.3% (98/303). The lowest proportion was observed in the Mixed6 group, and the highest proportion was found in the Blended6 group. In the multivariate analysis, high-quality CPR was negatively correlated with the Mixed12 training method (adjusted odds ratio 0.65, 95% CI 0.45-0.93; P=.02; Multimedia Appendix 6).
Table 2. Postinitial training evaluation (baseline) for the 4 training groups.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mixed6 (n=332)</th>
<th>Traditional6 (n=270)</th>
<th>Mixed12 (n=258)</th>
<th>Blended6 (n=303)</th>
<th>P value&lt;sup&gt;a&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>BLS&lt;sup&gt;b&lt;/sup&gt; knowledge score, mean (SD)</td>
<td>86.05 (11.38)</td>
<td>84.61 (12.96)</td>
<td>86.76 (11.79)</td>
<td>84.10 (11.19)</td>
<td>.23</td>
</tr>
<tr>
<td>Skill test, mean (SD)</td>
<td>35.09 (3.26)</td>
<td>35.81 (2.78)</td>
<td>35.73 (3.76)</td>
<td>35.26 (4.05)</td>
<td>.002&lt;sup&gt;c&lt;/sup&gt;</td>
</tr>
<tr>
<td>Average chest compression depth (cm), mean (SD)</td>
<td>5.07 (0.74)</td>
<td>5.01 (0.73)</td>
<td>5.23 (0.43)</td>
<td>5.33 (0.57)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Average chest compression rate (times per minute), mean (SD)</td>
<td>113.88 (13.87)</td>
<td>110.56 (14.34)</td>
<td>116.07 (11.33)</td>
<td>116.65 (10.28)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Correct compression depth, mean (SD)</td>
<td>70.79 (32.83)</td>
<td>71.24 (30.55)</td>
<td>74.75 (32.21)</td>
<td>75.88 (33.31)</td>
<td>.11</td>
</tr>
<tr>
<td>Correct compression rate, mean (SD)</td>
<td>61.14 (31.87)</td>
<td>66.16 (30.57)</td>
<td>68.61 (34.15)</td>
<td>61.98 (34.94)</td>
<td>.01</td>
</tr>
<tr>
<td>Correct recoil, mean (SD)</td>
<td>84.39 (35.29)</td>
<td>87.16 (30.32)</td>
<td>79.72 (37.57)</td>
<td>80.35 (35.65)</td>
<td>.20</td>
</tr>
<tr>
<td>High-quality CPR&lt;sup&gt;d,e&lt;/sup&gt;, n (%),</td>
<td>91 (27.4)</td>
<td>86 (31.8)</td>
<td>77 (29.8)</td>
<td>98 (32.3)</td>
<td>.52</td>
</tr>
</tbody>
</table>

<sup>a</sup>The P value was obtained from the general linear regression model adjusted for age, sex, educational level, exercise habits, whether CPR training was being received for the first time, and BLS pretest knowledge score.

<sup>b</sup>BLS: basic life support.

<sup>c</sup>Italic formatting indicates that there is a statistically significant difference in the P value.

<sup>d</sup>CPR: cardiopulmonary resuscitation.

<sup>e</sup>P values obtained from the chi-square test. High-quality CPR was denoted by an average compression depth between 5 and 6 cm, an average compression rate of 100-120 beats per minute, and 80% chest recoil.

**Posttraining Follow-Up and Maintenance**

Multimedia Appendix 7 provides the descriptive statistics for the posttraining follow-up data. The results revealed that the Mixed12 group exhibited consistent BLS knowledge scores at baseline (postinitial training), with the highest average scores observed at 12 and 24 months after training. The Traditional6 group exhibited the highest average scores on the skill test at all 3 measurement time points. Figure 3 illustrates the estimated mean scores of BLS knowledge and skill tests for each group, as assessed over time using GEE models. At 12 months after initial training, the Traditional6 group had the lowest average BLS knowledge score (mean 70.10, SE 0.854), which was significantly different from that of the Mixed12 group (mean 75.14, SE 0.762; Figure 3A presents a nonoverlapping 95% CI). Subsequently, at 24 months following initial training, the Mixed12 group exhibited significantly higher scores (mean 79.32, SE 0.741) compared with the other groups.

**Figure 3.** Estimated mean scores with 95% CI for (A) BLS knowledge and (B) skill tests in different training courses by generalized estimating equation models. BLS: basic life support.
Furthermore, at baseline, a notable difference was observed in the average scores of the skill tests between the Mixed6 and Traditional6 groups ($P=0.003$; Figure 3B shows a nonoverlapping 95% CI). Moreover, in the follow-up assessment, the Traditional6 group exhibited significantly higher scores than the other groups. Table 3 presents the proportion in each group for the achievement of high-quality CPR. At 12 and 24 months after initial training, this proportion in the Mixed12 group exhibited the most substantial decrease compared with those at 12 and 24 months after training. At baseline, no substantial differences were observed in these proportions among the 4 groups. However, no substantial differences were observed among these proportions among the Blend6, Mixed6, and Traditional6 groups at 12 or 24 months after initial training. We concurrently used multiple linear regression and GEE models to examine the performance indicators; the corresponding results are provided in Multimedia Appendices 5, 6, 8, and 9.

Table 3. Proportions of the achievement of high-quality CPRa at 0, 12, and 24 months after training for the different training courses.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mixed6 (n=332), n (%)</th>
<th>Traditional6(n=270), n (%)</th>
<th>Mixed12 (n=258), n (%)</th>
<th>Blended6 (n=303), n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Posttraining (0 month)</td>
<td>91 (27.4)</td>
<td>86 (31.9)</td>
<td>79 (30.6)</td>
<td>98 (32.3)</td>
</tr>
<tr>
<td>Posttraining (12 months)</td>
<td>83 (25)</td>
<td>61 (22.6)</td>
<td>2 (0.8)</td>
<td>63 (20.8)</td>
</tr>
<tr>
<td>Posttraining (24 months)</td>
<td>79 (23.8)</td>
<td>53 (19.6)</td>
<td>7 (2.7)</td>
<td>84 (27.7)</td>
</tr>
</tbody>
</table>

aCPR: cardiopulmonary resuscitation.

We used an alternative method to rank the 4 training methods based on objectively evaluated items. The scores were converted using percent ranking, and the average score was then calculated to represent the performance of each skill in each training method. Subsequently, we visualized the results as a radar chart (Figure 4). Overall, the 4 groups exhibited comparable average performance in the tests after the first training session. However, in the follow-up assessment (ie, 12 and 24 months after training), differences emerged among the groups (Multimedia Appendix 10). The Traditional6 group exhibited outstanding performance in the skill test and correct recoil rate. The Blended6 group demonstrated superiority in correct depth rate, whereas no significant difference was observed between the Blended6 and Traditional6 groups in terms of correct compression rate or high-quality CPR achievement. The Mixed12 group exhibited a lower correct recoil rate, compression rate, depth rate, and skill test performance compared with the other 3 groups.

**Figure 4.** Radar charts for posttraining evaluation at baseline and final visit (posttraining 24 months). BLS: basic life support.

**Discussion**

**Principal Findings**

This study provides 3 major findings regarding the effectiveness of traditional and blended training methods for CPR education. First, no significant difference was observed in knowledge acquisition after initial training, and all the training groups exhibited proficient CPR skills that met the requirements for high-quality CPR. However, a higher proportion of participants receiving blended training initially achieved high-quality CPR; this finding served as the basis for our comparative analysis. The second major finding highlights the importance of timely
retraining. When retraining was conducted 12 months after initial training, significant decreases were observed in the proficiency of CPR skills and the proportion of participants achieving high-quality CPR. Our third major finding suggests that more frequent retraining could maintain CPR skills more effectively. The participants who underwent retraining every 6 months exhibited slight decreases in their proficiency in CPR skills and their achievement of high-quality CPR. Additionally, we explored the potential of web-based self-directed learning as an alternative, and this learning method demonstrated effectiveness for skill retention regardless of the initial training method (traditional or blended), with no significant difference observed between the 2 methods.

Research has demonstrated that blended learning and traditional CPR methods [19,21,22] are practical and reasonably effective alternatives to traditional CPR training; however, large-scale comparisons of these methods or the integration of these instructional methods into CPR education have not been conducted. To the best of our knowledge, this study was the first study to demonstrate that blended learning and retraining stimuli are not inferior to traditional methods when it comes to CPR performance. Chien et al [15] found that blended learning for CPR training does not have inferior learning outcomes relative to traditional methods but that CPR skills at 6 months did not meet the AHA's CPR guidelines. This finding was consistent with our findings. Although traditional instruction may lead to slightly more favorable performance initially, providing self-directed blended learning stimuli every 6 months is effective for maintaining CPR skills. We found that among learners who received CPR training every 12 months, the performance of high-quality CPR decreased by 35% more than that of those retrained every 6 months. Therefore, consistent with previous research recommendations, stimulating learning every 6 months appears to be favorable to doing so every 12 months. This observation aligns with the AHA's 2020 guidelines, which suggest that for the general public, the use of convenient learning methods alongside retraining is a viable alternative to traditional face-to-face CPR training.

The blended learning method used in this study offers considerable economic benefits and is time saving for both learners and instructors. By incorporating 18 minutes of web-based learning and self-training into a course, the face-to-face instruction and retraining time were collectively shortened by approximately 72 minutes initially and by 12 minutes in subsequent training. These decreases reduced the expenditure, human resources, and time requirements for learners and instructors in CPR training courses [21]. One study investigated the cost-effectiveness of blended learning for CPR training: the results revealed that blended learning decreased training costs while achieving similar maintenance of CPR skills relative to the traditional method [23]. However, some researchers have indicated that despite the costs and time reductions offered by blended learning, such learning does not ensure that participants will acquire further professional knowledge and proficiency in a demanding training environment [22]. The maintenance of CPR skills contributes to the willingness of the public to perform CPR. When EMSs are activated, guiding individuals to identify cardiac arrest and to implement CPR with dispatcher assistance is challenging as is ensuring that members of the public are able to perform high-quality CPR [24]. Accordingly, blended teaching and retraining models, which appear to be as effective as traditional learning models, can address the challenge of instructing individuals during emergency calls. The characteristics of blended teaching models, including time saving and environmental efficiency, can be beneficial for promoting CPR education among the public and for addressing challenges in maintaining CPR skills among the public.

In this study, 95.1% (% (1106/1163) of the participants were high school graduates who were approximately 40 years old and who exhibited higher learning and web-based operating abilities. This demographic advantage likely contributed to the success of blended learning in this study. Moreover, this study used a participant-to-manikin ratio of 2:3:1, leading to higher costs compared with the traditional method (1 manikin to 6 students). The increased investment in training infrastructure may affect the overall cost-effectiveness of blended learning in various settings. The study did not record the frequency of learners' usage of blended relearning stimuli; the effectiveness of self-paced web-based learning may be related to the time spent engaging with the material. Nevertheless, the primary objective of blended web-based learning is to enable individuals to learn at their convenience. In contrast to traditional face-to-face classroom learning, in blended learning, participants have the flexibility to arrange their web-based and in-class training according to their convenience and location. Accordingly, this learner-centric approach can lead to an environment that is more conducive to the maintenance of CPR skills.

In this study, favorable exercise habits and previous CPR learning experiences enhanced the effectiveness of CPR training. Even if learning had occurred more than 2 years previously, blended CPR training could effectively maintain CPR skills. Ettl et al [20] found that incorporating CPR learning into fitness exercise training increased learners’ motivation and confidence in performing CPR. Therefore, establishing exercise habits helps maintain CPR skills and for fostering rescue skills.

Finally, although blended learning with a retraining frequency of 6 months demonstrated significant economic benefits and time-saving ability in this study, its cost-effectiveness depended on factors such as participant demographics, the training environment, and the level of engagement with web-based learning opportunities. Accordingly, consideration of these factors could maximize the potential of blended learning in various CPR training scenarios.

**Limitations**

This study had some limitations. First, in observational studies, the random allocation of samples is infeasible and could result in disparities between groups. Consequently, we used a multivariate regression model to mitigate the impact of variables; thus, we impartially assessed the differences between the groups. Moreover, this study involved tracking the training status of each group to understand the importance of the interval between retraining sessions and whether the given training method was appropriate. Second, we collected demographic data from a subset of learners, but our comprehension of these
learners’ economic backgrounds and technology use was limited; consequently, whether blended learning is effective among individuals with relatively low socioeconomic status should be further explored. Third, our research cohort lacked the representation of older adults. As a result, uncertainties persist regarding the applicability of blended training for this demographic; accordingly, future studies are recommended to address this crucial gap. Finally, the absence of an analysis of the participants’ willingness to perform CPR leaves a significant gap in our understanding. Accordingly, individuals’ willingness to administer CPR after blended retraining should be investigated in future research.

### Conclusions

Blended learning for CPR with a retraining frequency of 6 months provides higher retention of high-quality CPR skills than does retraining every 12 months. Notably, the blended method demonstrated effects similar to those of traditional relearning methods.

### Acknowledgments

This manuscript was edited by Wallace Academic Editing. We are also thankful for the support of Chang Gung Memorial Hospital, Taiwan (CMRPG1M0081 and CMRPG1N0081).

### Data Availability

The data sets generated or analyzed during this study are available from the corresponding author upon reasonable request.

### Conflicts of Interest

None declared.

### Multimedia Appendix 1

The written test of cardiopulmonary resuscitation knowledge.
[PDF File (Adobe PDF File), 291 KB - mededu_v10i1e52230_app1.pdf ]

### Multimedia Appendix 2

The skill test of cardiopulmonary resuscitation practice checklist.
[PDF File (Adobe PDF File), 169 KB - mededu_v10i1e52230_app2.pdf ]

### Multimedia Appendix 3

Generalized estimating equation models for the performance indicators.
[DOCX File , 26 KB - mededu_v10i1e52230_app3.docx ]

### Multimedia Appendix 4

Generalized estimating equation models for the performance indicators.
[DOCX File , 27 KB - mededu_v10i1e52230_app4.docx ]

### Multimedia Appendix 5

Multiple linear regression model for the performance indicators at baseline: basic life support knowledge, skill test, average compression depth, and rate.
[DOCX File , 27 KB - mededu_v10i1e52230_app5.docx ]

### Multimedia Appendix 6

Multiple analysis for the performance indicators at baseline: the proportion of correct compression depth, speed rate, and recoil.
[DOCX File , 27 KB - mededu_v10i1e52230_app6.docx ]

### Multimedia Appendix 7

Summary statistics for outcome assessment at baseline, post-12M, post- 24M in different training courses.
[DOCX File , 26 KB - mededu_v10i1e52230_app7.docx ]

### Multimedia Appendix 8

Estimated mean with 95% CI for compression depth and rate in different training courses by generalized estimating equation models.
[PDF File (Adobe PDF File), 25 KB - mededu_v10i1e52230_app8.pdf ]
References


12. Chien et al. JMIR MEDICAL EDUCATION Chien et al


Abbreviations

- **AED**: automated external defibrillator
- **AHA**: American Heart Association
- **BLS**: basic life support
- **bpm**: beats per minute
- **CPR**: cardiopulmonary resuscitation
- **EMS**: emergency medical service
- **GEE**: generalized estimating equation
- **OHCA**: out-of-hospital cardiac arrest
A Student's Viewpoint on ChatGPT Use and Automation Bias in Medical Education

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Related Article:
Comment in: http://mededu.jmir.org/2024/1/e50174/

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KEYWORDS
AI; artificial intelligence; ChatGPT; medical education

The editorial ChatGPT in Medical Education: A Precursor for Automation Bias? by Nguyen [1] is very timely, appropriate, and informative. Being a medical student myself, I find that it gives a balanced view on the use of ChatGPT, which is sweeping across the globe at a spectacular pace. One of the hallmarks of this tool is that it is almost universally accessible, even in parts of the world where there may be limited access to quality medical education. As authors have rightly pointed out, ChatGPT is useful for summarizing information, generating practice questions, and giving instantaneous feedback [2-4], and it could serve as an effective personalized tutor. It provides high-quality scientific text gleaned from a quick and comprehensive review of the literature and presents text in an efficient, readable, and versatile style [1]. It is no wonder that it is gaining immense popularity among students, including medical students, who are “burdened with the impossible task of balancing the need to continuously learn and retain competencies and the need to provide compassionate patient care,” as aptly underscored in the editorial [1].

The downside of this powerful tool has also been well portrayed. There is a very real risk of automation bias, especially among medical students in the younger generation, who are digitally savvy but often lack experience and confidence in their clinical skills. The blind dependence on ChatGPT and other artificial intelligence (AI) tools could corrode their thinking and decision-making skills and lead to erroneous medical outcomes. The clinical setting is undoubtedly the best classroom for students to develop the skills for understanding and accommodating the needs, expectations, and values of patients and their caregivers in the real-world scenario, as well as cultivate leadership qualities and work in a team. It is vital for us students to retain our originality, identity, and critical analytical skills to avoid falling into the trap of AI solutionism.

The need for AI education at this crucial juncture has been well brought out. At present, only a minority of students have received AI education [5]. Incorporating it into the medical curriculum is a challenging, multidisciplinary endeavor. Knowing how and when to use this powerful tool in a responsible manner, without clouding clinical judgment and in keeping with the tenets of medical ethics, is paramount. I agree with Nguyen’s [1] view that ChatGPT should be used as a supplementary tool rather than as the default resource for medical education. There is a need to exercise vigilance in the utilization of this tool right from the formative years of medical professionals.

AI is here to stay, and ChatGPT will undoubtedly have an all-pervading influence on medical education and the practice of medicine itself. Therefore, its optimal utilization is the need of the hour. Imparting AI education would help unleash the power of ChatGPT, but appropriate pre-emptive measures to keep its disruptive potential in check are needed to pave the way for an AI-savvy generation of medical professionals with sound clinical judgment and skills.

Editorial Notice
The corresponding author of “ChatGPT in Medical Education: A Precursor for Automation Bias?” declined to respond to this letter.

Conflicts of Interest
None declared.

References
https://mededu.jmir.org/2024/1/e57696


Abbreviations

AI: artificial intelligence

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Authors’ Reply: A Use Case for Generative AI in Medical Education

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Related Articles:
https://mededu.jmir.org/2023/1/e48780/
https://mededu.jmir.org/2024/1/e56117/

JMIR Med Educ 2024;10:e58370 doi:10.2196/58370

KEYWORDS
ChatGPT; undergraduate medical education; large language models

We thank the authors for their thoughtful comments on our paper titled, “Anki Tagger: A Generative AI Tool for Aligning Third-Party Resources to Preclinical Curriculum” [1,2]. The authors’ discussion of the ethical issues and limitations of generative artificial intelligence is both timely and important. As the capabilities of ChatGPT and other similar tools evolve, so must our conversations about the use of generative artificial intelligence in medicine and medical education.

With respect to the production of educational materials for medical trainees, ChatGPT’s ability to “hallucinate” and thereby provide misinformation should be of particular concern to educators. For example, when asked to summarize the research output of 50 scientists and cite relevant literature related to Chagas disease, ChatGPT made a major error in 86.7% of its outputs [3]. The problem of hallucination is more pronounced with smaller training data sets and may therefore disproportionately affect medical education content related to rare diseases, which are emphasized in licensing examinations. The problem of hallucination remains a substantial barrier to the widespread use of generative artificial intelligence in medical education.

We circumvented the issue of hallucination by embedding existing Anki flashcard decks in a large language model, rather than prompting ChatGPT to generate flashcards de novo from scientific literature [1]. Anki flashcard decks are among the third-party resources used by medical students to bridge perceived gaps in school curricula, especially regarding preparation for the USMLE (United States Medical Licensing Examination). Medical students report feeling overwhelmed with the number of third-party resources at their disposal and experience tension between these resources and their in-house curricula [4]. Their educators experience tension among different domains of responsibility including clinical practice, research, professional development, and education [5]. Therefore, it is beneficial to both teachers and students for medical education to be as efficient as possible. To this end, ChatGPT can organize and stratify third-party learning resources by relevance to lectures and other curricular elements [1].

While the integration of third-party resources into lesson plans for undergraduate medical education may be controversial, it is important to note that medical students are already using third-party resources instead of lectures by clinical educators [4]. Instead of viewing these learning materials as competition, our application of ChatGPT suggests the possibility of integrating third-party resources into existing medical curricula. Future studies should examine the impact of such an intervention on medical students’ academic performance and satisfaction as well as medical educator burnout.

Conflicts of Interest
None declared.

References


Abbreviations

USMLE: United States Medical Licensing Examination
Digital Skills to Improve Levels of Care and Renew Health Care Professions

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Related Article:
Companion article: https://mededu.jmir.org/2024/1/e51112

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KEYWORDS
digital competence; telehealth; nursing; health care workforce; health care professionals; informatics; education; curriculum; interdisciplinary education; health care education

We read with great interest the article by Rettinger et al [1], “Telehealth education in allied health care and nursing: web-based cross-sectional survey of students’ perceived knowledge, skills, attitudes, and experience,” recently published in JMIR Medical Education.

The authors, addressing an extremely current topic, highlight the need to integrate telehealth into health care education curricula. More generally, we think that the development of digital competence is essential for all health care professionals. The digitalization of care processes requires ever-greater digital skills to ensure high-level care suited to current knowledge. Another recent investigation [2] summarizes the educational intervention methods that have been implemented to develop digital competence and the effects of these educational interventions on health care workforce; this study suggests the best method for enhancing the digital skills of nurses and allied professionals in the context of continuing professional education. This research turned attention to the active workforce, who need to adapt their knowledge to renewed working contexts where digital technology is forcefully entering. However, we must note, as emphasized by Rettinger et al [1], that our curricula often neglect the need to equip health care degree students with adequate digital skills. We observe that few of our students are keeping up with the development of technology. Digital skills can range from the simplest to the most sophisticated technological applications commonly used in a hospital environment, including the use of virtual simulators and extending to artificial intelligence, which, especially in the coming years, will become a precious tool for improving care processes [3]. Even for delivering high-quality care in digitally enabled health care environments, nursing informatics competency is a required core competency [4]. In light of this, it would be necessary to introduce programs dedicated to the acquisition of these skills into our study courses; these programs could be spread across all curricular disciplines. To achieve these objectives, it is necessary to ensure that teachers have the necessary skills in this field or have the ability to acquire them to pass them on to their students. We are well aware that the nursing profession is going through a period of crisis and that it is essential to implement all available forces and strategies to renew it, making it attractive and satisfying again [5]. There are numerous proposals for this renewal, and they must also address the active workforce; however, the updating of the study contents for degree courses in health professions must be one of the first and fundamental steps to achieve these results. The acquisition of adequate digital skills is a necessity that can no longer be postponed to train professionals capable of providing the best levels of care possible today.

Editorial Notice
The corresponding author of “Telehealth Education in Allied Health Care and Nursing: Web-Based Cross-Sectional Survey of Students’ Perceived Knowledge, Skills, Attitudes, and Experience” declined to respond to this letter.
Conflicts of Interest
None declared.

References
A Use Case for Generative AI in Medical Education

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KEYWORDS
medical education; med ed; generative artificial intelligence; artificial intelligence; GAI; AI; Anki; flashcard; undergraduate medical education; UME

A recent study explored the novel application of generative artificial intelligence’s (GAI’s) capabilities with regard to Anki using a new methodology (“Anki Tagger”), leveraging OpenAI’s ChatGPT-3.5 to tag and stratify flashcards from the AnKing deck, which are most aligned with a medical school’s curriculum and involve a minimal cost and time expenditure [1]. To the best of our knowledge, their work represents the first publication demonstrating early proof of concept of GAI applied to Anki, a spaced repetition flashcard application designed to promote long-term retention of learned content. A major benefit of their approach is the ability to streamline and automate the otherwise time-consuming and resource-intensive process of manually comparing medical school curricula against the widely used and crowdsourced AnKing deck.

Medical students who use Anki may use decks prepared by more senior students at their medical school, the AnKing deck (a reputable and comprehensive set of >35,000 flashcards and growing daily, collaboratively maintained largely by current and graduated medical students), or a combination thereof. Research indicates that daily Anki use is associated with increased USMLE (United States Medical Licensing Examination) Step 1 scores and higher sleep quality—indicators of academic performance and personal well-being, respectively [2]. Given the prevalent usage and growing adoption of Anki among medical students, applications of GAI and large language models (LLMs) to Anki workflows may be beneficial. Even considering their present shortcomings, LLMs may provide a unique opportunity to significantly impact medical education in the intermediate term, especially given the propensity of contemporary medical students to supplement didactic learning with web-based learning resources [3].

Furthermore, LLMs with GAI capabilities, such as ChatGPT and Med-PaLM, have the potential to answer medically related questions [4] and—intriguingly for the medical education community—can pass the USMLE [5]. Such a notable feat by LLMs necessitates reevaluation of the future of medical training and practice while carefully considering the relevant ethical issues and current limitations of GAI, such as their susceptibility for generating misinformation through a process known as “hallucination.” As GAI and LLMs become increasingly integrated in daily practice, similar and iteratively improved methodologies represent a way for educators and learners alike to benefit considerably by better aligning flashcards from the comprehensive AnKing deck with in-house curricula in preparation for medical licensing examinations such as USMLE Step 1. Future applications of GAI in undergraduate medical education may involve the implementation of AI-assisted features directly built into preferred educational tools and resources, allowing students increased customization with options for multimodal output beyond solely text.

Conflicts of Interest
None declared.

References


Abbreviations

GAI: generative artificial intelligence
LLM: large language model
USMLE: United States Medical Licensing Examination
Measuring e-Professional Behavior of Doctors of Medicine and Dental Medicine on Social Networking Sites: Indexes Construction With Formative Indicators

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Abstract

Background: Previous studies have predominantly measured e-professionalism through perceptions or attitudes, yet there exists no validated measure specifically targeting the actual behaviors of health care professionals (HCPs) in this realm. This study addresses this gap by constructing a normative framework, drawing from 3 primary sources to define e-professional behavior across 6 domains. Four domains pertain to the dangers of social networking sites (SNSs), encompassing confidentiality, privacy, patient interaction, and equitable resource allocation. Meanwhile, 2 domains focus on the opportunities of SNSs, namely, the proactive dissemination of public health information and maintaining scientific integrity.

Objective: This study aims to develop and validate 2 new measures assessing the e-professional behavior of doctors of medicine (MDs) and doctors of dental medicine (DMDs), focusing on both the dangers and opportunities associated with SNSs.

Methods: The study used a purposive sample of MDs and DMDs in Croatia who were users of at least one SNS. Data collection took place in 2021 through an online survey. Validation of both indexes used a formative approach, which involved a 5-step methodology: content specification, indicators definition with instructions for item coding and index construction, indicators collinearity check using the variance inflation factor (VIF), external validity test using multiple indicators multiple causes (MIMIC) model, and external validity test by checking the relationships of the indexes with the scale of attitude toward SNSs using Pearson correlation coefficients.

Results: A total of 753 responses were included in the analysis. The first e-professionalism index, assessing the dangers associated with SNSs, comprises 14 items. During the indicators collinearity check, all indicators displayed acceptable VIF values below 2.5. The MIMIC model showed good fit ($\chi^2_{13}=9.4$, $P=.742$; $\chi^2/df=0.723$; root-mean-square error of approximation<.001; goodness-of-fit index=0.998; comparative fit index=1.000). The external validity of the index is supported by a statistically significant negative correlation with the scale measuring attitudes toward SNSs ($r=-0.225$, $P<.001$). Following the removal of 1 item, the second e-professionalism index, focusing on the opportunities associated with SNSs, comprises 5 items. During the indicators collinearity check, all indicators exhibited acceptable VIF values below 2.5. Additionally, the MIMIC model demonstrated a good fit ($\chi^2_{4}=2.5$, $P=.718$; $\chi^2/df=0.637$; root-mean-square error of approximation<.001; goodness-of-fit index=0.999; comparative fit index=1.000). The external validity of the index is supported by a statistically significant positive correlation with the scale of attitude toward SNSs ($r=0.338$, $P<.001$).

Conclusions: Following the validation process, the instrument designed for gauging the e-professional behavior of MDs and DMDs consists of 19 items, which contribute to the formation of 2 distinct indexes: the e-professionalism index, focusing on the dangers associated with SNSs, comprising 14 items, and the e-professionalism index, highlighting the opportunities offered by
SNSs, consisting of 5 items. These indexes serve as valid measures of the e-professional behavior of MDs and DMDs, with the potential for further refinement to encompass emerging forms of unprofessional behavior that may arise over time.

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KEYWORDS
e-professionalism; social media; formative index; social networking; doctors; medical; dental medicine

Introduction

Background
The development of social networking sites (SNSs) as a new form of media and communication channel has brought many changes to the health care system [1]. The widespread use of SNSs affects what we perceive as the professional behavior of health care professionals (HCPs) [2].

The rise in SNS users has sparked a growing interest in comprehending e-professionalism, particularly concerning SNSs. This specific facet of e-professionalism is becoming increasingly important. Over the past few years, numerous studies on the e-professionalism of HCPs have emerged [3,4], indicating a sustained momentum in generating scientific insights into e-professionalism.

Defining and Measuring e-Professionalism
The American Board of Internal Medicine (ABIM) guidelines on medical professionalism define 3 fundamental principles and a set of 10 professional responsibilities (or commitments). Fundamental principles are the importance of patient welfare, the principle of patient autonomy, and the principle of social justice. Professional responsibilities are commitments to professional competence, honesty with patients, patient confidentiality, maintaining appropriate relations with patients, improving the quality of care, improving access to care, a just distribution of finite resources, scientific knowledge, maintaining trust by managing conflicts of interest, and commitment to professional responsibilities [5].

E-professionalism is a specific type of professionalism. Cain and Romanelli [6] defined e-professionalism as the attitudes and behaviors (some of which may occur in private settings) reflecting traditional professionalism paradigms that are manifested through digital media.

A large number of previous research around e-professionalism measured the perception of e-professionalism [7-11] and attitude toward e-professionalism [12-18]. Through cross-validation, Kelley et al [19] created an instrument for measuring professional behaviors in pharmacy students, and even though there are some thematic overlaps, it is not suitable for measuring online behavior.

E-professionalism is often defined as a value which justifies the operationalization that directs the measurement of professionalism toward the measure of attitude. Nevertheless, from the perspective of the professions themselves, although professionalism is taught and transferred through socialization into the profession as a value, for assessing the level of e-professionalism of doctors of medicine (MDs) and doctors of dental medicine (DMDs) the behavioral component is of greater interest. Professional behavior, rather than just attitude, constitutes a visible aspect of professionalism. It is through professional behavior that not only patients and colleagues perceive a doctor’s professionalism, but also it is subject to internal control according to Freidsonian principles [20], enabling the profession to enforce sanctions on the professional. Professionalism is a behavior rather than an attitude because it should not be a hypothetical or idealized concept, as Evans [21] writes, but should be perceived as a reality—an actual entity. However, it is a real entity only if it is operational. To be real, professionalism must be something that people—professionals—actually “do,” not just something that the government or any other agency wants them to do, or wrongly imagines them to be doing [21]. The disconnection between behavior and attitude is termed “cognitive dissonance” [22], a phenomenon already acknowledged as a threat to the e-professionalism of HCPs on SNSs [4].

The research focused on the medical and dental professions as the target populations. These 2 fields were chosen due to their fundamental similarities, enabling comparisons, as well as their differences, suggesting potential variations in e-professionalism. Both medical and dental professions are sociologically recognized as professions [20] and share the commonality of providing health services. This entails a significant patient-practitioner relationship in both disciplines. Comparing various health professions is a valuable approach, and existing literature has already established overlaps in core competencies [23].

The primary distinction driving the selection of these 2 professions is the orientation of MDs, particularly in the Croatian context, toward the public sector, whereas DMDs are oriented toward the private sector.

This paper seeks to develop a reliable and valid instrument for assessing the e-professional behavior of both MDs and DMDs.

Normative Framework for Defining e-Professional Behavior
Overview
To define and measure e-professional behavior effectively, it is crucial to differentiate between professional and unprofessional behaviors. In our case, the primary objective of the normative framework is to delineate the content specifications, specifically the domains of instruments used to measure e-professional behavior.

The normative framework for assessing e-professionalism among MDs and DMDs draws upon 3 primary sources. While none of these sources alone is adequate for defining a comprehensive normative framework, each provides essential information crucial for its development. Some aspects of these
sources overlap conceptually, while others offer unique insights necessary for crafting the framework.

The first source comprises the e-professional conduct guidelines established by the ABIM [5]. These guidelines, among the earliest to be published, were developed through an international collaboration involving multiple institutions. They address the fundamental principles of professionalism and outline the professional responsibilities expected of MDs.

The second source consists of guidelines aimed at fostering e-professional behavior among medical and dental students [24]. While initially targeted at this specific demographic, a significant portion of the recommendations is applicable to the e-professionalism of MDs and DMDs. Consequently, these guidelines serve as a valuable resource for “reconstructing” the components of a normative framework for e-professionalism. They aid in delineating acceptable and unacceptable behaviors on SNSs within the context of medical and dental professions.

The third source is Julie Skrabal’s research [9], where she used the grounded theory method to develop a theoretical framework for e-professionalism. Her study empirically demonstrated which behaviors on SNSs are perceived as unprofessional. While the research focused on nursing students, the identification of key domains and indicators comprising professional behavior on SNSs holds significant value and applicability to MDs, DMDs, and all HCPs.

Based on the analysis of these 3 sources, e-professionalism, or e-professional behavior, can be categorized into 6 domains. Four of these domains pertain to the dangers associated with SNSs: confidentiality, privacy, contact with patients, and fair distribution of resources. The remaining 2 domains concern the opportunities afforded by SNSs: proactive dissemination of information relevant to public health and maintaining scientific objectivity. Each of these 6 domains is elaborated upon below.

Confidentiality

Confidentiality encompasses behaviors that primarily contravene the Health Insurance Portability and Accountability Act (HIPAA) of 1996. It entails safeguarding patient confidentiality to ensure that information regarding the patient is not disclosed, even to the patient’s relatives, without the patient’s explicit consent.

Concerning behavior on SNSs, HIPAA violations predominantly involve the unauthorized publication of photos or confidential patient information [9]. Additionally, adopting fake names (pseudonyms) to share posts containing medical or dental information constitutes another unprofessional behavior [24].

Privacy

This domain pertains to profile privacy settings and the management of post visibility. Barlow et al [25] established a correlation between privacy settings and unprofessional behavior, particularly among medical students. Consequently, they recommended the adoption of “private visibility settings” to mitigate such behaviors. Monitoring privacy settings [24], controlling post visibility [9,24], and seeking permission before tagging colleagues in posts to safeguard their privacy [24] are advocated practices. Furthermore, it is advisable to refrain from publishing professionally inappropriate content on SNSs, including posts containing curses, vulgar expressions, inappropriate attire, or behavior [9,24].

Contact With Patients

This domain encompasses direct contact with patients via SNSs. Inappropriate expressions, political incorrectness, or derogatory remarks toward patients or any individual or group can severely tarnish the public’s perception of doctors’ professional conduct [24]. Additionally, using unofficial channels, such as SNSs, to communicate sensitive professional information is considered unprofessional behavior within this domain [9].

Fair Distribution of Resources

Fair distribution of resources, as acknowledged in the ABIM guidelines, is considered an essential aspect of professional responsibility. While the ABIM guidelines emphasize the avoidance of unnecessary interventions and examinations, resource distribution also extends to SNSs. Time, a valuable resource allocated by MDs and DMDs to their patients, is particularly relevant in this context. Derived from the fundamental principle of professionalism known as the “Principle of Social Justice,” striving for a fair distribution of health care resources is imperative [5]. Communication with patients via SNSs typically requires the doctor’s time, often during their free time since it is an informal communication channel. According to the principle of fairness, it would be considered unprofessional behavior if a doctor selectively chooses which patients they are willing to communicate with on SNS and which they are not.

Proactive Publication of Information of Public Health Interest

The dimension of proactive publication of professional information of public health interest is one of the recognized aspects of e-professionalism that highlights the opportunity aspect of using SNSs. These behaviors are not deemed unprofessional when avoided; however, they can significantly contribute to e-professionalism when practiced by MDs and DMDs. While Skrabal [9] emphasizes creating positive postings as the absence of criticism and negative comments, proactive posting as a deliberate action toward e-professionalism is acknowledged in another research [26].

Scientific Objectivity

Sharing knowledge on SNSs is indeed desirable and constitutes professional behavior. However, it is essential to clearly differentiate between personal or subjective medical opinions and scientifically based facts [24].

Formative Approach in Measuring e-Professionalism

Most latent variables used in the social sciences are measured using reflective (effect) indicators [27,28]. According to a prevailing convention, indicators are seen as functions of the latent variable, whereby changes in the latent variable are reflected in changes in the observable indicators [27]. This is often true regarding constructs such as personality or attitude [28]. For example, attitude about SNSs affects respondents’ responses to the items posed to them. If someone has a negative attitude about SNSs, that attitude “guides” their responses.
However, in the case where the direction of “influence” is reversed, and where the indicators are “causing” the latent variable instead of “being caused by it,” then we can talk about formative measures [28].

Index construction focuses on explaining the abstract (unobserved) variance, considers multicollinearity among indicators, and emphasizes the role of an indicator as a “predictor” (latent variable) rather than “a predicted variable” [27].

The choice of approach (reflective vs formative) stems from the concept, that is, from the relationship between variables and constructs [29]. Jarvis et al [30] stated 4 conditions that can help discern whether a reflective or a formative model is appropriate: (1) the direction of causality between the construct and the indicator, (2) the interchangeability of the indicators, (3) covariance between indicators, and (4) the nomological network of construct indicators.

The first argument presented by Jarvis et al [30] is valid for our research because, unlike attitude, e-professional behavior stems from specific actions and decisions on SNSs. If someone refrains from posting pictures of patients, seeks permission from a colleague before mentioning them on SNS, actively controls the visibility of their posts, and takes similar actions, then these decisions contribute to their e-professional behavior.

For the second argument, e-professional behavior indicators are not interchangeable, even though they all measure e-professionalism. Posting a picture of a patient on an SNS is considered unprofessional behavior, but so is posting pictures from parties at work. Both behaviors are unprofessional, although they are not interchangeable in measurement (someone may frequently post photos of patients but rarely post workplace-related images).

The third argument states that covariance among indicators is unnecessary [30]. It is neither expected nor needed here because recognized behaviors within the normative framework can be entirely unrelated but still measure e-professional behavior (eg, sending a friend request to a patient and asking a colleague to mention them in a post).

The fourth argument suggests that the nomological network in the formative model can have different antecedents and consequences [30]. Indicators of e-professional behavior do not need to share the same antecedents because they can be driven by different motivations. A doctor may post pictures of patients because they believe it raises awareness about a particular illness (even though this act is unprofessional), while the motivation for unprofessional behavior, such as posting pictures from workplace parties, does not stem from the same motivation.

Based on these arguments, the behavioral component of e-professionalism measured in this paper conceptually corresponds to the formative approach.

We presume that other research in this area has not applied a formative approach in measuring e-professionalism because they have yet to define e-professionalism as a behavior.

Diamantopoulos and Winklhofer [28] proposed 4 key steps for validating indexes with formative indicators. The first step, content specification, refers to specifying the scope of the latent variable; in the second step, it is necessary to define the indicators; the third step refers to checking the collinearity of the indicators using the variance inflation factor (VIF) [28]. The fourth step is to assess the external validity of the index. Verification of the external validity of formative indices is often carried out by checking the relationship of the index with other measures and variables (as cited in [28]).

Although these 4 steps are sufficient for constructing and validating the index, it is possible to make an additional check of the external validity proposed by Diamantopoulos and Winklhofer [28]. This requires creating a model in which some reflective indicators are included (Diamantopoulos and Winklhofer [28] use 2) in the same model as the formative indicators. This model is called the multiple indicators multiple causes (MIMIC) model [28]. Acceptable overall model fit suggests retention of items in the formative model. If the exclusion of some items can significantly increase the model fit under the very strict condition that not a single exclusion would violate the content validity of the formative model, only then can the items be excluded.

In this paper, we have followed these 4 key steps for validating indexes with formative indicators. An additional step (the MIMIC model) was conducted before assessing the external validity of the index.

**Methods**

**Sample**

Quantitative survey data were collected using an online survey questionnaire. The Checklist for Reporting Results of Internet E-Surveys (CHERRIES) [31] is available in Multimedia Appendix 1. The required sample size was defined according to a conservative estimate often used for multivariate analyses, corresponding to a 10:1 ratio between the number of observations and the number of variables used in the questionnaire’s largest instrument [32]. In our case, that is a sample size of 280 (140 MDs and 140 DMDs). The type of sample was a nonprobabilistic purposive sample.

The study was a part of a long-term research project funded by the Croatian Science Foundation, UIP-05-2017 “Dangers and Benefits of Social Networks: E-Professionalism of Health Care Professionals – SMepROF” [33].

The mailing lists used to distribute the survey were the official full membership emailing lists of the Croatian Medical Chamber (CMC) and Croatian Chamber of Dental Medicine (CCDM). At the time of the survey, the CMC’s emailing list contained 15,562 email addresses of MDs, and the CCDM’s emailing list contained 7616 email addresses of DMDs. The email included a brief text about the study’s objective, the expected time to complete the survey, and the person and university responsible for conducting the study.

Participation in the survey was voluntary; there was no form of incentive to complete the survey. To ensure anonymity, no identification data were collected. Data were collected from February to July 2021, with 2 reminders sent in that period.
Ethics Approval
Both the study and the questionnaire were approved by the ethical boards of the University of Zagreb School of Medicine (641-01/18-02/01) and the University of Zagreb School of Dental Medicine (05-PA-24-2/2018). In addition, formal approval was obtained from the governing bodies of both the CMC and CCDM for the use of the complete mailing lists of MDs and DMDs who are members of the CMC (900-06/20-01/11) and CCDM (900-01/21-01/02).

Measures
The instrument for measuring the e-professional behavior of MDs and DMDs, presented in this study, is part of a more extensive questionnaire called SMePROF Project Survey Questionnaire on Social Media Usage, Attitudes, Ethical Values and E-professional Behaviour of Doctors of Medicine and Doctors of Dental Medicine, available at Viskić et al [34]. Although the questionnaire contained multiple instruments partially derived from previous studies [10,34,35], the instrument for measuring the e-professional behavior of MDs and DMDs is a novel instrument created by the authors. The instrument contains 20 items measured using the self-reporting approach, used to create 2 e-professionalism indexes, and the process is explained in the following parts of this paper. In validating indexes, an MIMIC model was used, which required 4 reflexive variables ($y_1$-$y_4$) measuring attitude toward e-professionalism. These items were taken from a validated instrument for measuring attitudes toward e-professionalism [35]. Descriptions of these 4 reflexive variables are shown in Multimedia Appendix 2. The MIMIC model was exclusively used as a method for validating the external validity of the indexes, and not for theory development.

The associations of indexes with theoretically related constructs were tested to assess the external validity. For this purpose, we used a validated instrument for measuring attitudes toward SNSs [36]. The instrument was translated into the Croatian language, and after additional reliability checks, 1 item was removed from the scale (“Potential and/or existing employers may use the information found on SNS to make decisions about prospective and/or existing employees”). The final instrument used had 12 items and Cronbach $\alpha=.70$.

Analytical Methods
A descriptive analysis of frequencies and percentage of responses was carried out, and distribution measures such as mean, range, SDs, and $\alpha_3$ measure of asymmetry were determined depending on appropriateness. Correlations between quantitative variables were tested with the Pearson correlation coefficient and phi coefficients of associations. The multicollinearity of the instruments was tested with the VIF. The MIMIC model was used to check the external validity of instruments with formative indicators. Data analysis was performed using IBM SPSS Statistics 26. IBM SPSS Amos 22 was used to test the MIMIC model.

Results
Survey Responses
A total of 1013 responses were collected. The response rate was 4.37% (1013/23,178). The final realized sample of the entire research contained the answers of 999 respondents, of which 75.4% (753/999) use at least one SNS, 67.3% (507/753) of the respondents were MDs and 32.7% (246/753) were DMDs. The sample was predominantly female (558/753, 74.1%) with an average age of 38 (SD 10.99) years. Most respondents worked in a public health institution (412/753, 54.7%), and the second most frequent type of workplace was a private institution with a contract with the Croatian Health Insurance Fund (CHIF; 148/753, 19.7%).

Previous research on the same sample [34] showed a significant difference in age, where MDs were older than DMDs with an average age of 39.26 years as opposed to 36.58 years, respectively, and in the type of employment, with more than two-thirds of DMDs (168/246, 68.2%) being employed in the private sector compared with only 20.5% (104/507) of MDs. All specialization status levels are included in the sample (Multimedia Appendix 3).

The Construction of the e-Professionalism Index—The Danger Aspect of SNSs
Following the first step in creating the index, according to Diamantopoulos and Winklhofer [28], the content for the latent variable is specified below. In the second step, e-professional behaviors described in the normative framework were operationalized into an instrument for measuring the aspect of e-professionalism related to the dangers of SNSs (Table 1). The identified indicators are grouped into 4 domains: confidentiality, privacy, contact with patients, and fair distribution of resources. Items were evaluated on a frequency rating scale: 0=Never, 1=Rarely, 2=Occasionally, 3=Often; and the option “I have never been in a situation where this could happen” was added. It was essential to distinguish behaviors that could have happened but did not from those for which the respondent was not even in a situation to practice them. Depending on the direction and content of the items, the difference between the opportunity to behave in a certain way and the frequency of that behavior can mean the difference between professional and unprofessional behavior. In the case of items formulated in a positive direction (marked +), a higher frequency measures a higher level of e-professionalism. In the case of items formulated in a negative direction (marked –), higher frequency measures a lower level of e-professionalism.
Table 1. Domains, indicators, and items for the instrument of e-professionalism—the danger aspect of SNSs.

<table>
<thead>
<tr>
<th>Domain and indicator</th>
<th>Item</th>
<th>Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Confidentiality</td>
<td>I published some information about my patient.</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>I posted a photo of my patient without their knowledge.</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>I shared medical/dental advice on SNS without my name being visible.</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>I shared some information about the patient I received through SNS with others.</td>
<td>–</td>
</tr>
<tr>
<td>Privacy of MDs and DMDs profiles</td>
<td>Depending on the appropriateness of the content of my posts, I determine to whom they will be visible.</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>If I notice that someone else has published something about me (eg, my picture, location, or similar), I control who will see it.</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>I asked a colleague’s permission to mention them in the post.</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>I have posted content that shows informal situations at my workplace (eg, drinks with colleagues or parties at work).</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>A curse word or some different vulgar expression occasionally slips out in my posts.</td>
<td>–</td>
</tr>
<tr>
<td>Contact with patients</td>
<td>In my posts, I am cautious that my expression is entirely professional.</td>
<td>+</td>
</tr>
<tr>
<td></td>
<td>I communicate with patients regarding medical/dental problems and treatment from a private profile.</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>I included information about the patient I found through SNS in the medical documentation without their knowledge.</td>
<td>–</td>
</tr>
<tr>
<td></td>
<td>Have you ever sent a “friend request” to a patient or a member of the patient’s family from a private profile on an SNS?</td>
<td>–</td>
</tr>
<tr>
<td>Fair distribution of resources</td>
<td>On SNS, I choose which patients I will make contact with and which I will not.</td>
<td>–</td>
</tr>
</tbody>
</table>

*SNS: social networking site.

bFor items formulated in a positive direction (marked +), a higher frequency measures a higher level of e-professionalism. In the case of items formulated in a negative direction (marked –), a higher frequency measures a lower level of e-professionalism.

The indicator “Sending a friend request to a patient or a member of the patient’s family” was not measured as frequency. Instead, the 4 offered answers were as follows: Yes, to the patient; Yes, to a family member; Yes, both; and No. The negative response is considered professional, while all other responses indicate unprofessional behavior.

The descriptive results for the items that measure the aspect of e-professionalism related to the dangers of SNSs are shown in Table 2. The items that measure e-professional behavior are marked with a “b.” All other items measure e-unprofessional behavior.
### Table 2. E-professionalism (the dangers aspect of SNSs) descriptives (N=753).

<table>
<thead>
<tr>
<th>Danger aspects</th>
<th>Never, n (%)</th>
<th>Rarely, n (%)</th>
<th>Occasionally, n (%)</th>
<th>Often, n (%)</th>
<th>I have never been in a situation where this could happen, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. I asked a colleague’s permission to mention them in the post.</td>
<td>170 (22.6)</td>
<td>117 (15.5)</td>
<td>71 (9.4)</td>
<td>50 (6.6)c</td>
<td>345 (45.8)c</td>
</tr>
<tr>
<td>2. I shared some information about the patient that I received through SNS with other people.</td>
<td>368 (48.9)c</td>
<td>61 (8.1)</td>
<td>26 (3.5)</td>
<td>3 (0.4)</td>
<td>295 (39.2)c</td>
</tr>
<tr>
<td>3. I posted a photo of my patient without their knowledge.</td>
<td>492 (65.3)c</td>
<td>14 (1.9)</td>
<td>7 (0.9)</td>
<td>2 (0.3)</td>
<td>238 (31.6)c</td>
</tr>
<tr>
<td>4. I included information about the patient I found through SNS in the medical documentation without their knowledge.</td>
<td>484 (64.3)c</td>
<td>3 (0.4)</td>
<td>2 (0.3)</td>
<td>0 (0.0)</td>
<td>264 (35.1)c</td>
</tr>
<tr>
<td>5. I shared medical/dental advice on SNS without my name being visible.</td>
<td>503 (66.8)c</td>
<td>39 (5.2)</td>
<td>6 (0.8)</td>
<td>4 (0.5)</td>
<td>201 (26.7)c</td>
</tr>
<tr>
<td>6. Depending on the appropriateness of the content of my posts, I determine to whom they will be visible.</td>
<td>295 (39.2)</td>
<td>99 (13.1)</td>
<td>93 (12.4)</td>
<td>71 (9.4)c</td>
<td>195 (25.9)c</td>
</tr>
<tr>
<td>7. If I notice that someone else has published something about me (eg, my picture, location, or similar), I control who will see it.</td>
<td>209 (27.8)</td>
<td>106 (14.1)</td>
<td>104 (13.8)</td>
<td>177 (23.5)c</td>
<td>157 (20.8)c</td>
</tr>
<tr>
<td>8. I have published content that shows informal situations at my workplace (eg, drinks with colleagues or parties at work).</td>
<td>354 (47.0)c</td>
<td>181 (24.0)</td>
<td>84 (11.2)</td>
<td>17 (2.3)</td>
<td>114 (15.1)c</td>
</tr>
<tr>
<td>9. I published some information about my patient.</td>
<td>579 (76.9)c</td>
<td>22 (2.9)</td>
<td>5 (0.7)</td>
<td>2 (0.3)</td>
<td>145 (19.3)c</td>
</tr>
<tr>
<td>10. I communicate with patients regarding medical/dental problems and treatment from a private profile.</td>
<td>423 (56.2)c</td>
<td>133 (17.7)</td>
<td>64 (8.5)</td>
<td>14 (1.9)</td>
<td>119 (15.8)c</td>
</tr>
<tr>
<td>11. On SNS, I choose which patients I will make contact with and which I will not.</td>
<td>293 (38.9)c</td>
<td>74 (9.8)</td>
<td>65 (8.6)</td>
<td>76 (10.1)</td>
<td>245 (32.5)c</td>
</tr>
<tr>
<td>12. In my posts, I am cautious that my expression is entirely professional.</td>
<td>51 (6.8)</td>
<td>61 (8.1)</td>
<td>111 (14.7)</td>
<td>366 (48.6)c</td>
<td>164 (21.8)c</td>
</tr>
<tr>
<td>13. A curse word or some other vulgar expression occasionally slips out in my posts.</td>
<td>494 (65.6)c</td>
<td>86 (11.4)</td>
<td>23 (3.1)</td>
<td>2 (0.3)</td>
<td>148 (19.7)c</td>
</tr>
<tr>
<td>14. Have you ever sent a “friend request” to a patient or a member of the patient’s family from a private profile on an SNS?</td>
<td>699 (92.8)c</td>
<td>33 (4.4)</td>
<td>3 (0.4)</td>
<td>18 (2.4)</td>
<td>N/Ae</td>
</tr>
</tbody>
</table>

aSNS: social networking site.  
bItem represents professional behavior on SNS.  
cResponse represents professional behavior on SNS.  
dThe options were “no,” “yes, to a patient,” “yes, to a family member,” and “yes, both,” respectively.  
eN/A: not applicable.

The answer “I have never been in a situation where this could happen” is not a missing value, but it carries a conceptual meaning that must be distinguished from the answer “Never.” The assessment of whether that answer is professional or unprofessional depends on the content and direction of the item. Respondents who have never engaged in unprofessional behavior are professional, but so are those who never had an opportunity to act unprofessionally. Respondents who often practice behaviors on items marked with “b” are professional, and so are those who have never been in a situation to practice these behaviors because they have not been in a situation to behave unprofessionally.

For example, in the case of positive items (those representing professional behavior), such as “I asked a colleague’s permission to mention him/her in the post,” professional behavior is defined as a situation where the individual has never violated this rule because they have never mentioned colleagues in their posts or seek permission each time they mention them. Any other frequency level implies that, at some point, the person has posted about colleagues without their consent, which constitutes unprofessional behavior on SNS.
It is crucial here to differentiate between the absence of behavior of interest (requesting permission from colleagues when mentioning them in posts) in situations where it should have been sought (if mentioning them in posts) from the situations where it should not have been sought (because they never mention colleagues).

By contrast, for negative items (those representing unprofessional behavior), such as “I shared some information about the patient that I received through SNS with other people,” professional behavior is defined as situations where the individual has never engaged in such behavior or has not even been in a situation where they could engage in such behavior (eg, they do not communicate with patients via SNS, so they cannot receive patient information through this channel).

Therefore, the context of the absence of specific behaviors plays a pivotal role in distinguishing between professional and unprofessional behaviors. It is essential to combine the response “I have never been in a situation where this could happen” with the level of behavior frequency.

To construct the index, the frequency of behavior on each indicator was not graded but only considered as a binary value (professional vs unprofessional).

For items that measure unprofessional behavior, any degree of frequency other than “never” was considered unprofessional behavior. For items that measure professional behavior (eg, asking a colleague’s permission to mention them in a post), all those who did this never, rarely, or occasionally were considered unprofessional on that indicator, because this is the behavior they are expected to do always (or often in our scale).

The Validation Process of the e-Professionalism Index—The Danger Aspect of SNSs

After specifying the scope and defining the indicators, the third step, according to Diamantopoulos and Winklhofer [28], refers to checking the collinearity of the indicators. Intercorrelations of the items in the e-professionalism instrument—the danger aspect of SNSs are shown in Multimedia Appendix 4. Given that these are binary variables, phi coefficients of associations were used. The correlation between the variables “On SNS, I choose with which patients I will make contact with and which I will not.” and “From a private profile, I communicate with patients regarding medical/dental problems and treatment.” ($r=0.568$) represents a moderate correlation and evokes the need to investigate potential multicollinearity. This suggests that those who communicated with patients via SNSs also chose with whom (patients) they would establish communication. As a formative approach is used, special care is needed before excluding indicators to preserve the instrument’s validity. Therefore, the VIF and MIMIC model were calculated. Multicollinearity was tested using a VIF with an additive index of e-professionalism, an aspect of the danger of SNSs that was constructed as the sum of values on binary indicators. According to the conservative threshold [37], VIF values on all indicators were below the value of 2.5, which suggests that multicollinearity is not an issue.

The MIMIC model was implemented to check the external validity of the instrument. The path diagram of the MIMIC model is shown in Multimedia Appendix 5. Variables $x_1$-$x_{14}$ correspond to the items from Table 2. Items $y_1$ (Communication with a patient through social media can be achieved without compromising doctor-patient confidentiality) and $y_2$ (Social media have the potential to improve communication between a doctor and a patient) were chosen as reflective indicators.

The model showed good fit ($\chi^2_{13}=9.4, P=.742; \chi^2/df=.723$; root-mean-square error of approximation<0.001; goodness-of-fit index=0.998; comparative fit index=1.000). However, 7 of the 14 items ($x_1$, $x_2$, $x_3$, $x_6$, $x_7$, $x_8$, and $x_{13}$) did not have significant regression coefficients ($\gamma$) that can also be interpreted as validity coefficients [28]. The probable reason is that the measured reflective indicators did not measure the same domains as e-professional behavior; instead, they measured an attitude toward e-professionalism. Both items 11 ($P<.001$) and 12 ($P=.02$), which were investigated as potential problems of multicollinearity, have significant validity coefficients. Considering that, as well as an acceptable VIF, they were retained in the index to preserve the content validity to which formative models are particularly sensitive.

A higher value on the index means a higher degree of e-professionalism, that is, a lower incidence of unprofessional behavior on SNSs. The index results ranged from 0 to 14, and the average value in our sample was 10.60 (SD 2.173). The distribution of the index was skewed toward higher values ($\alpha=-.44, P=.09$), that is, toward the professional behavior of our respondents on SNSs.

The external validity of the index is supported by the correlation with other measured constructs. There was a statistically significant negative correlation between the index of e-professionalism (aspects of the danger of SNSs) and the scale of attitude toward SNSs ($r=-.225, P<.001$).

The Construction of the e-Professionalism Index—The Opportunity Aspect of SNSs

The construction of the e-professionalism index—the opportunity aspect of SNSs follows the same validation steps as the aspect of the dangers of SNSs [28].

E-professional behaviors described in the normative framework were operationalized into an instrument for measuring e-professionalism through the opportunity aspect of SNSs. The instrument contains 2 domains, measured by 6 items. All items are formulated in the same direction so a higher frequency measures a higher level of e-professionalism (Table 3).
Table 3. Domains, indicators, and items for the instrument of e-professionalism—opportunity aspect of SNSs.

<table>
<thead>
<tr>
<th>Domain and indicator</th>
<th>Item</th>
<th>Direction</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Proactive posting of expert information of public health interest</strong></td>
<td>I share posts on social media that contain general medical advice.</td>
<td>+</td>
</tr>
<tr>
<td>Sharing posts that contain general medical advice</td>
<td>I use my profile to share information about new scientific knowledge in the field of medicine/dental medicine.</td>
<td>+</td>
</tr>
<tr>
<td>Sharing new scientific knowledge in the field of medicine</td>
<td>I debunk medical/dental myths and misinformation by posting on SNS.</td>
<td>+</td>
</tr>
<tr>
<td>Debunking medical myths and misinformation</td>
<td>I use SNS to raise public awareness of public health actions.</td>
<td>+</td>
</tr>
<tr>
<td>Calling for public health actions</td>
<td>I create posts on SNS that call for responsible health behavior.</td>
<td>+</td>
</tr>
<tr>
<td>Encouraging responsible behavior</td>
<td>In the posts, I clearly separate my personal opinion on a medical/dental issue from scientifically confirmed facts.</td>
<td>+</td>
</tr>
</tbody>
</table>

Scientific objectivity

**Emphasis on distinguishing personal medical opinions from facts**

The descriptive results for the items that measure the opportunity aspect of SNSs are shown in Table 4. While measuring the danger aspect of SNSs focused on occurrence, not on the frequency of occurrence, the frequency of each behavior is relevant with this instrument. All behaviors in this instrument have the characteristic of being desirable, but the absence of such behaviors is not unprofessional. If an MD or DMD practices these behaviors, they use opportunities of SNSs and contribute to their professionalism. However, if they do not practice any of these behaviors, or have never been in a situation where they can behave like that, it is not unprofessional, but misses the opportunity to use the advantages of SNSs.

The Validation Process of the e-Professionalism Index—Opportunity Aspect of SNSs

The correlations between the items that constitute this index have higher values than those in the aspect of dangers of the SNS index (Multimedia Appendix 6). The item “I create posts on SNS that call for responsible health behavior” moderately correlates with several items (from \( r = 0.418 \) to 0.714). To check
if multicollinearity is present in this instrument, paying attention to the VIF is necessary.

VIF was calculated with an additive index of e-professionalism—opportunity aspect of SNSs. VIF values on all indicators are below the value of 2.5, which suggests no risk of multicollinearity, even according to a conservative interpretation.

Before excluding the item “I create posts on SNS that call for responsible health behavior,” an MIMIC model was created with all the items included, and a second model without that item was created to check for any changes in the model fit. The diagram of the MIMIC model is shown in Multimedia Appendix 5. Variables $x_1$-$x_6$ correspond to the items from Table 4. Items $y_1$ (As MD/DMD, it is my duty to keep abreast of current trends in the use of SNS) and $y_2$ (Guiding patients to online information is a new responsibility of MDs/DMDs in the digital age) were chosen as 2 reflective indicators.

The MIMIC model with all 6 items showed good fit characteristics ($\chi^2=2.880$, $P=.718$; $\chi^2/df = 0.576$; root-mean-square error of approximation $<.001$; goodness-of-fit index $=0.999$; comparative fit index $=1.000$). However, 3 items ($x_1$, $x_3$, and $x_5$) did not have significant regression coefficients ($\gamma; P=.14$, $P=.44$, and $P=.19$, respectively).

Considering the high correlations with other items, the VIF value that exceeds the limit of 2.5, and the regression coefficient $\gamma$ that is not statistically significant ($P=19$), item $x_5$ was excluded from the e-professionalism index—opportunity aspect of SNSs. After excluding item $x_5$, the fit of the MIMIC model did not change significantly ($\Delta\chi^2=0.336$, $P=.56$) and the fit of the model was $\chi^2=2.544$, $P=.718$; $\chi^2/df = 0.637$; root-mean-square error of approximation $<.001$; goodness-of-fit index $=0.999$; comparative fit index $=1.000$.

The index of e-professionalism—opportunity aspect of SNSs was created as the sum of the values of the remaining 5 recoded variables. A higher value on the e-professionalism index means a higher degree of e-professionalism. The index results ranged from 0 to 15 (mean 4.13, SD 3.712). The distribution of the index was skewed toward lower values ($\alpha=0.67$, $P=0.9$), showing that 24% (181/753) of respondents do not take advantage of SNSs at all.

The external validity of the index of e-professionalism—opportunity aspect of SNSs is supported by the correlation with other measured constructs. There was a statistically significant positive correlation between the index and the scale of attitude toward SNSs ($r=0.338$, $P<0.001$).

Discussion

Principal Findings

As far as the authors are aware, this is the first measure constructed to measure the e-professional behavior of MDs and DMDs, with the created indexes of opportunity and the danger aspects of SNSs being the first attempt at using a formative approach in the research of professionalism in general and in e-professionalism. The final instrument for measuring the e-professional behavior of MDs and DMDs consists of 19 items that form 2 indexes. Index of e-professionalism—the danger aspect of SNSs, which is formed by 14 items, and the index of e-professionalism—opportunity aspect of SNSs, which is formed by 5 items.

These novel indexes can be used to measure the level of e-professional behavior among MDs and DMDs, which can have potential real-world applications. The main implications can be utilized in education for young medical and dental professionals and the development of guidelines for improving e-professionalism. If the instrument were applied on a representative sample, it could yield valuable data to enable the implementation of data-based policies with specific behaviors of interest. Investigation of the external validity of both e-professionalisms showed acceptable results. There was a statistically significant negative correlation between the index of e-professionalism—the danger aspect of SNSs and the scale of attitude toward SNSs ($r=-0.225$, $P<0.001$). This is the theoretically expected direction of the correlation because the more positive attitude the respondents have about SNSs, the more inclined they are to use them when working with patients, which according to the normative framework, represents unprofessional behavior. The statistically significant positive correlation between the index of e-professionalism—opportunity aspect of SNSs and the scale of attitude toward SNSs ($r=0.338$, $P<0.001$) is also theoretically expected because the more positive attitude toward SNSs doctors have, the more likely they will take advantage of the benefits of SNSs.

In the index of e-professionalism—the danger aspect of SNSs, all initially operationalized indicators were retained. In the index of e-professionalism—the opportunity aspect of SNSs, item $x_5$ (I create posts on SNS that call for responsible health behavior) measuring the indicator “Encouraging responsible behavior” was excluded. The formative approach suggests cautious consideration of managing the content validity of the model. It seems that respondents understood item $x_5$ very similarly to item $x_3$ (I use SNS to raise public awareness of public health actions.). After testing the indicators in the MIMIC model, the authors concurred that the content validity is not threatened by excluding this item, and multicollinearity would pose a more significant problem than losing a very subtle difference in the contents of these items.

Comparison With Prior Work

Conceptual domains recognized in this study only partially overlap with domains in the instrument of (offline) professional behavior [19] and the instrument for measuring attitudes toward e-professionalism [35]. Kelley et al [19] recognized a domain called “Upholding principles of integrity and respect,” which corresponds to the domain “Confidentiality” in this study, as well as “Citizenship and professional engagement” [19], which corresponds to “Proactive posting of expert information of public health interest.” In an instrument for measuring attitudes toward e-professionalism, Marelić et al [35] recognized the domain “Ethical aspects” that theoretically includes HIPAA violations and therefore corresponds to the domain “Confidentiality” in this study, and the domain “Physicians in

https://mededu.jmir.org/2024/1e/50156
the digital age” that corresponds to “Contact with patients”. However, the instrument of (offline) professional behavior contains domains that are not comparable to e-professional behavior, and the instrument for measuring attitudes toward e-professionalism contains domains that are not applicable for behavior measurement, and because of potential cognitive dissonance, measuring attitude is not a replacement for behavior measurement.

Limitations

The first limitation of this study is the low response rate (1013/23,178, 4.37%). Previous research has indicated that these professions have low survey response rates, especially in e-mailing surveys using web-based formats [38-42]. Time, confidentiality concerns, and topic relevance are some of the main reasons for their low survey participation [40]. Previous research has indicated that declining response rates among HCPs may be attributed to various factors, including heightened requests to participate in surveys and increased workloads. This increase in workload encompasses both the rising number of patients and administrative responsibilities [38,39].

One factor likely contributing to the low response rate in this study is the demanding schedule of MDs and DMDs. The estimated time required to complete our survey was lengthy, ranging from 10 to 15 minutes, due to the inclusion of a complex and comprehensive questionnaire containing 40 questions. Moreover, the survey was conducted during the COVID-19 pandemic (February to July 2021), a period marked by heightened strain on the health care system. MDs, especially those in Croatia, were confronted with extreme workloads and specific working conditions during this time. Additionally, MDs received numerous invitations to participate in web-based surveys, particularly regarding the impact of the COVID-19 pandemic on their physical or mental health. Given these circumstances, our study’s focus on e-professionalism may have been perceived as of lower interest, potentially further reducing doctors’ willingness to participate in research.

However, our objective in creating and validating new indexes did not prioritize achieving representativeness in our sample or generalizing our findings to the entire population of MDs and DMDs in Croatia. Instead, our focus was on assessing the suitability of the developed measurement instruments across various medical professions, using nonprobabilistic purposive sample. Our final sample comprised responses obtained from the population of interest for this study, specifically MDs and DMDs who use at least one SNS. It is worth noting that the number of responses received in our survey (507 MDs and 246 DMDs) exceeded the initially planned sample size (140 MDs and 140 DMDs) by a considerable margin.

The second limitation concerns a relatively large proportion of respondents (ranging from 69/753, 9.2%, to 371/753, 49.3%) who selected the option “I have never been in a situation where this could happen” for certain items. It remains unclear why they did not simply respond with “Never.” The reasons behind this choice are ambiguous. It is possible that some respondents are passive users of SNSs, thus not engaging in any content publication and consequently unable to exhibit unprofessional behavior. Alternatively, it could be that these respondents do not work directly with patients, rendering items related to violations of the HIPAA irrelevant to them. Another possibility is that they perceive their standards of professionalism to be exceptionally high, leading them to believe they would never engage in such behavior. While this issue does not affect the measurement of the occurrence of e-(un)professional behavior, it does impede a detailed understanding of the frequency of e-unprofessional behavior. Addressing this limitation could be a focus of future research and modifications to the measurement instrument, but this should be preceded by gaining new insights into the e-professional behaviors of MDs and DMDs.

The third limitation involves the potential for bias associated with using a self-reporting approach to measurement. Similar to other self-report measures in medicine, 2 key biases often arise: recall bias and social desirability bias [43]. Recall bias in our study could be attributed to the lack of a specified timeframe, such as “during the last year.” We chose this approach because it represents the initial assessment of such behaviors, and we faced a scarcity of existing data on this subject. Introducing a specific timeframe in future research could aid in mitigating potential recall bias. The potential for social desirability bias stems from 2 sources. First, the nature of the measurement itself requires HCP respondents to self-report potentially unprofessional behaviors, including some that may constitute violations of HIPAA. The other factor to consider is that respondents were contacted to participate in our research through the same institutions responsible for granting and revoking licenses to practice medicine/dental medicine. Despite our assurance of anonymity in the study, respondents may have felt compelled to provide socially desirable answers on certain items. One method to mitigate or control social desirability bias is to include positive items, such as those measuring professional behaviors, alongside other items. An additional approach to address both biases, which could serve as a recommendation for future research, involves further refinement and validation of the instrument. This could be achieved by comparing self-reported data with information obtained through web scraping of respondents’ SNS profiles, particularly focusing on visible behaviors.

The fourth limitation arises from the potential mismatch between the use of reflective indicators $y_1$ to $y_4$ in the MIMIC model and the nature of the created indexes, which are intended to measure e-professionalism as behavior. However, the reflective variables used in the model measure attitude. While this approach was necessary for creating the MIMIC model in this study, there is a possibility that cognitive dissonance [4,21] may compromise the fit of the model.

The fifth limitation to note is that the sources used to establish a normative framework were relevant to the time and location of this research. However, their applicability to other countries and populations of HCPs, or their accuracy over time, may be limited. For example, the ABIM e-professional conduct guidelines [5] are relatively dated, and while they represent fundamental values of professionalism, they may not fully encompass changes in societal values that have occurred since the emergence of SNSs. Specific behaviors measured in these indexes may require revision or supplementation in the future.
Moreover, additional studies conducted after the development of this index may offer new insights into creating a normative framework for defining e-professional behaviors [44].

**Future Directions**

In considering avenues for enhancing both the instruments used in this study and future research directions, it becomes apparent that there are opportunities for improvement and deeper exploration. One potential extension of this study, which could lead to a more thorough understanding of the topic, involves testing the indexes on specific subsamples, particularly within specialties such as dermatology and reconstructive and cosmetic surgery. These specialties may involve visual representations of procedures, such as “before and after” images [34], which could pose potential threats to e-professionalism.

Improving the quality of external validity assessment can be achieved by incorporating self-evaluation of e-professionalism into the MIMIC model. This addition would enhance the content validity of the model by supplementing existing reflective indicators used in the research. Furthermore, self-evaluation of e-professionalism would serve as a valuable tool for evaluating the nomological network of the instrument. It would provide insights into the direction and strength of correlation among individual indicators of e-professionalism, the e-professionalism indices themselves, and potential predictors for model creation.

Future attempts aimed at measuring e-professionalism could focus on investigating the underlying reasons behind responses such as “I have never been in a situation where this could happen.” It is plausible that a more precise definition of items or the inclusion of specific examples could serve as mechanisms to help respondents differentiate between behaviors they never engage in and those they may never encounter. By refining the clarity and specificity of survey items, researchers can facilitate a more accurate assessment of respondents’ experiences and perceptions related to e-professional behavior. This approach could lead to a deeper understanding of the nuances involved in professional conduct within the context of SNSs.

**Conclusions**

In this paper, an instrument for measuring the e-professional behavior of MDs and DMDs was developed and validated using the formative approach. Following the validation process, the instrument comprises 19 items, which contribute to the formation of 2 indexes. The first index, focusing on the danger aspect of SNSs, is composed of 14 items that were dichotomized before index construction. The second index, which examines the opportunity aspect of SNSs, is composed of 5 items that were recoded as 4-point items before index construction.

These innovative indexes offer a means to gauge the level of e-professional behavior among MDs and DMDs. This marks the first measure specifically designed to assess the e-professional behavior of MDs and DMDs. The paper demonstrates the feasibility of investigating e-professional behavior using a formative approach, representing an advancement over existing measuring instruments. This approach provides a means to mitigate the impact of cognitive dissonance between attitudes and the actual behavior of MDs and DMDs.

The validation process confirmed that these indexes serve as a robust measure of e-professional behavior. Nevertheless, the instrument has been scrutinized for potential areas of enhancement, and suggestions for improvements have been proposed for future iterations of the instrument.

**Acknowledgments**

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**Data Availability**

The data sets used or analyzed during this study are available from the corresponding author on reasonable request.

**Conflicts of Interest**

None declared.

Multimedia Appendix 1
Checklist for Reporting Results of Internet E-Surveys (CHERRIES).
[DOCX File, 23 KB - mededu_v10i1e50156_app1.docx]

Multimedia Appendix 2
Descriptive characteristics of reflective indicators for the MIMIC models of e-professionalism (N=753).
[DOC File, 34 KB - mededu_v10i1e50156_app2.doc]

Multimedia Appendix 3
Type of workplace and specialization status of the respondents.
References


Abbreviations

ABIM: The American Board of Internal Medicine
CCDM: Croatian Chamber of Dental Medicine
CHERRIES: Checklist for Reporting Results of Internet E-Surveys
CHIF: Croatian Health Insurance Fund
CMC: Croatian Medical Chamber
DMD: doctor of dental medicine
HCP: health care professional
HIPAA: Health Insurance Portability and Accountability Act
MD: doctor of medicine
MIMIC: multiple indicators multiple causes
SNS: social networking site
VIF: variance inflation factor

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Exploring Anesthesia Provider Preferences for Precision Feedback: Preference Elicitation Study

Zach Landis-Lewis¹, MLIS, PhD; Chris A Andrews², PhD; Colin A Gross³, BSc; Charles P Friedman¹, PhD; Nirav J Shah⁴, MD

Abstract

Background: Health care professionals must learn continuously as a core part of their work. As the rate of knowledge production in biomedicine increases, better support for health care professionals’ continuous learning is needed. In health systems, feedback is pervasive and is widely considered to be essential for learning that drives improvement. Clinical quality dashboards are one widely deployed approach to delivering feedback, but engagement with these systems is commonly low, reflecting a limited understanding of how to improve the effectiveness of feedback about health care. When coaches and facilitators deliver feedback for improving performance, they aim to be responsive to the recipient’s motivations, information needs, and preferences. However, such functionality is largely missing from dashboards and feedback reports. Precision feedback is the delivery of high-value, motivating performance information that is prioritized based on its motivational potential for a specific recipient, including their needs and preferences. Anesthesia care offers a clinical domain with high-quality performance data and an abundance of evidence-based quality metrics.

Objective: The objective of this study is to explore anesthesia provider preferences for precision feedback.

Methods: We developed a test set of precision feedback messages with balanced characteristics across 4 performance scenarios. We created an experimental design to expose participants to contrasting message versions. We recruited anesthesia providers and elicited their preferences through analysis of the content of preferred messages. Participants additionally rated their perceived benefit of preferred messages to clinical practice on a 5-point Likert scale.

Results: We elicited preferences and feedback message benefit ratings from 35 participants. Preferences were diverse across participants but largely consistent within participants. Participants’ preferences were consistent for message temporality (α=.85) and display format (α=.80). Ratings of participants’ perceived benefit to clinical practice of preferred messages were high (mean rating 4.27, SD 0.77).

Conclusions: Health care professionals exhibited diverse yet internally consistent preferences for precision feedback across a set of performance scenarios, while also giving messages high ratings of perceived benefit. A “one-size-fits-most approach” to performance feedback delivery would not appear to satisfy these preferences. Precision feedback systems may hold potential to improve support for health care professionals’ continuous learning by accommodating feedback preferences.

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KEYWORDS

audit and feedback; dashboard; motivation; visualization; anesthesia care; anesthesia; feedback; engagement; effectiveness; precision feedback; experimental design; design; clinical practice; motivational; performance; performance data
considered as best practice for feedback interventions has not changed meaningfully for decades, even after hundreds of trials and repeated calls for new approaches to feedback interventions [6-8].

To our knowledge, most clinical performance feedback interventions use a “one-size-fits-most” approach to both the prioritization of performance information and its visual display as feedback, with the same metrics and visualizations being sent to all recipients. One-size-fits-most feedback may not be effective due to a host of characteristics such as individuals’ knowledge, skills, and motivational orientation to their work [2,3,9-11]. Methods used by coaches, educators, and quality improvement facilitators to deliver feedback suggest that these factors are important [2,12,13]. Furthermore, in the context of routine feedback interventions (eg, with monthly or quarterly measurement cycles), the value of performance information [14-16] may be reduced when performance is stable, but feedback interventions are not commonly prioritized accordingly. Given the increasing use and digitization of performance measures and clinical quality dashboards [17,18], health care systems need to understand how to better accommodate health care professionals’ feedback preferences and the corresponding value of performance information.

**Precision feedback** is feedback that has been prioritized based on its motivational potential for a specific recipient [19-23]. Using this approach, high-value feedback messages can be selected to enhance reports and emails, such as “You reached the top performer benchmark” and “Your performance dropped below the peer average.” The potential impact of precision feedback increases with greater variability and differences in individuals’ knowledge, skills, and motivational orientation, but these differences and their interactions are not well understood, as studies of health care professionals’ feedback preferences appear to be scarce. Qualitative studies have explored feedback preferences by asking participants to discuss their experiences with prior feedback; for example, they can be prompted by a published feedback report [24] or a performance report belonging to the participant or their organization [25]. Quantitative preference elicitation methods have been used extensively in health decision-making [26,27], but uncertainty about the measurement properties of preferences contributes to controversy around their use [28]. To our knowledge, no instruments of health care professional feedback preferences with validity evidence have been developed. To begin to explore and understand these differences, we designed a preference elicitation study for motivating performance information and its display format.

We conducted this study in the context of anesthesia care quality improvement. In this context, data generated about care processes are produced primarily by anesthesia machines that report the administration of anesthetics and the patient’s corresponding state with relatively high accuracy and reliability. Attribution of performance to individual anesthesia providers is feasible due to their authenticated use of an anesthesia machine for each operative case. A national-scale quality improvement consortium, the Multicenter Perioperative Outcomes Group (MPOG) [29,30], has developed approximately 70 performance measures for anesthesia care quality and outcomes. Feedback is delivered through its infrastructure via monthly emails and a clinical quality dashboard to more than 8000 health care professionals in more than 20 US states. Thus, a relatively large set of measures are routinely assessed using high-quality clinical data, representing performance information that health care professionals have limited natural sources for across their patient populations.

Multiple types of motivation are recognized as mechanisms through which feedback influences performance [2,10,11,31-33]. These various types of motivation can be understood as a consequence of the cognitive processing of performance information. We use the term **motivating performance information** to mean performance information that has the potential to motivate a feedback recipient through a known mechanism of action (Table 1). A key type of motivating performance information is a **comparison** that represents a discrepancy between the performance level of a feedback recipient and some comparator [22]. There are multiple types of comparators, including **benchmarks** having a performance level that is determined by a population-based analysis. Benchmarks are commonly calculated as a summary statistic of top performers, such as choosing the performance level for a population that occurs at the 90th percentile, or the achievable benchmark of care (ABC) method [34]. Another type of comparator is an **explicit target**, including goals or standards that set expectations for attaining a specific performance level that is not necessarily dependent upon peers or another reference group’s performance [35]. The choice of comparators can result in the use of alternate mechanisms of motivation, such as motivation related to social norms versus personal goal-setting. Another key type of motivating information is **trends** that represent change in performance (getting better or worse) [22]. Comparisons and trends may co-occur in performance data to represent an **achievement**, such as reaching a goal, or a **loss**, such as losing top-performer status [22].
Comparisons and trends are represented using a wide range of visualizations in clinical quality dashboards and feedback reports [20]. These visualizations vary both in their content, such as the use of measures, comparators, and duration of time intervals, as well as the display format, such as bar charts, line charts, and tables to represent performance data. A review of published displays from feedback reports and dashboards identified 6 unique combinations of visualized performance information content [20]. For example, feedback displays vary in the number of performance measures, time intervals, and comparators that they visualize.

The display of feedback is theorized as one of many factors affecting the success of clinical performance feedback in Clinical Performance Feedback Intervention Theory (CP-FIT) [38], a leading theory of audit and feedback. Motivating performance information in clinical performance data concerns configurations of types of feedback display, but is also closely related to CP-FIT’s goal construct, which concerns the importance and relevance of feedback to health care professionals. Precision feedback may contribute to additional CP-FIT constructs, including health professional characteristics (knowledge and skills in quality improvement), feedback delivery (function), and implementation process (adaptability and ownership).

To understand anesthesia provider preferences for motivating performance information and feedback display format, we investigated the following four research questions:

1. To what extent do anesthesia providers’ selected messages reveal an overall preference for messages containing time series versus time point information (temporality)?
b. messages relative to benchmarks versus explicit performance targets (basis of comparison)?
c. messages formatted as bar charts versus line charts and text only (display format)?

2. How consistent are individual anesthesia provider preferences?
3. To what extent do anesthesia provider preferences depend on performance level, trend, and their professional background?
4. To what extent are preferred feedback messages perceived to hold potential to improve future clinical practice?

Methods

Overview

To address these questions, we developed a test set of feedback messages that a software application could generate. We formatted these as brief email messages, but designed them as “least common denominator” content that could also be delivered via other channels for feedback, such as clinical quality dashboards.

In the absence of instruments with validity evidence for assessing health care professional feedback preferences, we created an experimental design to elicit preferences that would expose participants, who were anesthesia providers, to contrasting message versions. To enable measurement validity assessment, we developed performance scenarios in which the same motivating performance information and display characteristics could be repeated in contrasting messages.

Ethical Considerations

This study was approved by the University of Michigan Health Sciences and Behavioral Sciences Institutional Review Board (IRB-HSBS HUM00167426). All participants provided consent to participate and were informed about the ability to opt out of the study. No participant identifiers were collected with the research data for this study, preventing the linking of participants’ responses with their identities. No incentives for participation were provided. We offered participants an opportunity to receive a copy of the study results upon completion.

Email Test Set Development

We developed the email message test set iteratively in three phases: (1) knowledge modeling, (2) display format development, and (3) message set development (Figure 1).
Phase 1: Knowledge Modeling

In the first phase we modeled knowledge about the elements of performance information, types of motivating information, and the influence of motivating performance information (Figure 1). We iteratively refined a model of the elements of performance information through an analysis of published feedback reports [20], resulting in the identification of 5 key elements: measures, recipients, comparators, performance levels, and time intervals. We developed a model of motivating information that combined the 5 elements of performance information into types of motivating information, including comparisons, trends, achievement, and loss. Each type of motivating information was defined using the elements of performance information. For example, a comparison (a kind of motivating performance information) was defined as a discrepancy between the performance levels of a feedback recipient and a comparator.

Through modeling types of motivating performance information, we recognized that the choice of comparator could affect which type of motivation was used to influence a recipient. For example, choosing a 90th-percentile peer benchmark as a comparator does not necessarily leverage motivation from goal-setting when recipients do not form an intention to reach the benchmark as their personal goal. By inviting anesthesia providers to set goals, feedback that shows performance improving toward a goal may leverage motivation arising from a desire for growth and achievement, rather than a desire for...
safety and avoidance of harm. These sources of motivation can differentially interact with the feedback sign (ie, valence) to have counterintuitive effects, such as goal abandonment, relaxation, or the delivery of low-value feedback [2,10].

To understand how different types of motivating performance information might relate to theoretical mechanisms of influence, we created causal pathway models [37] for each type of motivating information with benchmark and explicit target comparators (Multimedia Appendix 1). For example, in one causal pathway we modeled the expected influence of a feedback intervention that combines three elements of a recipient’s performance: (1) performance below a comparator (low performance level), (2) a benchmark (such as a peer average), and (3) performance getting better (improving trend). This pathway could represent the influence of precision feedback emails that show performance approaching a peer average, which could indicate to recipients that efforts to improve performance appear to be succeeding. Based on the theoretical construct of positive velocity [31] (ie, showing performance improvement), this causal pathway (which we named social approach due to the recipient reducing a performance gap with a peer benchmark) uses motivation as a mechanism of action, through which a feedback recipient may decide to increase or sustain effort to improve performance.

We drafted and refined example messages for each type of motivating information. For the causal pathway social approach, an example message is “Your performance is approaching the benchmark.” We implemented the causal pathway models in computer-interpretable form in a knowledge base to enable automation of the processing of performance information to identify motivating information in a precision feedback system.

Phase 2: Display Format Development

In the second phase we developed display formats for motivating information in the body of an email message. We selected visualizations (ie, bar charts and line charts) common in health care organizations so that a familiar format would convey the minimal amount of information necessary for each causal pathway. We developed software to generate visualizations within an email message using R (version 4.3.3; R Foundation for Statistical Computing). We included the absence of a visualization (ie, text only) to accommodate recipient preferences for concise, text-based communication (Figure 1).

Phase 3: Message Set Development

In the third and final phase we created a test set of email messages with balanced characteristics of motivating information and display formats. We began by creating four performance scenarios with alternate performance levels (high vs low) and trends (improvement vs worsening vs stable): (1) improvement to a high level, (2) worsening to a low level, (3) consistently high (stable) performance, and (4) consistently low (stable) performance (Table 2). In all scenarios, the recipient’s performance could be compared with either the peer average (benchmark comparator) or an organizational goal (explicit target comparator). We set the recipient’s performance level to have the same relationship with each comparator (better or worse), enabling either comparator to be displayed while maintaining balance with other elements.
We selected types of motivating information and their example messages across three characteristics: (1) performance temporality (time series vs time point), (2) performance comparison basis (benchmark vs explicit target), and (3) performance display format (bar chart or other). We selected the bar chart format as a key display format because of its common use in health care organizations. We further divided the other display format into line chart and text only. We composed emails with example messages from each type, based on a single quality measure (Avoiding postoperative nausea and vomiting [PONV-03]) for anesthesia providers. The resulting emails contained information from the same performance scenarios, but not all information from each scenario was provided in each message. For example, of the 4 emails that each participant read in each scenario, 2 messages contained a

<table>
<thead>
<tr>
<th>Performance data scenario</th>
<th>Motivating information characteristics</th>
<th>Key message</th>
<th>Display format</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Performance description</td>
<td>Temporality</td>
<td>Comparator</td>
</tr>
<tr>
<td>High</td>
<td>Improving</td>
<td>Time series</td>
<td>Benchmark</td>
</tr>
<tr>
<td></td>
<td>Performance level moves above comparators</td>
<td>Benchmark</td>
<td>You have become a top performer</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Explicit target</td>
<td>You reached the goal</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Time point</td>
<td>Benchmark</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Benchmark</td>
<td>You are a top performer</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Explicit target</td>
<td>Congratulations on your high performance</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Time point</td>
<td>Benchmark</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Benchmark</td>
<td>You are not a top performer</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Explicit target</td>
<td>You may have an opportunity to improve</td>
</tr>
<tr>
<td>Low</td>
<td>Worsening</td>
<td>Time series</td>
<td>Benchmark</td>
</tr>
<tr>
<td></td>
<td>Performance level moves below comparators</td>
<td>Benchmark</td>
<td>You are no longer a top performer</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Explicit target</td>
<td>Your performance dropped below the goal</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Time point</td>
<td>Benchmark</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Benchmark</td>
<td>You are not a top performer</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Explicit target</td>
<td>You may have an opportunity to improve</td>
</tr>
<tr>
<td>High</td>
<td>No change</td>
<td>Time series</td>
<td>Benchmark</td>
</tr>
<tr>
<td></td>
<td>Performance level is consistently above comparators</td>
<td>Benchmark</td>
<td>You are a consistent top performer</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Explicit target</td>
<td>Your performance is consistently high</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Time point</td>
<td>Benchmark</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Benchmark</td>
<td>You are a top performer</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Explicit target</td>
<td>Congratulations on your high performance</td>
</tr>
<tr>
<td>Low</td>
<td>No change</td>
<td>Time series</td>
<td>Benchmark</td>
</tr>
<tr>
<td></td>
<td>Performance level is consistently below comparators</td>
<td>Benchmark</td>
<td>Your performance has remained low</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Explicit target</td>
<td>Your performance has not improved</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Time point</td>
<td>Benchmark</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Benchmark</td>
<td>You are not a top performer</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Explicit target</td>
<td>You may have an opportunity to improve</td>
</tr>
</tbody>
</table>

We selected types of motivating information and their example messages across three characteristics: (1) performance temporality (time series vs time point), (2) performance comparison basis (benchmark vs explicit target), and (3) performance display format (bar chart or other). We selected the bar chart format as a key display format because of its common use in health care organizations. We further divided the other display format into line chart and text only. We composed emails with example messages from each type, based on a single quality measure (Avoiding postoperative nausea and vomiting [PONV-03]) for anesthesia providers. The resulting emails contained information from the same performance scenarios, but not all information from each scenario was provided in each message. For example, of the 4 emails that each participant read in each scenario, 2 messages contained a
goal comparator (explicit target), while the other 2 messages showed a peer benchmark comparator instead.

Study Design
We designed a within-subjects, repeated measures study of anesthesia provider preferences for precision feedback using a test set of prototype email messages printed on paper. We created 2 versions of the test set with alternate display formats for each message (group A vs group B) to enable randomization of the pairing of display format with motivating information. We created a document containing all of the email messages in the test set (Multimedia Appendix 2). We printed paper copies of the messages and organized them into packets in varying order for a paper card selection task. Based on our experience, we estimated that a sample of more than 30 participants would provide adequate power to detect meaningful differences in summary statistics and internal consistency of preferences.

Population and Setting
We recruited anesthesia providers from a single academic medical center in the midwestern United States. Anesthesiologists (physicians) and certified registered nurse anesthetists (CRNAs) were eligible to participate. A member of the study team recruited anesthesia provider participants by email. All participants received monthly anesthesia provider feedback emails from MPOG.

Data Collection
Upon enrollment, we scheduled a 15-minute proctored video call with each participant and sent them a paper packet with email prototypes before the call. Participants were randomized to receive a paper packet of messages from either group A or group B of the message test set, each of which contained 16 email messages grouped in 4 packets of 4. Each packet of 4 messages contained alternate message formats for 1 of 4 performance scenarios, with balanced message formats and performance information across the 4 scenarios. We created a questionnaire to collect data from participants about their preferred emails using Qualtrics (Qualtrics, Inc). We created 2 versions of the questionnaire (A and B), 1 for each message group to be used based on the participant’s random assignment at the time of enrollment. At the time of enrollment, we also instructed participants to have a desk space or table available for placing printed email messages in front of them, and to wait to open the packets until asked to do so during the video call.

Preference Elicitation and Message Usability Assessment
At the start of the proctored video call, a research team member introduced the study, confirmed the participant’s preparation, and provided a link to the questionnaire. During the completion of the questionnaire, the participant repeated a preferred email message selection task 4 times, following the instructions in their packet, once for each performance data scenario. The questionnaire software randomized the scenario presentation order. We described the scenarios as hypothetical performances that the participant could imagine as being their own. At the start of each scenario, participants were asked to find the corresponding set of emails, identified with a cover sheet. Participants were then asked to lay out all 4 of the printed email messages for that scenario in front of them. Next, participants read each message and selected their preferred message. After selecting a preferred message, participants responded to the following statement: “I gained information from this email that would benefit my practice.” We adapted this question from an instrument with good validity evidence for assessing the usability of feedback displays [39]. Responses were collected on a 5-point Likert scale, ranging from strongly disagree to strongly agree. The survey questions did not ask directly about preference for information content or display format. Instead, participants’ preferences were inferred through the types of content and display format that the selected message contained. After participants completed the questionnaire, we conducted brief interviews and collected qualitative data that were analyzed separately and will be reported elsewhere.

Analysis
To identify preferences, we analyzed 2 characteristics of the selected messages: motivating information (including temporality type and comparator type) and display format. We summed the selected messages with each type of motivating information and display format and calculated descriptive statistics for these sums (Q1). To investigate the consistency of participants’ preferences, we calculated the Cronbach α for each preference characteristic in participants’ selected messages across the 4 performance scenarios (Q2). We used descriptive statistics to assess relationships between participants’ preferences and the characteristics of the 4 performance scenarios, including performance level (high vs low) and trend presence (present vs absent). Similarly, we considered relationships between participants’ preferences and their professional background using descriptive statistics (Q3).

To understand participants’ perceptions of the potential benefit of precision feedback to their clinical practice, we analyzed ratings of perceived benefit for selected messages using descriptive statistics (Q4). We conducted analyses using R and Google Sheets (Google LLC).

Results
We recruited 35 anesthesia providers, including 18 anesthesiologists and 17 CRNAs (Table 3). All participants completed all message selection tasks, resulting in the selection of 140 preferred precision feedback messages.
To What Extent Do Anesthesia Providers’ Selected Messages Reveal an Overall Preference for Temporality (Q1a), Basis of Comparison (Q1b), and Display Format (Q1c)?

An overall preference for multiple time intervals (ie, time series) was apparent, with 110 of 140 (79%) messages being selected over those with a single time interval (ie, time point) (Q1a).

Preferences for display format were highly varied, with selected messages being equally distributed between bar charts versus other formats (Table 4) (Q1c). Preferred messages were also highly varied in their comparators, with 74 of 140 (53%) preferred cards containing explicit target comparators (ie, organizational goals not dependent on population performance) (Q1b), but our assessment of the consistency suggests that the comparator result was not reliable as a preference characteristic (see Q2 below).

How Consistent Are Individual Anesthesia Provider Preferences (Q2)?

Participants’ preferences were consistent for temporality ($\alpha=.85$) and display format ($\alpha=.80$). For performance comparators, participants’ selected messages were negatively correlated ($\alpha=-.40$), indicating an absence of consistency, perhaps from an incorrect measurement model [40]. We consider this result to be an artifact of the study design, given that our message test set balanced several characteristics and created opportunities to select them in combination. We anticipate that comparators were not salient for participants, relative to the visual display and temporality characteristics; therefore, we are unable to draw conclusions about preferences for comparators.

To What Extent Do Anesthesia Provider Preferences Depend on Performance Level and Trend and Their Professional Background (Q3)?

Participant preferences for temporality and display format did not appear to depend on the messages’ performance level, with relatively similar means for the selection of each type of message content. Similarly, these preferences did not appear to vary with the presence or absence of performance trends (Table 5).
Table. Precision feedback preferences by performance scenario characteristics.

<table>
<thead>
<tr>
<th>Temporality preference, mean (SD)</th>
<th>Comparator preference, mean (SD)</th>
<th>Display format preference, mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time series</td>
<td>Time point</td>
<td>Benchmark</td>
</tr>
<tr>
<td>1.60 (0.69)</td>
<td>0.40 (0.69)</td>
<td>0.91 (0.56)</td>
</tr>
<tr>
<td>Level: high</td>
<td></td>
<td>0.94 (0.87)</td>
</tr>
<tr>
<td>1.06 (0.87)</td>
<td>0.77 (0.88)</td>
<td>0.29 (0.62)</td>
</tr>
<tr>
<td>Level: low</td>
<td></td>
<td>0.66 (0.84)</td>
</tr>
<tr>
<td>1.06 (0.87)</td>
<td>0.94 (0.87)</td>
<td>0.29 (0.62)</td>
</tr>
<tr>
<td>Trend present</td>
<td></td>
<td>0.60 (0.84)</td>
</tr>
<tr>
<td>1.09 (0.89)</td>
<td>0.91 (0.89)</td>
<td>0.23 (0.60)</td>
</tr>
<tr>
<td>Trend absent</td>
<td></td>
<td>0.74 (0.85)</td>
</tr>
<tr>
<td>1.09 (0.85)</td>
<td>0.74 (0.85)</td>
<td>0.34 (0.64)</td>
</tr>
</tbody>
</table>

Preferences for temporality and display format varied with participants’ professional background (Table 6). Some professional role-based differences in means were apparent, such as a higher preference for time point messages among CRNAs than anesthesiologists (mean message characteristics preference 1.18, SD 1.59 vs mean message characteristic preference 0.56, SD 1.10). However, a majority of CRNAs preferred time series messages, and all message characteristics were repeatedly observed in selections by participants from both professional background–based groups.

Table. Precision feedback preferences by professional background.

<table>
<thead>
<tr>
<th>Temporality preference, mean (SD)</th>
<th>Comparator preference, mean (SD)</th>
<th>Display format preference, mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time series</td>
<td>Time point</td>
<td>Benchmark</td>
</tr>
<tr>
<td>3.44 (1.10)</td>
<td>0.56 (1.10)</td>
<td>1.83 (0.79)</td>
</tr>
<tr>
<td>Anesthesiologist</td>
<td></td>
<td>2.17 (0.79)</td>
</tr>
<tr>
<td>2.28 (1.60)</td>
<td>1.72 (1.60)</td>
<td>1.33 (1.68)</td>
</tr>
<tr>
<td>Certified registered nurse anesthetist</td>
<td></td>
<td>0.39 (0.78)</td>
</tr>
<tr>
<td>2.82 (1.59)</td>
<td>1.18 (1.59)</td>
<td>1.94 (0.97)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.06 (0.97)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.71 (1.61)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2.29 (1.61)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.53 (1.55)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.76 (1.48)</td>
</tr>
</tbody>
</table>

To What Extent Are Preferred Feedback Messages Perceived to Hold Potential to Improve Future Clinical Practice (Q4)?

Participants’ ratings of perceived benefit from all precision feedback messages were positive, with a mean rating of 4.27 (SD 0.77). Although positive overall, the anesthesiologists’ ratings were lower than the CRNAs’ ratings (mean rating 4.08, SD 0.85 vs mean rating 4.47, SD 0.61). Ratings for messages did not appear to vary across performance levels or with trends (Table 7). Average ratings of perceived benefit were similar across message content characteristics. One exception to this was for explicit target comparators, which appeared to receive slightly higher ratings (mean rating 4.38, SD 0.7) over benchmark comparators (mean rating 4.15, SD 0.83).
**Table.** Perceived benefit of selected messages.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Mean rating (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Participant professional background</strong></td>
<td></td>
</tr>
<tr>
<td>Anesthesiologist</td>
<td>4.08 (0.85)</td>
</tr>
<tr>
<td>Certified registered nurse anesthetist</td>
<td>4.47 (0.61)</td>
</tr>
<tr>
<td><strong>Performance scenario</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Performance level</strong></td>
<td></td>
</tr>
<tr>
<td>High performance</td>
<td>4.23 (0.76)</td>
</tr>
<tr>
<td>Low performance</td>
<td>4.31 (0.77)</td>
</tr>
<tr>
<td><strong>Performance trend</strong></td>
<td></td>
</tr>
<tr>
<td>Trend present</td>
<td>4.34 (0.72)</td>
</tr>
<tr>
<td>Trend absent</td>
<td>4.2 (0.81)</td>
</tr>
<tr>
<td><strong>Message content</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Temporality</strong></td>
<td></td>
</tr>
<tr>
<td>Time series</td>
<td>4.27 (0.81)</td>
</tr>
<tr>
<td>Time point</td>
<td>4.27 (0.58)</td>
</tr>
<tr>
<td><strong>Comparator</strong></td>
<td></td>
</tr>
<tr>
<td>Benchmark</td>
<td>4.15 (0.83)</td>
</tr>
<tr>
<td>Explicit target</td>
<td>4.38 (0.7)</td>
</tr>
<tr>
<td><strong>Display format</strong></td>
<td></td>
</tr>
<tr>
<td>Bar chart</td>
<td>4.27 (0.76)</td>
</tr>
<tr>
<td>Other display</td>
<td>4.27 (0.78)</td>
</tr>
<tr>
<td>Other display: Line chart</td>
<td>4.28 (0.83)</td>
</tr>
<tr>
<td>Other display: text only</td>
<td>4.25 (0.64)</td>
</tr>
</tbody>
</table>

**Discussion**

**Principal Results**

In this study, we found that anesthesia provider preferences for motivating information and display format varied, which suggests that individual difference characteristics may represent a barrier to improving the effectiveness of feedback interventions. Across a set of 4 diverse performance scenarios, we observed preference variability that precision feedback could better address than one-size-fits-most feedback in this anesthesia provider population.

We observed consistency in participant preferences for the temporality of motivating information and for display format. Even though a large majority of participants preferred messages with time-series information, the participants who preferred time-point messages reliably selected them. The consistency of preferences for display format was similar, and also more varied, with exactly half of participants choosing bar charts over other visual displays. We also did not observe differences in preferences associated with performance scenario characteristics or professional background that could be used to design one-size-fits-most feedback interventions.

While participants exhibited diverse preferences, their ratings of the benefit of the messages were consistently high across performance scenarios. These findings suggest that anesthesia providers would welcome the enhancement of feedback interventions with precision feedback that prioritizes motivating information. These findings are important because they point to a possible approach for improving audit and feedback that can leverage both high and low performance, as well as increasing or decreasing trends, to prioritize performance feedback.

To our knowledge, this is the first quantitative study of preferences for clinical performance feedback. As an exploratory study, the findings primarily demonstrate the existence of differences in preferences for feedback, rather than speaking to the significance of their role in the success of clinical performance feedback. Our findings are related to CP-FIT, which recognizes that health professional knowledge and skills for engaging with feedback can be important factors for the success of feedback [38]. Differences in feedback preferences could be driven by differences in health care professionals’ knowledge and skills related to the interpretation of performance data. For example, participants’ variable and consistent selection of messages could be related to their graph literacy skills [41,42]. Precision feedback could be used to accommodate these and other individual differences by enabling health professionals to configure their feedback delivery and display, which further holds potential to increase feelings of ownership of feedback.
By prioritizing motivating information according to recipients’ preferences, precision feedback could be a strategy for reducing the cognitive load required by health professionals to recognize and assess the priority of learning opportunities. Precision feedback has also potential to improve feedback cycle completion by delivering information that is more likely to be perceived and accepted, resulting in increased formation of intentions to sustain or improve performance. In terms of CP-FIT, precision feedback can be understood as an approach for prioritization of feedback messages that are more likely to result in successful completion of the feedback cycle.

Our findings are aligned with the idea that positive feedback can be effective for learning and improvement [13], as well as sustainment of high performance. It is noteworthy that participants rated precision feedback messages as beneficial even when performance was high, such as the messages “you are a top performer” or “you reached the goal.” This finding points to the possibility that a key function of feedback may be to motivate recipients through appreciation of accomplishments [43], including recognition of high performance, in addition to motivating recipients to learn to improve.

Limitations
As an exploratory study for a novel type of feedback intervention, there are several important limitations for this study. The poor consistency of preferences demonstrated for performance comparators suggests that participants did not meaningfully differentiate between peer-based benchmarks and explicit targets, as presented in the message test set. This may be a function of the labels used for the comparators message test set, and during the study we discovered that some of the printed messages contained the abbreviation “ave” instead of “avg” for the peer average comparator. Competing explanations are that (1) anesthesia providers equated the value of both comparator types or did not perceive them as fundamentally different, and (2) that this characteristic was less salient than the others, such that its significance was negligible.

Using performance scenarios based on synthetic performance data may have introduced bias in participants’ responses. However, the consistency of participant preferences for temporality of motivating information and display format suggests that this bias was not significant. Nevertheless, our study design assessed preferences within types of motivating information (eg, high and improving performance or low and worsening performance) that were presented with unambiguous motivating information, such as trends showing marked improvement or worsening. As such, our results do not address the appropriateness of using performance scenarios to elicit the strength of anesthesia provider preferences directly; rather, they primarily demonstrate the existence of individual differences as an exploration of factors that may moderate the influence of feedback on health care professional learning and improvement.

We asked participants to rate the perceived benefit of messages that they had already selected as their preferred message, which may have resulted in positively biased ratings. Furthermore, we used a single performance measure for all messages (avoiding postoperative nausea and vomiting) that may not be representative of other performance measures, both in terms of perceived benefit and preferences for motivating information. We did not evaluate feedback about clinical outcome measures, which may have resulted in a different preference profile across this population. We also did not evaluate participants’ skills or knowledge to engage effectively in feedback, which is a recognized factor [38] that may have resulted in further insight into participant preferences.

Additional limitations include the context and nature of the preference elicitation task, which was done in a video call with paper prototypes and thus differed from the context of email use in health care organizations. When designing this study, we chose to use email messages printed on paper because we could not identify a remote, video call–proctored approach that would allow participants to consider 4 different messages types in the same field of view on their personal or work computer without a risk of technical complications from participants’ particular computer monitor and device configurations.

Our model of preferences in this study was linear and static and assumed that available information was complete, but anesthesia provider preferences may be nonlinear, dynamic, and depend on missing information that we did not consider. When designing the test set of messages, we paired the text-only display format consistently with time-point information, and line charts with the time-series format. As such, preferences for line charts and text-only display formats were not independent from temporality. We recruited anesthesia providers from a single academic institution whose population is not necessarily representative of other anesthesia provider populations. We did not recruit any anesthesia providers who identified as Black or Hispanic, increasing the likelihood that our results are racially and ethnically biased toward the perspectives of anesthesia providers who identify as White and non-Hispanic. In spite of all of these limitations, we note that the variability that we observed demonstrates that preferences were nonuniform in this small population, which suggests that a one-size-fits-all solution may be inadequate for feedback reporting to anesthesia providers more generally.

Future Studies
We anticipate that preference clusters may exist and may be identifiable in studies that are better powered to detect such differences. Such clusters could be used to develop profiles for precision feedback, such as profiles for anesthesia providers who prefer text-only messages about low performance or those who prefer visualization of performance changes (ie, trends) using time-series displays in line charts. Future studies may be able to detect preference clusters to better understand the diversity of preferences for performance feedback across a larger anesthesia provider population that is more racially, ethnically, and geographically diverse. Furthermore, we would welcome studies that aim to better understand the diversity of anesthesia provider preferences in association with additional anesthesia provider characteristics, such as duration of professional experience, clinical setting, and organization type.

Conclusions
Clinical performance feedback to health care professionals has potential to support continuous learning and influence practice,
but this potential is frequently not achieved. By prioritizing motivating performance information based on the preferences and needs identified for a healthcare professional population, precision feedback may increase the effectiveness of clinical performance feedback for healthcare professionals’ continuous learning and resulting quality improvement. Among a sample of anesthesia providers, preferences for precision feedback were varied, yet consistent within participants. Furthermore, participants’ perceived benefits of precision feedback messages were observed to be high across a diverse set of performance scenarios. Based on these findings, it appears that precision feedback holds potential to improve support for healthcare professionals’ continuous learning.

Acknowledgments
The authors would like to thank Ms Astrid Fishstrom for contributing to the investigation. We are grateful to Dr Anne Sales, Dr John Rincón-Hekking, Ms Dahee Lee, Mr Cooper Stansbury, and Ms Veena Panicker for their contributions to foundational work for this study. We thank the NIH (National Institutes of Health) National Library of Medicine for funding this research. This study was funded by a grant from the NIH National Library of Medicine (K01LM012528; principal investigator ZLL) paid to the University of Michigan.

Data Availability
Data collected without identifiers are included as a supplementary file (Multimedia Appendix 3).

Authors’ Contributions
ZLL and CPF conceptualized this study. ZLL and NJS contributed to the investigation. Formal analysis of the study was conducted by ZLL, CPF, and CAA. ZLL, NJS, CAG, and CPF contributed to the methodology. CAG developed the software for this study. ZLL and CAG developed the visualizations. ZLL wrote the original draft, and ZLL, CAA, CAG, CPF, and NJS contributed to the review and editing. No generative artificial intelligence was used in any portion of the manuscript writing.

Conflicts of Interest
ZLL has received research support paid to the University of Michigan and related to this work from the National Library of Medicine (K01LM012528; R01 LM013894). NJS has received research support paid to University of Michigan and unrelated to this work from Merck & Co. NJS received support paid to the University of Michigan for his role as program director of the Anesthesiology Performance Improvement and Reporting Exchange (ASPIRE) Collaborative Quality Initiative, and has received research support from Edwards Lifesciences, Apple Inc, and the National Institute on Aging (R01 AG059607) paid to the University of Michigan and unrelated to this work.

Multimedia Appendix 1
Causal pathway models for precision feedback interventions.
[PDF File, 51 KB - mededu_v10i1e54071_app1.pdf ]

Multimedia Appendix 2
Test set of precision feedback emails.
[PDF File, 1400 KB - mededu_v10i1e54071_app2.pdf ]

Multimedia Appendix 3
Study data.
[XLSX File, 61 KB - mededu_v10i1e54071_app3.xlsx ]

Checklist 1
STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) statement.
[PDF File, 104 KB - mededu_v10i1e54071_app4.pdf ]

References


19. Landis-Lewis et al. JMIR MEDICAL EDUCATION -2016-018


Abbreviations

ABC: achievable benchmark of care
CP-FIT: Clinical Performance Feedback Intervention Theory
CRNA: certified registered nurse anesthetist
MPOG: Multicenter Perioperative Outcomes Group

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Exploring the Performance of ChatGPT Versions 3.5, 4, and 4 With Vision in the Chilean Medical Licensing Examination: Observational Study

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Abstract

Background: The deployment of OpenAI’s ChatGPT-3.5 and its subsequent versions, ChatGPT-4 and ChatGPT-4 With Vision (4V; also known as “GPT-4 Turbo With Vision”), has notably influenced the medical field. Having demonstrated remarkable performance in medical examinations globally, these models show potential for educational applications. However, their effectiveness in non-English contexts, particularly in Chile’s medical licensing examinations—a critical step for medical practitioners in Chile—is less explored. This gap highlights the need to evaluate ChatGPT’s adaptability to diverse linguistic and cultural contexts.

Objective: This study aims to evaluate the performance of ChatGPT versions 3.5, 4, and 4V in the EUNACOM (Examen Único Nacional de Conocimientos de Medicina), a major medical examination in Chile.

Methods: Three official practice drills (540 questions) from the University of Chile, mirroring the EUNACOM’s structure and difficulty, were used to test ChatGPT versions 3.5, 4, and 4V. The 3 ChatGPT versions were provided 3 attempts for each drill. Responses to questions during each attempt were systematically categorized and analyzed to assess their accuracy rate.

Results: All versions of ChatGPT passed the EUNACOM drills. Specifically, versions 4 and 4V outperformed version 3.5, achieving average accuracy rates of 79.32% and 78.83%, respectively, compared to 57.53% for version 3.5 ($P<.001$). Version 4V, however, did not outperform version 4 ($P=.73$), despite the additional visual capabilities. We also evaluated ChatGPT’s performance in different medical areas of the EUNACOM and found that versions 4 and 4V consistently outperformed version 3.5. Across the different medical areas, version 3.5 displayed the highest accuracy in psychiatry (69.84%), while versions 4 and 4V achieved the highest accuracy in surgery (90.00% and 86.11%, respectively). Versions 3.5 and 4 had the lowest performance in internal medicine (52.74% and 75.62%, respectively), while version 4V had the lowest performance in public health (74.07%).

Conclusions: This study reveals ChatGPT’s ability to pass the EUNACOM, with distinct proficiencies across versions 3.5, 4, and 4V. Notably, advancements in artificial intelligence (AI) have not significantly led to enhancements in performance on image-based questions. The variations in proficiency across medical fields suggest the need for more nuanced AI training. Additionally, the study underscores the importance of exploring innovative approaches to using AI to augment human cognition and enhance the learning process. Such advancements have the potential to significantly influence medical education, fostering not only knowledge acquisition but also the development of critical thinking and problem-solving skills among health care professionals.

(JMIR Med Educ 2024;10:e55048) doi:10.2196/55048

KEYWORDS
artificial intelligence; AI; generative artificial intelligence; medical education; ChatGPT; EUNACOM; medical licensure; medical license; medical licensing exam

Introduction

The launch of OpenAI’s ChatGPT-3.5 in November 2022 has impacted various fields, including medical education [1]. On September 25, 2023, OpenAI announced the release of a highly anticipated new functionality, ChatGPT-4 With Vision (4V; also known as “GPT-4 Turbo With Vision”), to support multimodal interaction and further exploration [2]. ChatGPT has shown promise, or some would argue that it is a threat, for medical education with its outstanding performance in several medical examinations. For example, in the Médicos Internos Residentes examination in Spain [3], ChatGPT
answered 51.4% of the questions correctly [3]. In the United States, different studies have reported an accuracy of 80%-90% on the United States Medical Licensing Examination [4]. These results highlight ChatGPT’s potential to impact the future of medical education. However, there is a limited understanding of ChatGPT’s performance in non-English examinations in Latin America, such as Chile’s EUNACOM (Examen Único Nacional de Conocimientos de Medicina).

The EUNACOM comprises 180 multiple-choice questions from various medical areas such as internal medicine, pediatrics, obstetrics and gynecology, surgery (general surgery and anesthesia, traumatology, and urology), psychiatry, specialties (including dermatology, ophthalmology, and otorhinolaryngology), and public health. The examination assesses topics such as diagnosis, treatment, and follow-up care. Passing the EUNACOM is vital for foreign-trained doctors to practice in Chile and for Chilean medical students to complete their studies and transition to medical practice [5]. This examination, central to Chilean medical education, can potentially pose linguistic, cultural, and contextual challenges to ChatGPT. This study aimed to evaluate the performance of ChatGPT versions 3.5, 4, and the recently released 4V on EUNACOM practice drills, with the intent to guide future improvements—specifically, the integration and use of artificial intelligence (AI) in medical education—across various cultural and linguistic contexts, thereby contributing to the ongoing debate on the role and efficacy of AI as an educational tool in the global medical community.

**Methods**

**Study Design**

We adopted a quantitative, descriptive, cross-sectional approach to evaluate ChatGPT’s performance in the EUNACOM practice drills. We gathered a data set of EUNACOM practice questions, categorized them, and analyzed the responses of ChatGPT versions 3.5, 4, and 4V.

**EUNACOM Data Set**

It is challenging to obtain an authentic and representative set of questions from the EUNACOM, as the examination is not publicly accessible for integrity and security reasons. Therefore, we used 3 official practice drills designed by the University of Chile as preparatory material for its students. These drills are not included in the data used to train ChatGPT due to their limited public availability. Each drill consists of 180 multiple-choice questions with 5 options, where only 1 is correct. The number of questions across medical areas in each drill reflects the specifications of the EUNACOM’s administrative office (ie, internal medicine, n=67; pediatrics, n=29; obstetrics and gynecology, n=29; surgery, n=20; psychiatry, n=14; specialties, n=12; and public health, n=9).

**Classification of Questions**

The categorization of EUNACOM’s questions in this study is in line with that of Carrasco et al [3] in 2023 on the Médicos Internos Residentes examination in Spain. Two of our research team members classified the questions as follows:

1. **Medical area** according to the EUNACOM: internal medicine, pediatrics, obstetrics and gynecology, surgery, psychiatry, specialties, and public health.
2. **Category of questions**: “clinical case” if they presented a clinical case in the stem of the question, or “medical knowledge” if the question asked for the retrieval of knowledge of medical content.
3. **Type of question** in clinical case questions: diagnosis, treatment, or follow-up.

**Prompting and Application of ChatGPT**

We used ChatGPT versions 3.5, 4, and 4V, trained up to January 2022, to respond to the 3 EUNACOM drills in October 2023. Each drill was conducted 3 times with each version of ChatGPT using the prompt, “Which is the correct answer to the following questions?” We excluded “EUNACOM” from the prompt to guarantee ChatGPT’s responsiveness to the questions, since, according to OpenAI’s policies, the model abstains from taking official assessments. When using version 4V, we prompted questions with images (eg, x-ray) individually, attaching the image to its corresponding question.

The 3 attempts at providing responses in each drill allowed us to address the variability in ChatGPT’s answers, attributable to its probabilistic nature, by estimating an average performance.

**Data Analysis**

Data analysis was conducted using Stata (version 16.0; StataCorp). We computed the percentage of correct responses for each drill and set the passing score at >51% in accordance with the EUNACOM standard [6]. We used a 2-sample test of proportions to test for differences in performance among different versions of ChatGPT [7].

**Ethical Considerations**

The Human Research Ethics Committee of the Faculty of Medicine at the University of Chile determined that this study presented no ethical concerns that warranted institutional review board oversight. We used EUNACOM drills authorized by the University of Chile’s School of Medicine because access to the actual examination is restricted.

**Results**

The three versions of ChatGPT successfully passed EUNACOM drills on average. Notably, version 4 exhibited superior performance to that of version 3.5 across all drills and attempts, while version 4V did not show a statistically significant advantage over version 4. The only instance of not passing the EUNACOM was observed with version 3.5, specifically during its third attempt at drill 2. Detailed performance metrics for each drill and attempt are provided in Table 1. To assess the robustness of our results, we also compared the performance of ChatGPT by each attempt and by each drill. The results are qualitatively similar.
Table. Correct answers of ChatGPT versions 3.5, 4, and 4 With Vision on each of the EUNACOM\textsuperscript{a} drills (each with 180 multiple-choice questions) per attempt.

<table>
<thead>
<tr>
<th>EUNACOM drill and attempt</th>
<th>Correct answers provided by each version of ChatGPT, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3.5\textsuperscript{b}</td>
</tr>
<tr>
<td>Drill 1</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>105 (58.33)</td>
</tr>
<tr>
<td>2</td>
<td>109 (60.56)</td>
</tr>
<tr>
<td>3</td>
<td>103 (57.22)</td>
</tr>
<tr>
<td>Drill 2</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>93 (51.67)</td>
</tr>
<tr>
<td>2</td>
<td>94 (52.22)</td>
</tr>
<tr>
<td>3</td>
<td>86 (47.78)\textsuperscript{e}</td>
</tr>
<tr>
<td>Drill 3</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>112 (62.22)</td>
</tr>
<tr>
<td>2</td>
<td>114 (63.33)</td>
</tr>
<tr>
<td>3</td>
<td>116 (64.44)</td>
</tr>
</tbody>
</table>

\textsuperscript{a}EUNACOM: Examen Único Nacional de Conocimientos de Medicina.
\textsuperscript{b}Mean accuracy rate 57.53\% (95\% CI 55.12\%-59.94\%).
\textsuperscript{c}Mean accuracy rate 79.32\% (95\% CI 77.35\%-81.29\%); $z_{3.5 \text{ vs } 4} = -13.34$, $P < .001$ (2-sample test of proportions).
\textsuperscript{d}Mean accuracy rate 78.83\% (95\% CI 76.84\%-80.82\%); $z_{4 \text{ vs } 4V} = 0.35$, $P = .73$ (2-sample test of proportions).
\textsuperscript{e}This is the only instance of not passing the EUNACOM practice drill.

Across all attempts and the 3 practice drills, we observed a variation in average accuracy rates by both medical area and clinical case question type. In an evaluation across various medical areas, all 3 ChatGPT versions demonstrated distinct high and low performances. For version 3.5, the highest accuracy was observed in psychiatry (average 69.84\%), while the lowest accuracy rate was observed in internal medicine (average 52.74\%). Version 4 excelled in surgery with a 90.00\% average accuracy rate, whereas its weakest performance was observed in internal medicine (average 75.62\%). Similarly, version 4V’s performance was strongest in surgery (average 86.11\%) and weakest in public health (average 74.07\%). When analyzing performance across different medical areas, ChatGPT-3.5 had the highest accuracy in psychiatry (average 69.84\%), while the lowest accuracy rate was observed in internal medicine (average 52.74\%). ChatGPT-4 excelled in surgery with a 90.00\% average accuracy rate, whereas its weakest performance was observed in internal medicine (average 75.62\%). Similarly, version 4V’s performance was strongest in surgery (average 86.11\%) and weakest in public health (average 74.07\%). When analyzing performance across different medical areas, ChatGPT-4 consistently outperformed ChatGPT-3.5. However, ChatGPT-4V did not significantly outperform ChatGPT-4.

The 3 drills included a total of 501 clinical case questions and 39 medical knowledge questions. In answering clinical case questions, the average accuracy rate of ChatGPT across the 3 attempts was as follows: 57.22\% for version 3.5, 80.11\% for version 4, and 79.71\% for version 4V. In answering medical knowledge questions, the average accuracy rate of ChatGPT was as follows: 61.54\% for version 3.5, 74.36\% for version 4, and 67.52\% for version 4V.

Among the clinical case questions, ChatGPT performed best in follow-up questions, with version 4 scoring 88.89\%, while the lowest performance was observed in treatment questions, with version 3.5 scoring 48.50\%. On analyzing performance over different types of clinical case questions, ChatGPT-4 regularly outperformed ChatGPT-3.5. Nonetheless, ChatGPT-4V showed no significant difference in performance compared to ChatGPT-4. Comprehensive data on average performances across all medical areas and types of clinical case questions are included in Multimedia Appendix 1.

The 3 drills had a total of 50 questions with images; therein, ChatGPT-4 had an average accuracy rate of 70.67\% and version 4V had an average accuracy rate of 70.00\% across the 3 attempts.

Discussion

Principal Findings

This study shows that ChatGPT successfully passed the EUNACOM, with version 4 showing a superior performance to that of version 3.5. However, interestingly, version 4V did not significantly outperform version 4 in this examination. All versions demonstrated proficiency in various medical specialties, with version 3.5 excelling in psychiatry and versions 4 and 4V in surgery. However, unexpectedly, version 4V did not outperform the other 2 versions in questions including images. The differences in performance among versions are likely due to continuous enhancements in training and knowledge with each update, which improve the models’ grasp of complex medical subjects. Nevertheless, varying success rates in specific medical fields could stem from the complexities of those specialties, unique terminologies, or the specific structure of the questions in those areas, which may align differently with the data the models were trained on.

In particular, when analyzing the question categories, all versions presented a lower accuracy rate in medical knowledge questions than in clinical case questions, indicating a possible...
gap in the models’ data regarding specific content knowledge. In clinical case questions, versions 4 and 4V consistently outperformed version 3.5, possibly due to the AI’s advancement in pattern recognition. Interestingly, each version performed differently across various types of questions in the clinical case category: version 3.5 showed a lower performance on treatment and follow-up questions, whereas versions 4 and 4V performed better on follow-up questions, suggesting an enhanced ability to handle dynamic, evolving clinical scenarios in later versions.

The modest enhancements in visual data interpretation from ChatGPT-4 to ChatGPT-4V indicate that improvements in later versions focused more on specific refinements rather than on broad upgrades to support image processing. This trend is evident in image-based questions, where version 4V did not outperform version 4 in questions including images. For example, while ChatGPT showed improved accuracy in interpreting electrocardiograms, its performance was less consistent with dermatological images. A striking instance was its misdiagnosis of a *Staphylococcus aureus* skin infection in a toddler, where ChatGPT incorrectly identified the condition as Molluscum contagiosum, erroneously attributing significance to an area of the image that was, in fact, the patient’s belly button. These variations underscore the intricate challenges AI faces in processing multimodal medical information and suggest that while ChatGPT’s textual understanding has advanced, its image processing requires further contextual depth and fine-tuning.

ChatGPT’s strong performance on medical licensing examinations from different parts of the world and in different languages demonstrates its adaptability and potential in medical education despite not being specifically designed for such specialized content [3,4,8-10]. However, its varying responses highlight the model’s limitations in handling the depth and variability of real-life medical expertise.

This study is one of the first to evaluate ChatGPT-4, including its vision-enhanced iteration, in medical licensing examinations, notably being the first to evaluate its performance in Chile’s EUNACOM. The multiple attempts per practice drill approach in our methodology is a significant strength of our study, facilitating a thorough examination of ChatGPT’s response consistency. Despite these strengths, the study has some limitations. The reliance on practice drills from the University of Chile may not encompass the full breadth of the EUNACOM’s questions, potentially narrowing the scope of our findings. The focus on specific versions of ChatGPT could also limit the generalizability of our results to other iterations of the model. Inherent biases in the AI’s training data pose another challenge, potentially affecting the accuracy of responses.

Future studies should expand AI evaluations in medical training by including diverse medical examinations and question types, assessing adaptability to various contexts. Exploring newer AI models and their performance in practical medical scenarios will also be crucial. This research will enhance the understanding of AI’s role in medicine, guiding its effective integration into health care education and practice.

The rise of generative AI in medicine, highlighted by tools such as ChatGPT and upcoming models such as Med-PaLM [11], signals a need to evolve medical education. While these tools provide extensive resources, the essence of medical practice extends beyond simple access to data, necessitating reflective and critical application of this knowledge. Therefore, medical curricula must prioritize critical thinking, enabling future practitioners to discern the quality and relevance of AI-generated information. Similarly, reflective practices are crucial, promoting continuous self-assessment and adaptation in a rapidly advancing technological landscape. As AI becomes integral, especially in diagnostics, professionals must merge AI insights with human-centric care, underscoring that medical expertise is not only about accessing information but also involves deep understanding and evaluation of that information, empathy, and ethical judgment.

**Conclusions**

In conclusion, this study shows the performance of ChatGPT versions 3.5, 4, and 4V in successfully passing the EUNACOM, underscoring the evolving role of AI in the field of medicine and its potential in medical education. Future studies should encompass a wider array of AI models and diverse question types, contributing to a deeper understanding of how AI can enhance medical education. Moreover, it is imperative to explore innovative directions in the application of AI, such as leveraging AI to augment human cognition and optimize the learning process. Embracing these possibilities can lead to a more profound impact on medical education, fostering not only knowledge acquisition but also critical thinking and problem-solving skills among future health care practitioners.

**Acknowledgments**

We thank the School of Medicine, University of Chile, for providing the EUNACOM (Examen Único Nacional de Conocimientos de Medicina) drills essential for this research. We would like to express our gratitude to Mridul Joshi for his invaluable assistance with the statistical analysis.

**Disclaimer**

This manuscript was prepared without the assistance of ChatGPT or similar artificial intelligence tools for writing, editing, or proofreading.
Conflicts of Interest
None declared.

Multimedia Appendix 1
Average accuracy rate per medical area and clinical case question type.
[DOCX File, 21 KB - mededu_v10i1e55048_app1.docx ]

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5. Fechas EUNACOM-ST de julio y cierre de inscripciones. EUNACOM. URL: https://www.eunacom.cl/home.html [accessed 2024-04-19]

Abbreviations
4V: ChatGPT-4 With Vision
AI: artificial intelligence
EUNACOM: Examen Único Nacional de Conocimientos de Medicina

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Abstract

Medical advice is key to the relationship between doctor and patient. The question I will address is “how may chatbots affect the interaction between patients and doctors in regards to medical advice?” I describe what lies ahead when using chatbots and identify questions galore for the daily work of doctors. I conclude with a gloomy outlook, expectations for the urgently needed ethical discourse, and a hope in relation to humans and machines.

(KEYWORDS: chatbot; ChatGPT; medical advice; ethics; patients; doctors)

Introduction

While I strive to provide accurate and helpful information, I am not a substitute for medical advice or professional judgment, and it’s always important for patients and healthcare providers to work together to develop a personalized treatment plan that takes into account a patient’s individual needs and circumstances. [ChatGPT, 2023]

Medical advice (MA) is key to the relationship between doctor and patient. The question I will address is “how may chatbots affect the interaction between patients and doctors in regards to medical advice?” To this end, I shall consider—and go beyond—what was recently outlined regarding MA in “A Conversation With ChatGPT” [1].

Advances in artificial intelligence (AI) and chatbots are changing the world, including medicine [2-4]. ChatGPT is a generative pretrained transformer model based on GPT-3 from OpenAI. Based on word correlations in its 175 billion-parameter database, ChatGPT floods us with meaningful but also nonsensical information.

Concerning the interaction between patients, doctors, and chatbots, I describe what lies ahead when using chatbots and identify many questions for the daily work of doctors. I conclude with a gloomy outlook, expectations for urgently needed ethical discourse [5,6], and a hope in relation to humans and machines [3,7].

Weighing ChatGPT’s Quote

How ChatGPT describes its role [1]—“I am not a substitute for medical advice”—should be a fact. Doctors, as the only authoritative providers of professional MA, must always be in the driver’s seat. Chatbots have the potential to help with the task of contributing general information to an information chain. Importantly, doctors need to review and question all AI output and see if and how it contributes to a patient’s understanding and fits within MA. Depending on the expectations and hopes that ChatGPT raises in patients, this task could become an unprecedented challenge.

With their up-to-date knowledge and medical experience and expertise, doctors need to integrate personal, specific, and general information into their comprehensive MA to the patients. Chatbots are limited to general information stored in databases. Concerningly, ChatGPT invents facts, called a hallucination in
AI [3]. Moreover, ChatGPT can produce nonsensical or “bullshit” [8] information, nicely worded and seemingly justified but disregarding truth and facts—disconcertingly, we do not readily know how often and when ChatGPT offers “bullshit” or nonsense responses.

The Daily Work of Doctors: Question Galore

Nevertheless, ChatGPT will be used by many simply because it is there and seemingly easy and, importantly, free to use.

Is it, therefore, likely that we can do without chatbots? No, because society will not abandon ChatGPT or other advanced chatbot tools [3]. The sooner we understand chatbot information for patients, the better. Realistically, ChatGPT is just the tip of an AI iceberg. The “Godfather of AI” [9] Hinton and OpenAI’s chief executive officer Altman [10] have warned forcefully about the speed, impact, and inevitability of AI developments.

Doctors routinely deal with both informed and misinformed patients, fuelled by online health searches (eg, “Dr Google” [11]). Indeed, the internet has become the starting point for many to ask questions about health, disrupting traditional doctor-patient relationships [12] and leading to potential harm from online misinformation [11]. Importantly, neither patients nor doctors should give away too much information when using AI. Even if MA could get better with more details, can we know if this information is being used beyond MA? Indeed, to what extent may creating MA be used as an AI Trojan horse to extract information for other purposes, including business benefits? Which biases go into AI-based medical information, for instance, through training data that neither represent the ethnicity nor the financial options of diverse patients? That medically advanced AI may become expensive raises questions of equity: who will have access to these technologies?

What knowledge do doctors need to understand medical AI advice? How can AI-based medical information be used [13], and how do you deal with medical information that AI cannot explain [14]? Could doctors working with chatbot-provided diagnoses and AI-recommended treatments miss the true picture and become overly reliant on AI? Who is liable when doctors use AI medical information, and to come full circle, who is liable when they do not [2,15]? Could there come a time when not considering AI such as ChatGPT constitutes less than adequate advice and nonstandard care [15]? Doctors should ask their liability insurer how (ie, under what conditions) and to what extent the insurer covers the use, or nonuse, of AI in practice [15].

Key orientation for interactions between patients, doctors, and chatbots regarding MA can come from physicians’ professional organizations and the US Food and Drug Administration. Similar to practice guidelines [15], recommendations and guardrails for practice-specific medical information via chatbots may have to be developed.

A Gloomy Outlook, Expectations From Much-Needed Ethical Discourse, and a Hope in Relation to Humans and Machines

That ChatGPT “strive(s) to provide accurate and helpful information” [1] has a stale empirical aftertaste. In fact, according to OpenAI, advanced AI [16] will make reviewing chatbot information even more difficult. GPT-4 (eg, in Microsoft Bing and ChatGPT Plus), with 571 times as many learned parameters as GPT-3, has “learned” to deliver incorrect work more convincingly than earlier models. Such mistakes will pose severe problems even if “[ChatGPT] admits these when challenged” [1].

PubMed-listed comparisons between GPT-3 and GPT-4 suggest that the latter may provide more accurate patient information in nuclear medicine [17]. Another study suggested that both free and paid versions of ChatGPT risk providing misleading responses when used without expert MA [18]. Chatbot medical information written at a college reading level suggested that such AI devices may be used supplementarily but not as a primary source for medical information [19], emphasizing the doctor’s key role in MA. More research is needed on MA in numerous medical fields and settings, for numerous applications, and for various populations.

Overall, when AI experts at the University of California, Berkeley explored and discussed the implications of ChatGPT and AI and future challenges in the spring of 2023, there was an explicit call for more ethical considerations [6,20]. Priority safety measures include strict regulations for patient privacy and ethical practices [21]. While the questions above are not exhaustive, it is time to systematically answer them regarding MA and the unavoidable interaction of patients, doctors, and chatbots.

Ultimately, we can only hope that the boundaries between humans and machines [3] will never become so blurred that patients cannot distinguish the MA of a human doctor from the general information provided by ChatGPT [22] or other AI.

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Conflicts of Interest

None declared.
References


Abbreviations

- **AI**: artificial intelligence
- **MA**: medical advice
Generative Language Models and Open Notes: Exploring the Promise and Limitations

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Abstract

Patients' online record access (ORA) is growing worldwide. In some countries, including the United States and Sweden, access is advanced with patients obtaining rapid access to their full records on the web including laboratory and test results, lists of prescribed medications, vaccinations, and even the very narrative reports written by clinicians (the latter, commonly referred to as “open notes”). In the United States, patient’s ORA is also available in a downloadable form for use with other apps. While survey studies have shown that some patients report many benefits from ORA, there remain challenges with implementation around writing clinical documentation that patients may now read. With ORA, the functionality of the record is evolving; it is no longer only an aide memoire for doctors but also a communication tool for patients. Studies suggest that clinicians are changing how they write documentation, inviting worries about accuracy and completeness. Other concerns include work burdens; while few objective studies have examined the impact of ORA on workload, some research suggests that clinicians are spending more time writing notes and answering queries related to patients’ records. Aimed at addressing some of these concerns, clinician and patient education strategies have been proposed. In this viewpoint paper, we explore these approaches and suggest another longer-term strategy: the use of generative artificial intelligence (AI) to support clinicians in documenting narrative summaries that patients will find easier to understand. Applied to narrative clinical documentation, we suggest that such approaches may significantly help preserve the accuracy of notes, strengthen writing clarity and signals of empathy and patient-centered care, and serve as a buffer against documentation work burdens. However, we also consider the current risks associated with existing generative AI. We emphasize that for this innovation to play a key role in ORA, the cocreation of clinical notes will be imperative. We also caution that clinicians will need to be supported in how to work alongside generative AI to optimize its considerable potential.

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KEYWORDS
ChatGPT; generative language models; large language models; medical education; Open Notes; online record access; patient-centered care; empathy; language model; online record access; documentation; communication tool; clinical documentation

Introduction

Patient online record access (ORA) is growing globally [1]. Access includes test and laboratory results, secondary or hospital care letters, lists of prescribed medications, and the narrative reports written by clinicians after visits (the latter referred to as “open notes”). Already, patients across an estimated 30 countries can access some of their records via secure web portals including
health apps. In some countries, this innovation is advanced [1]. Since 2021, the federally enacted 21st Century Cures Act in the United States mandated that providers offer all patients access to download their electronic health records without charge [2]. In the Nordic countries, ORA has been implemented incrementally, starting around 2010 [3]. The Finnish patient portal OmaKanta was rolled out with stepwise implementation of functionality between 2010 and 2015 [4]. Patients in Sweden first obtained ORA in one of 21 regions in 2012 [5] with nationwide implementation achieved by 2018. Implementation in Norway began in 2015, reaching patients in 3 out of 4 regions by 2019 [6]. In England, from October 31, 2023, it is mandatory for general practitioners to offer ORA to their adult patients, albeit on a prospective basis [7].

Patients with access to their records report using them to become more involved in their care, to follow up on doctors’ visits, and to obtain an overview of their test results and treatment history [3,8,9]. Multiple surveys show that patients using ORA are positive about the experience after reading their notes. They report many benefits including understanding their care plans better [9], improved communication with and greater trust in their provider [10], and feeling more in control of their health and care [6,8], including doing a better job taking their medications [11,12].

Despite the patient benefits with ORA, challenges with their implementation in clinical practice remain. In this viewpoint paper, we identify outstanding concerns with ORA, which encompass a range of unintended consequences for clinician work burdens, and for the substantial task of conveying bespoke, compassionate, and understandable information to each unique patient who accesses their records. Currently, it has been proposed that a range of targeted patient training and medical education strategies may be sufficient to resolve at least some of these challenges [13-17]. We believe that such interventions are valuable; however, in this viewpoint paper, we explain why the ambitions of such training interventions may be limited.

As a solution, we explain why the use of generative artificial intelligence (AI) may offer more tangible long-term promise than clinician training alone in helping to resolve problems with ORA implementation. While generative AI itself is not new, recent technical advances and the increased accessibility of large language models (LLMs; GPT-4 by OpenAI, LLaMA by Meta, and PaLM2 by Google) have made clinical use increasingly feasible. LLMs are an application of generative AI technology, often defined as machine learning algorithms that can recognize, summarize, and generate content based on training on large data sets. Unlike search engines, which offer pages of internet links in response to typed queries, generative LLMs such as GPT-4 simulate well-reasoned answers couched as conversations. In addition, these models can “remember” previous prompts, helping to build up the perception of dialogic exchange. We review the strengths and limitations of generative AI and emphasize that for this innovation to play a key role in ORA, it will be imperative for humans to be involved as overseers of computer input.

Current Challenges With Open Notes

Evolving Functionality of Records

Guidelines, such as those issued by the British General Medical Council, state that clinicians should keep clear, accurate, contemporaneous records that include “…any minor concerns, and the details of any action you have taken, information you have shared and decisions you have made relating to those concerns” [18]. In the era of ORA, clinicians will also need to consider if what they write will be understandable, accessible, and supportive for patients [19]. With the knowledge that patients will read what they write, the functionality of the record is evolving, and this incurs changes with respect to how clinical information is documented [20,21]. Clinicians must uphold the original functionality of the record—documenting the patient’s medical information in clinical detail, but also communicating this information to the patient. With respect to the latter function, it is argued that for records to be understandable and acceptable to a lay audience, clinicians should ideally remove or explain medical acronyms, omit medical vernacular that may be perceived as offensive (such as “patient denies” or “patient complains of”), and strive to convey information in a manner that it is straightforward, comprehensive, and empathic in tone [14]. This is not an easy undertaking for clinicians tasked with pitching information at a literacy level that accommodates diverse patient populations while maintaining the clinical utility of records and adequately serving their medicolegal functions. Indeed, whether such dual functionality is even possible has been questioned [22].

Documentation Changes

To date, it is unclear whether ORA diminishes the clinical value of documentation [19,23]. However, there is evidence that clinicians may be undermining the accuracy or completeness (or both) of their records, perhaps in attempts to reduce patient anxieties, minimize follow-up contact, or reduce the likelihood of potential complaints [24,25]. For example, in the largest study conducted on clinicians’ experiences of open notes, a 3-center study at 3 diverse health systems in the United States (1628 of 6054, 27% clinicians responded), DesRoches et al [26] found that around 1 in 4 physicians admitted that they changed how they wrote differential diagnoses (23%, n=176), though the nature of these changes is not understood. More worryingly, more than 1 in 5 physicians (22%, n=168) believed that their notes were now less valuable for other clinicians [26].

Conceivably, other changes following implementation of ORA might be more positive. In the study by DesRoches et al [26], 22% (n=166) of physicians reported changes to the use of a partnering language, and 18% (n=139) of them reported changes to how they used medical jargon or acronyms. However, it remains unknown whether such changes improve the comprehensibility of clinical records among patients or whether amendments come with a trade-off in terms of documentation quality.

With ORA, there is also the potential for notes to convey bias of stigmatizing language. For example, in the United States, recent linguistic analysis studies have shown that negative patient descriptors in notes are considerably more common for
non-Hispanic black patients and for patients with diabetes, those with substance use disorders, and those with chronic pain [27,28]. It is unclear whether with the knowledge patients may now read what they write, the use of stigmatizing language among these patient populations is being effectively omitted and “cleaned up” by clinicians.

Work Burdens

Time spent on documentation and patient portal messages remains a growing cause of clinician dissatisfaction and burnout [29]. The impact is exacerbated for clinicians with lower levels of digital competencies, and this “technostress” has been found to directly correlate with burnout [30]. Even tech-savvy young resident physicians have reported the use of the electronic health record as a leading cause of burnout [31]. In the United States, the study by DesRoches et al [26] on clinicians’ experiences, 37% (n=292) of physicians reported spending more time writing notes after patient access was enabled.

Few studies have explored objective measures of the impact of ORA, however, where these measures have been implemented, some of them signal potential for increased patient contact. For example, Mold et al [32] found that the provision of ORA in primary care settings resulted in a moderate increase in email traffic from patients, with no change in telephone contact and variable changes to face-to-face contact. A recent Canadian study found that registration with a primary care web-based portal was associated with an increase in the number of visits to physicians, calls to practice triage nurses, and an increase in clerical workload [33]. Another recent study at an academic medical center in the United States reported a doubling in the number of messages sent by patients within 6 hours after ORA was implemented [34]. It seems reasonable to postulate that at least some of this increased contact may be driven by patients who desire clarifications about diagnoses, results, or other information that is documented in their records.

Currently Proposed Solutions

To encourage confidence with ORA and to overcome some of these challenges, targeted educational programs have been proposed. Among them are short lists of tips and advice to clinicians, and brief web-based training interventions [13,14,24]. More recently, some medical schools have taken this further. For example, Harvard Medical School has embedded within its curriculum practical training in how to write notes that patients will read [16], and similar work is underway in England [35]. The expressed aim of such training programs is to support physicians in writing notes efficiently and clearly, preserving the necessary clinical details. These programs also encourage students and clinicians to write sensitively and empathically, removing loaded jargon or acronyms that may be perceived as offensive (eg, “follow-up” instead of “F/U,” or “shortness of breath” instead of “SOB”) [14,16]. Notably, however, calls for curricular adaptations are isolated, perhaps reflecting wider uncertainty about ORA among the medical community and the perception that the innovation has been foisted on them.

Similarly, interventions to advise patients about how to engage with ORA appear limited [14,36]. This may be owed to a fear among clinicians that encouraging access to web-based records may exacerbate patient anxiety, lead to increased contact time, or risk disagreements and requests to change documentation. We observe that current recommendations in the published and gray literature offer advice on the benefits and risks of accessing ORA, how to maintain password or portal security, and how to discuss errors or disagreements in their notes with clinicians [14,36].

Combined, these clinician and patient support strategies are valuable but have inherent limitations. Training interventions may be variously implemented and take time to become established in mainstream medical education. Even beyond mainstream inclusion of training in medical curricula, it will also be necessary to target the so-called “hidden curriculum”—the set of unspoken and implicit rules and values that trainees may pick up from their mentors and colleagues within clinical practice [37]. It is unclear whether even those strategies that attempt to convert senior or experienced doctors to the cause are sufficient to counter the hidden curriculum or to neutralize the formation of documentation habits that may not be in keeping with the ORA mandate whereupon clinical notes may now be read by patients and caregivers.

Other recommendations that clinicians should remove all acronyms and medical jargon may present practical dilemmas for upholding the quality of documentation. Aside from extra time spent typing documentation, the capacity to shift from expert to patient perspectives poses unappreciated difficulties. Undoubtedly, many clinicians, as domain experts, might not always fully appreciate when they are using specialist or technical language, nor do they have the attendant skills to convey what they know to patients in an understandable way—a cluster of problems collectively referred to as “the curse of expertise” [38]. Using imprecise language may also have future medical consequences and might result in harm if later clinicians misinterpret what was written [39].

Relatively, it seems a significant request that clinicians write notes that are bespoke for every patient’s level of health literacy. Yet, each person who attends a clinical visit will have specific health literacy needs. We suspect that the trade-off may lead to clinicians writing notes that are more suited to a readership like them—individuals with higher health literacy and more years of formal education.

Similarly, while often considered a “soft skill,” the adoption of empathetic, encouraging, and supportive language might be a taller order than is frequently assumed. For example, psychologists report that negative biases can curb expressions of empathy [40-44]. Studies show that empathy can be influenced by patients’ race or ethnicity and may be diminished among people presenting with disabilities or already stigmatized conditions [40-44]. Making matters worse, self-inspection may be a particularly weak tool for clinicians to excavate and monitor their own prejudices [45]. Furthermore, the demand that clinicians tailor their notes in ways that are optimized to every patient’s understanding and their emotional needs may lead to not only increased workload but also higher risk of burnout [46].
So far, no objective measures have assessed whether targeted training strategies are effective at improving clinical documentation in terms of preserving medical detail and utility, strengthening patient understanding and patients’ perceptions of clinician support and empathy. We emphasize that while commonly used in training evaluation, self-report surveys will not be sufficient to establish whether educational interventions work in terms of both preserving the detail in clinical notes and supporting patient understanding. Finally, perhaps most crucial of all, and as already noted, it is unclear whether narrative notes can ever uphold a genuine dual functionality targeting the needs of both clinician and patient readerships [22]. Conceivably, both needs are incommensurable and there will always be a trade-off in detail and understanding should the patient, or the clinician, be given primacy as target reader.

Generative Language Models Writing Clinical Notes

Strengths of Generative AI

Doctors strongly desire support with documentation including note writing with surveys showing that they forecast a role for AI in assisting in these tasks [47,48]. Because of their promise with respect to administrative and documentation tasks in health care contexts, LLMs have been described as “the ultimate paperwork shredder” [49]. Owing to the sheer speed and scope of information upon which they draw, LLMs hold considerable potential in generating up-to-date, comprehensive clinical information for patients [50]. This makes the approach particularly promising in generating detailed narrative explanations and summaries of visit encounters. This may help to reduce work burdens on physicians tasked with writing clinical notes.

Another striking strength of LLMs is their capacity to write responses in a requested style or by adopting a specific tone or conversational emphasis. This makes LLMs particularly promising in assisting with writing notes that omit the use of medical jargon or acronyms that are suitable for patients with different levels of health literacy, or among speakers of languages that differ from their provider’s language. This capacity may also help avoid the extra burdens on clinicians attempting to document notes that are tailored to the highly diverse range of unique patient readers.

Preliminary research also suggests that LLMs may help with writing consistently sensitive or empathic notes. In 2023, a highly publicized study suggested that ChatGPT may have better bedside manners than actual human doctors [51]. A team compared written responses of doctors and ChatGPT offered to patients’ real-world health queries using Reddit’s AskDocs forum, where nearly half a million people post their medical problems and verified and credentialed clinicians offer suggestions. On average, ChatGPT responses were 4 times longer than doctors’ replies. A panel of health care professionals—blinded to who or what did the writing—preferred ChatGPT’s responses nearly 80% of the time. The panel ranked chatbot answers as being of significantly higher quality than web-based posts reportedly from doctors; they also judged these reported web-based doctors’ answers as more unacceptable responses to patients. ChatGPT’s responses were rated as “good” or “very good” nearly 4 times more often than those written by the reported web-based doctors, and ChatGPT’s responses were rated as almost 10 times more empathic than those by the reported web-based doctors. At the other end of the scale, these web-based physicians’ replies were perceived to lack empathy approximately 5 times more often than responses produced by ChatGPT.

Limitations of Generative AI

Despite their potential, LLMs have multiple limitations. The nature of the data sets the models are trained on is critical, as it will determine the scope and nature of responses possible. Of special relevance here, none of the easily accessible LLMs have yet been trained on medical texts and thus lack the core substrate to generate the most appropriate responses. Any bias in the source the models are trained on will also be reflected in answers or text provided. Thus, while a study in March 2023 showed that ChatGPT (version 3) Could pass the United States Medical Licensing Examination [52], the authors of the study noted that to truly assess the potential of such LLMs, there is a need for “controlled and real-world learning scenarios with students across the engagement and knowledge spectrum.” Still, the results of that study were acknowledged by the American Medical Association, which noted that it intends to begin considering how tools such as ChatGPT need to be incorporated into the education process [53].

Indeed, the full extent to which LLMs embed discriminatory biases has not been fully explored. However, it would be surprising if these models did not replicate many of the same biases that already exist in clinical research, and consequently medical education, in part because of the underrepresentation of women, racial and ethnic minorities, and older people. Such skewing is already recognized as a source of disparity with the potential to perpetuate errors or misjudgments in clinical decisions [54-58]. Studies suggest that gender and racial biases are indeed coded into LLMs [59]. It remains unknown whether the potential for such discriminatory errors might prove worse than today with standard human-mediated care; however, some preliminary research suggests that negative stereotyping may be compounded by LLMs [60].

Another concern is the lack of consistency in responses proffered by LLMs. Inputting the same question to GPT-4, for example, rarely elicits the same response. Of course, human responses are rarely consistent as well; however, the extent to which generative AI, relying on LLMs, offers the same level of reliable outputs is uncertain. This is a particular concern given that LLMs are prone to yield falsehoods—a phenomenon referred to as “hallucination.” Moreover, the persuasive conversational tone of LLMs such as GPT-4 means that narrative responses may appear compelling but factually incorrect.

The extent to which doctors may already be adopting generative AI tools, such as OpenAI’s ChatGPT, is not yet known. In the United States, under the 1996 Health Insurance Portability and Accountability Act (HIPAA), which established national standards in the United States to protect patients’ health...
information from being shared by “covered entities”—that is, providers—to other third parties. Therefore, the use of OpenAI, for example, is precluded under the HIPAA. At the time of writing, in the most common use cases, uploading patient details to versions of generative AI would breach patient trust and medical confidentiality due to privacy concerns.

However, the scope for this is quickly changing. Epic—the US software giant which has an estimated 78% of the share of hospital medical record use in the United States [61]—is currently piloting the integration of HIPAA-compliant GPT services [62]. In addition, an Azure HIPAA–compliant GPT-4 service already exists [63]. Voice-to-text clinical note generation products now represent a growing space in health care. For example, a new app called Ambient Experience from Nuance can listen to the physician’s conversation and, using ChatGPT (version 4), help create the clinical note that is ready for physicians to review [64]. In the United States, such capacities are set to become embedded into electronic health systems, signaling revolutionary changes in medical documentation practices.

Clinicians and Computers as Coauthors

Combined, the aforementioned discourse suggests that LLMs are far from ready to disintegrate clinicians when it comes to writing clinical notes. We argue that the innovation will play a key role if humans are involved. Thus, this promise could be harnessed if clinicians oversee the cocreation of clinical documentation. In this scenario, LLMs might offer initial draft documentation, which, crucially, should be supervised, and edited by clinicians whose key role in documentation will be to keep a check and balance on the current limitations with these models.

Considering the scope of generative AI, we therefore propose that current training interventions might be constructively adapted to better prepare clinicians to oversee the writing of patient-facing clinical documentation, for example, by editing and checking the quality of clinical information constructed by generative AI and reviewing the sensitivity of the language used. Preliminary studies already show that when humans collaborate with LLMs to coproduce replies to patients, this can enhance patients’ ratings of levels of empathy compared with human-only produced responses [65]. Such partnership could offer a more robust and safe form of documentation quality control—one that could potentially avoid the work burdens associated with documentation burdens and, therefore, the potential for burnout from ORA. We emphasize, however, that training should reinforce the importance of using generative AI as an assistant narrative scribe and not as a substitute for writing notes.

Furthermore, if health systems adopt this approach, we suggest that 2 (or even multiple) versions of clinical documentation may be feasible. Using LLMs, there is scope to not only a complete medical narrative pitched at the level of the domain expert or specialist, but also to document notes couched at the level of health literacy, language, and empathy of the individual patient who might be reading them. This could help overcome the current dilemma of documenting information in a way that is accessible for patients, but which does not diminish the clinical detail for health professionals.

Future Research Directions

Many research questions could usefully explore generative AI in cowriting clinical notes, especially dual-purpose documentation for both patients and clinicians. We suggest a few novel directions. First, qualitative studies could usefully explore how successfully generative AI translates clinical documentation into patient-friendly language. For example, studies could examine the accuracy and fidelity of generative AI in translating acronyms or other medical jargon, as well as the understandability of the notes, and the level of empathy embedded in patient-facing documentation. Second, experimental studies could probe whether documentation embeds biases or a higher likelihood of containing stigmatizing language for different patient demographics or health conditions. Third, pilot studies could help determine the satisfaction and administrative work burden of dual documentation among clinicians.

Conclusions

Generative AI is ready for mass use when it comes to writing or cowriting clinical notes, and its potential is enormous. We emphasize, however, that there remain evidence-based risks associated with existing generative AI, which relate to inconsistencies, errors, and hallucinations and the real potential to embed harmful biases in documentation. If carefully implemented, in the long term, doctors who write documentation using generative AI may do a better job of adapting to the evolving functionality of the electronic records than doctors who do not. This adoption may address the potential risk of “dumbing down” clinical documentation while conveying understandable and empathetic information to patients using plain and sensitive language. We also forecast that doctors who cowrite their documentation with LLMs will experience fewer work burdens.


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### Abbreviations

AI: artificial intelligence  
HIPAA: Health Insurance Portability and Accountability Act  
LLM: large language model  
ORA: online record access

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Original Paper

Pure Wisdom or Potemkin Villages? A Comparison of ChatGPT 3.5 and ChatGPT 4 on USMLE Step 3 Style Questions: Quantitative Analysis

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Abstract

Background: The United States Medical Licensing Examination (USMLE) has been critical in medical education since 1992, testing various aspects of a medical student’s knowledge and skills through different steps, based on their training level. Artificial intelligence (AI) tools, including chatbots like ChatGPT, are emerging technologies with potential applications in medicine. However, comprehensive studies analyzing ChatGPT’s performance on USMLE Step 3 in large-scale scenarios and comparing different versions of ChatGPT are limited.

Objective: This paper aimed to analyze ChatGPT’s performance on USMLE Step 3 practice test questions to better elucidate the strengths and weaknesses of AI use in medical education and deduce evidence-based strategies to counteract AI cheating.

Methods: A total of 2069 USMLE Step 3 practice questions were extracted from the AMBOSS study platform. After including 229 image-based questions, a total of 1840 text-based questions were further categorized and entered into ChatGPT 3.5, while a subset of 229 questions were entered into ChatGPT 4. Responses were recorded, and the accuracy of ChatGPT answers as well as its performance in different test question categories and for different difficulty levels were compared between both versions.

Results: Overall, ChatGPT 4 demonstrated a statistically significant superior performance compared to ChatGPT 3.5, achieving an accuracy of 84.7% (194/229) and 56.9% (1047/1840), respectively. A noteworthy correlation was observed between the length of test questions and the performance of ChatGPT 3.5 ($\rho=-0.069; P=.003$), which was absent in ChatGPT 4 ($\rho=.87$). Additionally, the difficulty of test questions, as categorized by AMBOSS hammer ratings, showed a statistically significant correlation with performance for both ChatGPT versions, with $\rho=-0.289$ for ChatGPT 3.5 and $\rho=-0.344$ for ChatGPT 4. ChatGPT 4 surpassed ChatGPT 3.5 in all levels of test question difficulty, except for the 2 highest difficulty tiers (4 and 5 hammers), where statistical significance was not reached.
Conclusions: In this study, ChatGPT 4 demonstrated remarkable proficiency in taking the USMLE Step 3, with an accuracy rate of 84.7% (194/229), outshining ChatGPT 3.5 with an accuracy rate of 56.9% (1047/1840). Although ChatGPT 4 performed exceptionally, it encountered difficulties in questions requiring the application of theoretical concepts, particularly in cardiology and neurology. These insights are pivotal for the development of examination strategies that are resilient to AI and underline the promising role of AI in the realm of medical education and diagnostics.

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KEYWORDS
ChatGPT; United States Medical Licensing Examination; artificial intelligence; USMLE; USMLE Step 1; OpenAI; medical education; clinical decision-making

Introduction
Since its inception in 1992, the United States Medical Licensing Examination (USMLE) has been considered an integral milestone in medical education [1]. The 3 USMLE steps are jointly sponsored by the Federation of State Medical Boards and the National Board of Medical Examiners. Each step is designed to specifically test another facet of the examinee’s skill set. For instance, USMLE Step 1 assesses a student’s understanding and application of basic sciences relevant to the field of medicine (eg, anatomy and physiology), while USMLE Step 2 tests the examinee’s clinical knowledge (USMLE Step 2 CK) and communication skills (USMLE Step 2 CS). USMLE Step 3 evaluates the student’s understanding of biomedical and clinical science [2-4]. USMLE scores have been associated with the selection of residency programs and future career perspectives [5].

Artificial intelligence (AI)–supported tools have been proposed for a variety of medical scenarios, including preoperative outcome simulation, patient education, and automated disease grading [6-9]. Recently, chatbots such as ChatGPT have emerged as next-generation AI technology. The strengths of this novel AI-powered approach include 24-7 availability, cost efficiency, and individualization [10]. A mounting body of evidence has investigated ChatGPT’s performance on different standardized exams. For instance, Hoch et al [11] reported that ChatGPT answered 57% of facial surgery board certification test questions correctly, while Kung et al [12] used a limited set of USMLE test questions (USMLE Step 1: 119; USMLE Step 2 CK: 102; USMLE Step 3: 122) and found that ChatGPT achieved performance levels near the passing threshold for all 3 steps.

However, there is a scarcity of studies that comprehensively investigate overall ChatGPT performance on USMLE Step 3 test questions in a large-scale study and compare test performances between ChatGPT 3.5 and ChatGPT 4. This knowledge gap may increase the risk of AI cheating in such career-deciding exams and cloud the vision of ChatGPT’s strengths and limitations.

Therefore, we aimed to determine ChatGPT’s performance on USMLE Step 3 practice test questions based on 1840 AMBOSS USMLE Step 3 Style Questions. This line of research may serve as a primer elucidating the strengths and weaknesses of multiple ChatGPT versions and deducing evidence-based strategies to counteract AI cheating.

Methods
Access to Question Bank and Data Entry Procedure
From June 12, 2023, to June 19, 2023, we obtained access to the AMBOSS question bank [13]. Within this time frame, we collected a total of 1840 practice questions specifically designed for the USMLE Step 3 exam. Before initiating our study, we acquired official permission from AMBOSS (AMBOSS GmbH) to use their USMLE Step 3 question bank for research purposes. To ensure the reliability of our data, 2 examiners (MA and LK) cross-checked the question inputs randomly to confirm that none of the answers were indexed on Google before June 19, 2023. Many USMLE questions are on the internet, including USMLE sample questions as well as a few AMBOSS questions; however, we ensured that those questions were not included in this analysis to minimize the risk of prior memorization of the questions by ChatGPT. July 19, 2023, was chosen since it represents the most recent accessible date within the training data set of ChatGPT. There are many forms of AI versions with capabilities to answer USMLE Step 3 practice test questions; however, ChatGPT is the most widely used AI at the time of this study, making it the best fit for our study.

Question Screening and Categorization
To maintain the quality of our sample questions, we subjected all test questions to independent screening by 4 examiners (MA, SK, CCH, and LK). Questions containing clinical images and photographs were excluded from the study, resulting in the removal of 229 image-based questions. Subsequently, the remaining 1840 test questions were classified based on their respective specialties, using the categorization provided by AMBOSS. All questions included in our study followed a multiple-choice single-answer format. The questions used for both ChatGPT 3.5 and ChatGPT 4 were matched for content and difficulty based on the standardized definitions provided by the AMBOSS question bank to ensure consistent analysis between both AI versions.

Comparison of ChatGPT Versions and Analysis of Question Stems
To evaluate any performance differences between ChatGPT 3.5 and ChatGPT 4, we conducted a subgroup analysis specifically focusing on ChatGPT 4. Additionally, we analyzed the question stems of both ChatGPT 3.5 and ChatGPT 4, specifically looking for specific buzzwords related to diagnostic methods and patient information, such as “Ultrasound,” “Serology,” and “Nicotine Abuse.” These particular words and phrases may suggest one...
answer over another and thus are essential for test-taking. For example, if the question states “Nicotine Abuse,” which is suggestive of cigarette or tobacco use, the patient in the question stem is more likely to have cancer. The purpose of this analysis was to identify any variations in accuracy based on the presence of these factors. Furthermore, we assessed performance differences between ChatGPT 3.5 and ChatGPT 4 based on the length of the test questions.

Assessment of Question Difficulty
To assess the difficulty of the test questions, we used the proprietary rating system of the AMBOSS question bank. This system assigns a difficulty level to each question based on a scale of 1 to 5 hammers. A rating of 1 hammer corresponds to the easiest 20% of questions, while 5 hammers indicate the most challenging 5% of questions.

Data Entry Process
One examiner (MA) manually inputted the test questions into ChatGPT. The questions were transcribed verbatim from the AMBOSS question bank, preserving the original text and answer choices. To ensure the integrity of ChatGPT’s performance, no additional prompts were introduced intentionally by the authors, thereby minimizing the potential for systematic errors. Each question was treated as a separate chat session in ChatGPT to minimize the impact of memory retention bias. As an example, the following provides a standard test question from the category “Competency: Patient Care Content Area: General Principles”:

- **What is the most suitable course of action to take next in the case of a 54-year-old man, previously in good health, who presents to the emergency department after being bitten by a stray dog in South America?**
  - The bite punctured his right leg, but he has diligently cleaned the wound daily with soap and peroxide. The patient is not experiencing pain, fever, or chills, and his vital signs are normal. The examination reveals healing puncture wounds with minimal redness, and there is no fluctuation or palpable lymph nodes in the groin. The patient had a tetanus booster vaccination three years ago.
- (A) Provide rabies vaccination
- (B) Administer tetanus immune globulin
- (C) Request cerebrospinal fluid analysis
- (D) Order an MRI [magnetic resonance imaging] scan of the brain and spinal cord
- (E) No immediate action is required at this time

Recording and Evaluation of ChatGPT Responses
The answers generated by ChatGPT were documented and incorporated into the corresponding AMBOSS USMLE Step 3 practice question. Subsequently, we systematically gathered and recorded information regarding the accuracy of these responses in a separate data spreadsheet.

Statistical Analysis
We used the Pearson chi-square test to determine differences in question style and categories. Bivariate correlation analysis between ChatGPT performance, test question length, and difficulty was conducted using the Spearman correlation coefficient (ρ). IBM SPSS Statistics 25 (IBM Corp) was used for statistical analysis, and a 2-tailed P value ≤.05 was considered statistically significant.

Results
General Test Question Characteristics and Performance Statistics
The overall accuracy of ChatGPT 3.5 for USMLE Step 3 was 56.9% (1047/1840), while ChatGPT 4 answered 84.7% (194/229) of test questions correctly (P <.001). Specialty-specific number of test questions and performance scores are presented in Tables 1 and 2. ChatGPT 3.5 received the greatest number of questions on the nervous, cardiovascular, and gastrointestinal systems, while ChatGPT 4 received the greatest number of questions on behavior health, the female reproductive system, as well the blood and lymphatic system. When considering the accuracy of ChatGPT based on the category of questions, ChatGPT 3.5 performed the best on behavioral health, multisystem processes and disorders, and pregnancy-related questions. On the other hand, ChatGPT 4 had the greatest accuracy on questions related to the endocrine and musculoskeletal systems as well as biostatistics and multisystem processes and disorders.
### Table 1. The number of test questions answered by ChatGPT 3.5 and its performance, stratified by questions category (N=1840).

<table>
<thead>
<tr>
<th>Question category</th>
<th>Test questions answered, n</th>
<th>Correct questions, n/N (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male reproductive system</td>
<td>28</td>
<td>17/28 (60.1)</td>
</tr>
<tr>
<td>General principles and foundational science</td>
<td>29</td>
<td>16/29 (55.2)</td>
</tr>
<tr>
<td>Immune system</td>
<td>40</td>
<td>25/40 (62.5)</td>
</tr>
<tr>
<td>Skin and subcutaneous tissue</td>
<td>72</td>
<td>39/72 (54.2)</td>
</tr>
<tr>
<td>Renal and urinary systems</td>
<td>72</td>
<td>39/72 (54.2)</td>
</tr>
<tr>
<td>Biostats and epidemiology</td>
<td>87</td>
<td>45/87 (51.7)</td>
</tr>
<tr>
<td>Female reproductive system and breast</td>
<td>88</td>
<td>48/88 (54.5)</td>
</tr>
<tr>
<td>Musculoskeletal system</td>
<td>94</td>
<td>56/94 (58.5)</td>
</tr>
<tr>
<td>Endocrine system</td>
<td>103</td>
<td>58/103 (56.3)</td>
</tr>
<tr>
<td>Blood and lymphoreticular system</td>
<td>105</td>
<td>55/105 (52.4)</td>
</tr>
<tr>
<td>Pregnancy, childbirth, and puerperium</td>
<td>111</td>
<td>66/111 (59.5)</td>
</tr>
<tr>
<td>Behavioral health</td>
<td>115</td>
<td>73/115 (63.5)</td>
</tr>
<tr>
<td>Multisystem processes and disorders</td>
<td>122</td>
<td>73/122 (59.8)</td>
</tr>
<tr>
<td>Respiratory system</td>
<td>130</td>
<td>71/130 (54.6)</td>
</tr>
<tr>
<td>Social sciences</td>
<td>141</td>
<td>86/141 (61.0)</td>
</tr>
<tr>
<td>Gastrointestinal system</td>
<td>156</td>
<td>87/156 (55.8)</td>
</tr>
<tr>
<td>Cardiovascular system</td>
<td>161</td>
<td>89/161 (55.3)</td>
</tr>
<tr>
<td>Nervous system and special senses</td>
<td>186</td>
<td>104/186 (55.9)</td>
</tr>
</tbody>
</table>

### Table 2. The number of test questions answered by ChatGPT 4 and its performance, stratified by questions category (N=229).

<table>
<thead>
<tr>
<th>Question category</th>
<th>Test questions answered, n</th>
<th>Correct questions, n/N (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Endocrine system</td>
<td>1</td>
<td>1/1 (100)</td>
</tr>
<tr>
<td>Biostats and epidemiology</td>
<td>14</td>
<td>13/14 (92.3)</td>
</tr>
<tr>
<td>General principles and foundational science</td>
<td>17</td>
<td>14/17 (82.4)</td>
</tr>
<tr>
<td>Multisystem processes and disorders</td>
<td>17</td>
<td>15/17 (88.2)</td>
</tr>
<tr>
<td>Pregnancy, childbirth, and puerperium</td>
<td>19</td>
<td>15/19 (79.0)</td>
</tr>
<tr>
<td>Gastrointestinal system</td>
<td>21</td>
<td>18/21 (85.7)</td>
</tr>
<tr>
<td>Cardiovascular system</td>
<td>21</td>
<td>15/21 (71.4)</td>
</tr>
<tr>
<td>Nervous system and special senses</td>
<td>21</td>
<td>15/21 (71.4)</td>
</tr>
<tr>
<td>Blood and lymphoreticular system</td>
<td>23</td>
<td>20/23 (87.0)</td>
</tr>
<tr>
<td>Female reproductive system and breast</td>
<td>23</td>
<td>20/23 (87.0)</td>
</tr>
<tr>
<td>Behavioral health</td>
<td>24</td>
<td>21/24 (87.5)</td>
</tr>
</tbody>
</table>

### Test Question Length and ChatGPT Performance Scores

The mean character count was 1078 (SD 308). Test question length was significantly correlated with the performance of ChatGPT 3.5 ($p=-0.069; P=.003$) while not yielding significance for ChatGPT 4 ($P=.87$). For ChatGPT 3.5, the mean number of characters was 1062 (SD 310) for correct answers versus 1100 (SD 304) for falsely answered questions ($P=.009$). However, the mean character count was comparable for test questions answered by ChatGPT 4 (mean correct answers 1068, SD 274 vs mean false answers 1056, SD 233; $P=.80$).

### Test Question Difficulty and the Performance of ChatGPT

Question distribution and performance scores sorted by level of test question difficulty are illustrated in Figure 1. Test question difficulty, defined by AMBOSS hammer categorization, and the performance of ChatGPT 3.5 were significantly correlated ($p=-0.289; P<.001$). This was reproducible in ChatGPT 4 ($p=-0.344; P<.001$). ChatGPT 4 statistically significantly outperformed ChatGPT 3.5 for each hammer category except for the 4- and 5-hammer test difficulty levels. For 1-, 2-, and 3-hammer questions, ChatGPT 4 had a statistically significant increase in accuracy compared to...
ChatGPT 3.5 ($P = .04$; $P = .02$; and $P = .03$; respectively). For the most difficult questions, ChatGPT 4 still had greater accuracy than ChatGPT 3.5; however, there was no statistical significance shown. The percentage of correct responses from ChatGPT 3.5 versus ChatGPT 4 sorted by specialty is illustrated in Figure 2.

Relative to ChatGPT 3.5, ChatGPT 4 performed better on questions from every specialty category. The biggest differences in accuracy were in biostatistics, epidemiology, the endocrine system, and the musculoskeletal system.

**Figure 1.** Question distribution and performance scores sorted by level of test question difficulty.
Buzzwords and the Performance of ChatGPT
ChatGPT 4 performed significantly better on ultrasound-related questions ($P=.04$), while ChatGPT 3.5 answered significantly more questions correctly if they contained serology- or smoking-related information ($P=.008$ and $P=.03$, respectively). Performance scores of ChatGPT 3.5 versus ChatGPT 4 sorted by buzzwords are depicted in Figure 3. Overall, ChatGPT 4 outperformed ChatGPT 3.5, regardless of whether the question included buzzwords.
Discussion

Principal Findings

This investigation was designed to empirically evaluate and contrast the competencies of the 2 most contemporary iterations of the AI-powered large language model, ChatGPT, in relation to their performance in taking the USMLE Step 3. An aggregate of 1840 representative practice questions, derived from the AMBOSS question bank, were presented to ChatGPT version 3.5. The model delivered an overall accuracy rate of 56.9% (1047/1840). In juxtaposition, ChatGPT version 4 was assessed using a subset of 229 practice questions and achieved an overall accuracy rate of 84.7% (194/229). This difference in performance is both statistically and practically significant. Achieving a score of 84.7%, ChatGPT 4 falls within the top 10% of all test takers. In contrast, a score of 56.9% places ChatGPT 3.5 near the passing threshold. This significant difference provides empirical evidence of the substantial enhancements and refinements embedded within ChatGPT 4 and elucidates the leap in proficiency this iteration has attained, pushing the boundaries of AI capabilities in medical knowledge comprehension and application.

While ChatGPT 3.5 hovered around the approximate passing threshold of 60%, ChatGPT 4 not only passed the examination but merely excelled at it. According to the score interpretation guide provided by the National Board of Medical Examiners, an accuracy rate of 84.7% approximates placement within the 90th to 92nd percentile [14]. This signifies that ChatGPT 4 would be situated among the elite stratum, encompassing the top 10% of USMLE Step 3 candidates. The impressive escalation in performance exhibited by ChatGPT 4 makes the delineation of strengths and limitations difficult [15]. The model’s evolution seems to have attenuated discernible weaknesses, indicating a more well-rounded overall proficiency in the medical domain [12].

However, nothing is perfect. Although ChatGPT 4 accesses detailed, comprehensive, and up-to-date knowledge bases to optimize its response patterns, we could reveal minor
performance weak points. We found that ChatGPT 4 was more prone to errors when answering test questions on cardiology (mean test accuracy: n=89, 71.4% vs n=15, 84.7% correct questions) and neurology (mean test accuracy: n=104, 71.4% vs n=15, 84.7% correct questions). Interestingly, these subjects often test the examinee’s transfer knowledge skills. Based on theoretical concepts (eg, Frank-Starling law and dermatome map), examinees are asked to filter the question stem for relevant patient data and adapt the underlying theory to the patient case. This novel insight into ChatGPT points toward persistent deficits in abstract thinking. Therefore, test question writers for the USMLE or other medical examinations may use this question style for other subjects to reduce the risk of AI cheating. Further, our analysis demonstrated that the performance of ChatGPT 4 significantly correlated ($\rho=–0.344$; $P<0.001$) with the level of test question difficulty. This indicates that sophisticated USMLE questions still challenge and fool both human examinees and AI chatbots. Typically, the most difficult USMLE questions include distractors as well as irrelevant or additional information.; they also require high-level reasoning and interdisciplinary thinking. Our group previously showed that ChatGPT 3.5, similar to the human user peer group, struggled to answer 4- and 5-hammer questions [11]. Such pitfalls continue to perplex the next generation of AI-powered chatbots. Therefore, a thorough analysis of 4- and 5-hammer questions may help examiners refine their test questions and shield the USMLE against AI cheating.

Overall, the phenomenal improvement in the test-taking performance of ChatGPT 4 compared to ChatGPT 3.5 raises intriguing questions regarding future applications and implications of AI in medical education and diagnostics. AI has shown its prowess not only on the USMLE examinations in medical education but also on advanced examinations, such as the neurosurgical written boards [16]. This phenomenon ventures into other aspects of medicine as well, including research and clinical performance [17]. It is imperative that future research ventures into a deeper analysis of the performance of ChatGPT 4 by conducting thorough investigations that probe its strengths and limitations in a more granulated manner, potentially employing diversified medical question banks, simulating real-world scenarios, and engaging experts for analysis and evaluation to allow for the best possible medical education and ultimately patient health care [18].

**Limitations**

This study needs to be interpreted in the light of the following limitations: first, due to the restricted use of ChatGPT (only 25 entries every 3 hours) we were not able to perform a direct comparison of ChatGPT 3.5 and ChatGPT 4 for all test questions included in this study, which might limit its validity. Furthermore, although we attempted to ensure that the questions provided for analysis were not freely available on the internet to minimize the risk of ChatGPT having already seen the exact question, students and researchers around the world may have input certain AMBOSS USMLE Step 3 Style Questions into ChatGPT. This adds a potential confounding factor of ChatGPT memorizing the correct answer from seeing the question beforehand. We used the 2 most recent versions of ChatGPT (ie, ChatGPT 3.5 and ChatGPT 4) to test and compare the performance of large language models on 1840 AMBOSS USMLE Step 3 questions. Thus, the findings of this study should be revalidated for upcoming ChatGPT versions. Future studies may involve additional chatbots, question banks, and image-based test questions. Further, the performance of ChatGPT on USMLE steps could be compared to other national medical licensing exams.

**Conclusions**

This study is the first direct comparison of ChatGPT 4 and ChatGPT 3.5 based on 1840 AMBOSS USMLE Step 3 test questions. Our analysis showed that ChatGPT 4 outperformed its predecessor version across different specialties and difficulty levels, ultimately yielding accuracy levels of 84.7%. However, we could identify persisting weak points of ChatGPT 4, including abstract thinking and elaborated test questions. This line of research may serve as an evidence-based fundament to safeguard the USMLE steps and medical education against AI cheating while underscoring the potency of AI-driven chatbots.


13. AMBOSS question bank. URL: https://www.amboss.com/us [accessed 2023-12-18]


Abbreviations
- **AI**: artificial intelligence
- **CK**: clinical knowledge
- **CS**: communication skills
- **MRI**: magnetic resonance imaging
- **USMLE**: United States Medical Licensing Examination

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Artificial Intelligence in Medicine: Cross-Sectional Study Among Medical Students on Application, Education, and Ethical Aspects

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Abstract

Background: The use of artificial intelligence (AI) in medicine not only directly impacts the medical profession but is also increasingly associated with various potential ethical aspects. In addition, the expanding use of AI and AI-based applications such as ChatGPT demands a corresponding shift in medical education to adequately prepare future practitioners for the effective use of these tools and address the associated ethical challenges they present.

Objective: This study aims to explore how medical students from Germany, Austria, and Switzerland perceive the use of AI in medicine and the teaching of AI and AI ethics in medical education in accordance with their use of AI-based chat applications, such as ChatGPT.

Methods: This cross-sectional study, conducted from June 15 to July 15, 2023, surveyed medical students across Germany, Austria, and Switzerland using a web-based survey. This study aimed to assess students’ perceptions of AI in medicine and the integration of AI and AI ethics into medical education. The survey, which included 53 items across 6 sections, was developed and pretested. Data analysis used descriptive statistics (median, mode, IQR, total number, and percentages) and either the chi-square or Mann-Whitney U tests, as appropriate.

Results: Surveying 487 medical students across Germany, Austria, and Switzerland revealed limited formal education on AI or AI ethics within medical curricula, although 38.8% (189/487) had prior experience with AI-based chat applications, such as ChatGPT. Despite varied prior exposures, 71.7% (349/487) anticipated a positive impact of AI on medicine. There was widespread consensus (385/487, 74.9%) on the need for AI and AI ethics instruction in medical education, although the current offerings were deemed inadequate. Regarding the AI ethics education content, all proposed topics were rated as highly relevant.

Conclusions: This study revealed a pronounced discrepancy between the use of AI-based (chat) applications, such as ChatGPT, among medical students in Germany, Austria, and Switzerland and the teaching of AI in medical education. To adequately prepare future medical professionals, there is an urgent need to integrate the teaching of AI and AI ethics into the medical curricula.

Keywords: artificial intelligence; AI technology; medicine; medical education; medical curriculum; medical school; AI ethics; ethics

Introduction

Background

Artificial intelligence (AI) has attracted both public and scientific interest and is amplified by the emergence and greater accessibility of chat-based applications such as ChatGPT (OpenAI, LLC) and Bard (Google, LLC). For several years, the medical field has been an active and expanding area of research on the application of AI [1]. As of now, AI is used in diverse medical specializations, including dermatology, radiology, and pathology [2-4].
Although the history of AI can be traced back to the 1950s, the public’s unrestricted access to highly advanced large language models, such as ChatGPT, can be seen as a significant turning point in the history of AI [5,6]. Early studies demonstrated that ChatGPT is capable of successfully completing the written portion of the United States Medical Licensing Examination [7]. Given the capabilities of AI-based chat applications such as ChatGPT in medicine, further studies have highlighted their potential use in providing information on cancer, assisting in clinical diagnoses, authoring scientific research articles, and patient communication [8-10]. Considering the wide availability and integration of medical knowledge in this application, its increasing use in medicine and among medical students is foreseeable [11].

Despite the long history of AI and the increasing adoption of this technology, there is disagreement regarding its definition among the scientific community [12]. There is a consensus within the scientific community on distinguishing between the so-called strong AI, also known as “artificial general intelligence,” and weak AI or “artificial narrow intelligence” [13]. This categorization is based on the capabilities of AI or its areas of application [13]. Strong AI, recognized for its human-equivalent intellectual abilities and knowledge, stands in contrast to weak AI, which refers to AI solutions capable of accomplishing specific tasks effectively [13]. The area of weak AI can be further divided into the so-called statistical AI and symbolic AI. The field of statistical AI also includes machine learning and deep learning, on which large language models such as ChatGPT are based [13]. Areas of application for symbolic AI in medicine include expert systems (eg, clinical decision support systems), which make decisions based on explicit knowledge in the form of predefined rules [14].

Considering the likely significant impact the implementation and use of AI in medicine is poised to make, a growing body of literature advocates the inclusion of AI-related content in medical curricula [15-18]. In addition to implications for the medical profession and patient care, medical students are expected to face new ethical challenges posed by the use of AI in medicine [15,19]. Despite the potentially significant ethical challenges anticipated from the deployment of AI in medicine, such as the possibility of discrimination due to biases in the data used for training or effects on patient autonomy, there is a near-complete absence of scientific publications on specific teaching content or methods related to AI ethics as part of medical higher education.

In addition to the lack of specificity regarding teaching content on AI and AI ethics, the absence of studies on medical students’ perception of AI ethics education (including teaching content) is notable [20,21]. It is essential to point out that the current state of research regarding medical students’ perceptions and assessments of AI application in medicine largely represents a knowledge base that predates the advent of large language models such as ChatGPT. With the ubiquity of the aforementioned AI applications at the time of this publication, it is reasonable to expect that medical students’ assessments of AI implementation in medicine will deviate significantly from earlier publications within this area of research, highlighting the need for further research.

Objective
This study aimed to explore how medical students perceive the use of AI in medicine, as well as the teaching of AI and AI ethics (including prospective AI ethics teaching topics). In this context, the introduction and accessibility of large language models such as ChatGPT should be emphasized, leading to the following research question: how do medical students from Germany, Austria, and Switzerland perceive (1) the application of AI in medical practice, (2) the integration of AI and AI ethics into medical education, and (3) AI ethics teaching content in their curriculum in accordance with the use of AI-based chat applications such as ChatGPT?

To address this research question, the participating medical students were divided into 2 groups based on their prior use of AI-based (chat) applications, such as ChatGPT.

Methods

Overview
This cross-sectional study was conducted between June 15 and July 15, 2023. During this time frame, an invitation to participate in the study was sent to medical students who were regularly enrolled in universities in Germany, Austria, and Switzerland. The study sample included medical students from all academic semesters, including those in practically oriented semesters such as the practical year in Germany. Participation in the study was voluntary and there were no consequences for nonparticipation. The study used an anonymous web-based survey, with recruitment facilitated through email invitations and assistance from various medical student associations, unions, and councils in their respective countries. To minimize potential selection bias, the survey invited medical students from various universities and academic semesters in Germany, Austria, and Switzerland. This strategy ensured a broad and representative sample of the participants. Moreover, careful construction and pretesting of the survey were conducted to minimize potential response biases. Before the official data collection, a pretest was conducted with 11 medical students from the target population. The web-based survey provider, “LimeSurvey” was used for both the pretest and the main study.

Ethical Considerations
The Research Committee for Scientific Ethical Questions granted ethical approval for this study (3181) on January 16, 2023.

Survey Development
The survey used for data collection was developed based on existing scientific publications [15,22]. Owing to the lack of references in the areas of AI teaching, AI ethics, and recent developments in AI, most items used for the survey were newly formulated. The survey comprises 53 items, including both questions and statements. During the development process, these items were distributed across 6 parts, with some contingent on the responses to the preceding items. The first part aimed to collect information on the demographic characteristics and educational background of the participants. To address the research question of this study, participants were divided into...
2 groups based on their responses to questions related to their prior use of AI-based (chat) applications such as ChatGPT. The second part sought to gather information about the students’ previous experiences with AI-based (chat) applications. In the third part, the students were asked to rate various statements regarding the use of AI in medicine. The fourth and fifth parts aimed to capture students’ evaluations of statements about AI teaching and ethics, respectively. The sixth part assessed the perceived relevance of the potential teaching content to AI ethics. The items in parts 3 to 6 were evaluated using a 5-point Likert scale. Before the survey was conducted, 2 experts in ethics and AI evaluated the survey and their recommendations were incorporated. Upon receiving expert feedback, the teaching topic of “data privacy” was introduced as a distinct subject under AI ethics. Previously, this was encompassed within the broader “safety” category. Furthermore, to enhance clarity, the term “knowingly” was incorporated into Q12. This adjustment acknowledges that the application of AI in medicine may not always be transparent.

Survey Pretest
To assess the comprehensibility and relevance of the survey, a pretest was conducted with 11 medical students, who subsequently provided feedback. This feedback led to 6 relevant modifications aimed at enhancing clarity, relevance, and user-friendliness. Because of the feedback provided, questions Q1 through Q4 and Q6 were specified by adding examples following each question. The changes made to the questions are highlighted in italics:

1. Q1. Have you already received education in the field of ethics within your regular medical studies? (eg, as part of the History, Ethics, and Theory of Medicine course)
2. Q2. Have you already received education in the field of AI in your regular medical studies? (eg, as part of medical statistics or informatics)
3. Q3. Have you already received education in the field of AI outside of your regular medical studies? (eg, in the form of further training, own research)
4. Q4. Have you already received education in the field of AI ethics within your regular medical studies? (eg, as part of the History, Ethics, and Theory of Medicine course)
5. Q6. Have you already received instruction in the field of AI ethics outside of your regular medical studies? (eg, in the form of further training, own research)

Similarly, statement 27 (S27) was further improved by adding examples from various fields to underscore the multidisciplinary context: “AI ethics should be taught by experts from various fields (eg, medicine, computer science, philosophy) to ensure a multidisciplinary perspective on AI ethics.”

To improve the survey’s user experience, conditional logic was integrated so that questions Q5 and Q7 appeared only in response to the specific preceding answers. Both question Q5 and question Q7 were designed to explore the specific content covered in AI ethics education. These questions were identical in wording: “Which of the following contents were covered as part of the instruction/education?” Question Q5 was presented exclusively to participants who answered “yes” to question 4, which focused on AI ethics education within their regular medical studies. Similarly, question Q7 was shown only to those who responded “yes” to question 6, focusing on AI ethics education outside of their regular medical curriculum. This strategic modification not only streamlined the survey’s presentation but also minimized the immediate visual content, reducing complexity.

Sample Size Calculation
The sample size for this study was calculated before data collection using Cochran sample size formula \( n = \left( \frac{Z^2 \cdot p \cdot (1-p)}{E^2} \right) \) [23]. The total population size used for the calculation, which represents the number of medical students enrolled at the end of the winter semester in 2022, was 130,601 across the 3 countries included in the study. This figure includes 105,275 medical students from Germany (accounting for 80.61% of the total), 17,826 from Austria (13.65%), and 7500 from Switzerland (5.74%) [24-26]. This summation was performed based on the primary research question and was predicated on the assumption that the prevalence of AI-based (chat) applications, such as ChatGPT, among medical students does not vary significantly across these countries. A confidence level of 95% (\( Z=1.96 \)) and a margin of error of 5% were used to determine the sample size. The proportion (p) was derived from a pretest involving a separate group of 11 medical students of which 5 were already using large language models such as ChatGPT before the study (\( P=.45 \)). Cochran’s formula yielded a sample size of 380 medical students. As the study was conducted using a web-based survey with recruitment via email, an estimated dropout rate of 40% was factored in. To achieve a calculated sample size of 380 participants, at least 532 students were targeted during the recruitment process. To ensure adequate representation based on the proportion of medical students within each country of interest, the study aimed to include at least 306 medical students from Germany, 52 from Austria, and 22 from Switzerland in the data collection and analysis process. Note that these are rounded values given that the actual calculations result in noninteger numbers.

Data Analysis
Collected data were evaluated using SPSS (version 28; IBM Corp), LimeSurvey (LimeSurvey GmbH), and Microsoft Excel (version 16.73). Descriptive statistics were calculated for all survey variables, including the median, IQR, mode, total number, and percentages. For further statistical analysis, the chi-square test of independence was used to compare the 3 groups. When significant differences were observed in the chi-square test, post hoc analysis was performed using the adjusted residuals method to specify which specific groups or categories contributed to the observed significance. In addition, \( z \) scores were calculated to facilitate the comparison of responses across different groups. These were computed using the 2-sided test formula \( z = (X - \mu) / \sigma \), where \( X \) represents the value of the response, \( \mu \) is the mean of the responses for the group, and \( \sigma \) is the SD within that group. The calculation of \( z \) scores enabled the quantification of the deviation of each response from the group mean in terms of SDs. The Mann-Whitney \( U \) test was used for the statistical comparison of 2 independent groups; for further statistical analysis, the chi-square test of independence was used to compare the 3 groups, and the Mann-Whitney \( U \)
test was used for the statistical comparison of 2 independent groups. For statistical analysis, the responses to the Likert scale were recoded into a numerical format (“I strongly disagree”=1, “I disagree”=2, “undecided”=3, “I agree”=4, “I strongly agree”=5). For all statistical tests performed, the significance level was set at $\alpha=.05$, and a value of $P \leq .05$ was considered statistically significant. Only complete data sets were included in the data analysis to avoid potential biases that could arise from replacing or estimating the missing values (list-wise deletion).

**Results**

**Overview**

In total, 521 medical students participated in the survey, yielding 487 complete and valid data sets for the statistical analysis. The survey invitations were disseminated via email with the help of medical student associations, unions, and councils. The total number of medical students reached and the precise response rate could only be approximated. On the basis of the feedback received from the engaged medical student councils, we estimated that at least 2000 medical students were approached. This would be equal to a response rate of 24.35% (487/2000). Our sample size calculation was based on the assumption that the use of AI-based (chat) applications such as ChatGPT does not diverge markedly among medical students from each of the countries of interest, namely Germany, Austria, and Switzerland. Consequently, the chi-square test of independence was used for statistical evaluation. We posited a null hypothesis (H) asserting no association between the variables (use of AI-based applications and country of study) and an alternative hypothesis ($H_1$) suggesting an association between these variables. The chi-square test returned a value of $P=.96$, which exceeded the predetermined level of significance. As such, we did not reject the null hypothesis, leading us to conclude that there is no statistically significant association between the use of AI-based (chat) applications and country of study among the surveyed medical students, given that each individual fits into one category for each variable.

**Part 1: Demographics and Educational Background**

Of the medical students who participated in the survey, the majority were women (270/487, 55.4%). The largest demographic age was between 20 and 25 years (301/487, 61.8%), and most students were enrolled in Germany (296/487, 60.7%). The German contingent of respondents was slightly below our target size of 306, representing a 3.3% (296/306) shortfall. However, participation from Austria exceeded our initial target of 52 students by a substantial margin, with 105 respondents indicating enrollment in Austria, denoting an overachievement rate of 202% (105/52). Similarly, Swiss representation surpassed our initial target of 22 students, with 86 respondents registered in Switzerland, marking an overachievement of 391% (86/22). Most of the surveyed students were in the clinical stage (CS) of their study (277/487, 56.9%), followed by those in their practical years (63/487, 12.9%). Comprehensive demographic characteristics are presented in Table 1.

The respondents were also asked about their educational backgrounds in ethics, AI, and AI ethics. Most participants (425/487, 87.2%) reported having received ethics education. However, a considerably smaller proportion of respondents claimed that they had received prior education in AI as part of their medical curriculum (26/487, 5.3%), with an additional 10.5% (51/487) having obtained such knowledge outside of their regular medical studies. Few participants had been exposed to AI ethics education within their medical curriculum (21/487, 4.3%), with a small number reporting having learned about AI ethics outside their regular curriculum (51/487, 6.8%). The most common subjects covered in AI ethics education were bias (15/487, 3.1% within and 14/487, 2.9% outside regular studies) and explainability (12/487, 2.5% within and 20/487, 4.1% outside regular studies). Detailed responses related to the participants’ educational background are shown in Table 2.
Table 1. Demographic characteristics of medical students (n=487).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Medical students, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
</tr>
<tr>
<td>Woman</td>
<td>270 (55.4)</td>
</tr>
<tr>
<td>Man</td>
<td>203 (41.7)</td>
</tr>
<tr>
<td>Nonbinary</td>
<td>3 (0.6)</td>
</tr>
<tr>
<td>Prefer not to say</td>
<td>11 (2.3)</td>
</tr>
<tr>
<td><strong>Age (y)</strong></td>
<td></td>
</tr>
<tr>
<td>&lt;20</td>
<td>56 (11.5)</td>
</tr>
<tr>
<td>20-25</td>
<td>301 (61.8)</td>
</tr>
<tr>
<td>26-30</td>
<td>92 (18.9)</td>
</tr>
<tr>
<td>31-35</td>
<td>28 (5.7)</td>
</tr>
<tr>
<td>&gt;35</td>
<td>10 (2.0)</td>
</tr>
<tr>
<td><strong>Country of enrollment (medical studies)</strong></td>
<td></td>
</tr>
<tr>
<td>Germany</td>
<td>296 (60.7)</td>
</tr>
<tr>
<td>Austria</td>
<td>105 (21.5)</td>
</tr>
<tr>
<td>Switzerland</td>
<td>86 (17.7)</td>
</tr>
<tr>
<td><strong>Stage of study</strong></td>
<td></td>
</tr>
<tr>
<td>Preclinical</td>
<td>57 (11.7)</td>
</tr>
<tr>
<td>Clinical</td>
<td>277 (56.9)</td>
</tr>
<tr>
<td>Practical year</td>
<td>63 (12.9)</td>
</tr>
<tr>
<td>Elective year</td>
<td>26 (5.3)</td>
</tr>
<tr>
<td>Bachelor</td>
<td>46 (9.4)</td>
</tr>
<tr>
<td>Master</td>
<td>18 (3.7)</td>
</tr>
</tbody>
</table>
Table 2. Educational background of the participating medical students from Germany, Austria, and Switzerland (n=487).

<table>
<thead>
<tr>
<th>Question</th>
<th>Participants, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q1: Have you already received education in the field of ethics within your regular medical studies? (eg, as part of the History, Ethics, and Theory of Medicine course)</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>425 (87.2)</td>
</tr>
<tr>
<td>No</td>
<td>62 (12.7)</td>
</tr>
<tr>
<td>Q2: Have you already received education in the field of artificial intelligence within your regular medical studies? (eg, as part of medical statistics or informatics)</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>26 (5.3)</td>
</tr>
<tr>
<td>No</td>
<td>461 (94.7)</td>
</tr>
<tr>
<td>Q3: Have you already received education in the field of artificial intelligence outside of your regular medical studies? (eg, in the form of further training, own research)</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>51 (10.5)</td>
</tr>
<tr>
<td>No</td>
<td>436 (89.2)</td>
</tr>
<tr>
<td>Q4: Have you already received education in the field of artificial intelligence ethics within your regular medical studies? (eg, as part of the History, Ethics, and Theory of Medicine course)</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>21 (4.3)</td>
</tr>
<tr>
<td>No</td>
<td>466 (95.7)</td>
</tr>
<tr>
<td>Q5: Which of the following contents were covered as part of the education?</td>
<td></td>
</tr>
<tr>
<td>Informed consent</td>
<td>11 (2.3)</td>
</tr>
<tr>
<td>Bias</td>
<td>15 (3.1)</td>
</tr>
<tr>
<td>Data privacy</td>
<td>13 (2.7)</td>
</tr>
<tr>
<td>Explainability</td>
<td>12 (2.5)</td>
</tr>
<tr>
<td>Safety (of AI-based applications)</td>
<td>10 (2)</td>
</tr>
<tr>
<td>Fairness</td>
<td>5 (1)</td>
</tr>
<tr>
<td>Autonomy</td>
<td>8 (1.6)</td>
</tr>
<tr>
<td>Responsibility</td>
<td>8 (1.6)</td>
</tr>
<tr>
<td>Q6: Have you already received education in the field of artificial intelligence ethics outside of your regular medical studies? (eg, in the form of further training, own research)</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>33 (6.8)</td>
</tr>
<tr>
<td>No</td>
<td>454 (93.2)</td>
</tr>
<tr>
<td>Q7: Which of the following contents were covered as part of the education?</td>
<td></td>
</tr>
<tr>
<td>Informed consent</td>
<td>10 (2)</td>
</tr>
<tr>
<td>Bias</td>
<td>14 (2.9)</td>
</tr>
<tr>
<td>Data privacy</td>
<td>17 (3.5)</td>
</tr>
<tr>
<td>Explainability</td>
<td>20 (4.1)</td>
</tr>
<tr>
<td>Safety (of artificial intelligence-based applications)</td>
<td>18 (3.7)</td>
</tr>
<tr>
<td>Fairness</td>
<td>12 (2.5)</td>
</tr>
<tr>
<td>Autonomy</td>
<td>14 (2.9)</td>
</tr>
<tr>
<td>Responsibility</td>
<td>19 (3.9)</td>
</tr>
</tbody>
</table>

*a* Question 5 was exclusively displayed to participants who responded to question 4 with “yes.”

*b* An explanation of the contents of Q5 and Q7 is provided in the text.

*c* Question 7 was exclusively displayed to participants who responded to question 6 with “yes.”
Part 2: Use of AI-Based (Chat) Applications

With regard to the use of AI-based (chat) applications such as ChatGPT (OpenAI), Bard (Google), Bing Chat (Microsoft Inc), and Jasper Chat (Jasper AI, Inc), 38.8% (189/487) of the respondents reported prior use of these platforms. Conversely, the vast majority (438/487, 89.9%) indicated that they did not knowingly use other AI-based medical applications. Of the 298 respondents who had not previously used an AI-based chat application, 76.9% (n=229) expressed an interest in future use. Among the respondents who reported prior use of AI-based (chat) applications, nearly half had used such an application for 1-3 hours over the past week (91/189, 48.2%). Of this group, 73% (138/189) indicated using an AI-based (chat) application in a medical context, with the most common use being querying medical knowledge (74/138, 53.6%). The results of this survey are summarized in Table 3.

Table 3. Answers to the use of AI-based (chat) applications of participants (n=487).

<table>
<thead>
<tr>
<th>Question</th>
<th>Participants, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q8: Have you already used an AI-based (chat) application such as ChatGPT (OpenAI), Bard (Google), Bing chat, or Jasper Chat?</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>189 (38.8)</td>
</tr>
<tr>
<td>No</td>
<td>298 (61.2)</td>
</tr>
<tr>
<td>Q9: Have you knowingly ever used AI-based medical applications, such as image-based diagnostic tools in radiology?</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>49 (10.1)</td>
</tr>
<tr>
<td>No</td>
<td>438 (89.9)</td>
</tr>
<tr>
<td>Q10: Are you interested in using an AI application as part of your medical studies in the future?a, n=298</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>229 (76.9)</td>
</tr>
<tr>
<td>No</td>
<td>69 (23.1)</td>
</tr>
<tr>
<td>Q1: Approximately how many hours have you used the AI-based (chat) application in the last week (7 d)ab; (n=189)</td>
<td></td>
</tr>
<tr>
<td>&lt;1 h</td>
<td>73 (38.6)</td>
</tr>
<tr>
<td>1-3 h</td>
<td>91 (48.2)</td>
</tr>
<tr>
<td>4-6 h</td>
<td>19 (10)</td>
</tr>
<tr>
<td>7-9 h</td>
<td>3 (1.6)</td>
</tr>
<tr>
<td>10-12 h</td>
<td>2 (1.1)</td>
</tr>
<tr>
<td>&gt;12 h</td>
<td>1 (0.5)</td>
</tr>
<tr>
<td>Q12: Have you already used the AI-based (chat) application in a medical context? (eg, for explaining medical conditions or medical questions)c, (n=189)</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>138 (73)</td>
</tr>
<tr>
<td>No</td>
<td>51 (26.7)</td>
</tr>
<tr>
<td>Q13: For which of the following objectives have you already used the AI-based (chat) application in the medical context?d, (n=138)</td>
<td></td>
</tr>
<tr>
<td>Therapy suggestions</td>
<td>18 (13)</td>
</tr>
<tr>
<td>Querying medical knowledge</td>
<td>74 (53.6)</td>
</tr>
<tr>
<td>Diagnostic support</td>
<td>5 (3.6)</td>
</tr>
<tr>
<td>Explanation of pathologies</td>
<td>41 (29.7)</td>
</tr>
</tbody>
</table>

Part 3: AI in Medicine

In the third part of the survey, participants’ attitudes toward the role of AI’s in medicine were examined. Of the 487 respondents, 71.7% (n=349) agreed or strongly agreed that the use of AI would bring about positive changes to medicine (S1). Similarly, 72.1% (350/487) believed that AI could find practical applications in medicine (S2). When comparing the responses between those who had used AI-based applications and those who did not, significant differences were identified for each statement using the Mann-Whitney U test (S1: P=.003; S2: P=.002). Although both groups shared the same median and mode responses, their z scores suggested variations in their agreement levels. Specifically, respondents who had not

https://mededu.jmir.org/2024/1/e51247 JMIR Med Educ 2024 | vol. 10 | e51247 | p.510 (page number not for citation purposes)
previously used AI-based chat applications displayed a higher level of agreement with the statement in S1 (z score: -2.991). Conversely, those who had used AI-based applications exhibited greater concurrence with the statement in S2 (z score: 3.105).

When comparing the responses of those who had used AI-based chat applications and those who had not, no significant difference was observed regarding the subsequent 2 statements, S3 and S4, which were related to the influence on the choice of medical specialization and the potential reduction of jobs for medical staff. However, marked differences were identified when comparing the responses to statements S5 to S7 concerning improvements in patient care quality (S5: $P<.001$), diagnostic processes (S6: $P=.002$), and therapy selection (S7: $P<.001$). Although the overall agreement (either “agree” or “strongly agree”) was high for these statements (S5: 71%; S6: 76.4%; S7: 77.9%), z scores indicated greater agreement within the subgroup that had previously used AI-based (chat) applications (S5: z score=3.570; S6: z score=3.089; S7: z score=3.865).

No significant difference was found for statements S8 to S11 between the 2 groups, with comparable levels of overall agreement (“agree” or “strongly agree“) for each statement (S8: 31.8%; S9: 29.6%; S10: 25.9%; S11: 31.8%). However, a significant difference was observed for statement S12 ($P=.02$), with 95.3% of all respondents agreeing or strongly agreeing that the use of AI in medicine presents new ethical challenges. The z score (2.302), median (5), and mode (5) suggested a higher level of agreement among the groups that had previously used AI-based (chat) applications, such as ChatGPT. A statistical analysis of the third part of the survey is presented in Table 4.

A detailed illustration of the perceptions of the surveyed medical students regarding the use of AI in medicine is provided in Table S1 in Multimedia Appendix 1.
Table 4. Statistical analysis of the perceptions of medical students regarding the use of artificial intelligence (AI)-based (chat) applications such as ChatGPT (OpenAI), Bard (Google), Bing Chat (Microsoft Inc), and Jasper Chat (Jasper AI, Inc) in medicine (n=487).

<table>
<thead>
<tr>
<th>Statement and subgroup</th>
<th>Scores, median (IQR)</th>
<th>Scores, mode</th>
<th>P value</th>
<th>Z score</th>
</tr>
</thead>
<tbody>
<tr>
<td>The use of AI in medicine will...</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>S1: ...positively change medicine</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (3.75-4.25)</td>
<td>4</td>
<td>.003</td>
<td>−2.990</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>S2: ...find useful applications in medicine</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (3.5-4.5)</td>
<td>4</td>
<td>.002</td>
<td>3.101</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>S3: ...influence the choice of my medical specialization</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>3 (2-4)</td>
<td>2</td>
<td>.52</td>
<td>−1.474</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>3 (2-4)</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>S4: ...reduce the number of jobs for medical staff</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>3 (3-5)</td>
<td>4</td>
<td>.09</td>
<td>−1.707</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>3 (2-4)</td>
<td>2</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>S5: ...improve the quality of patient care</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (0)</td>
<td>4</td>
<td>&lt;.001</td>
<td>3.570</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3.5-4.5)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>S6: ...improve the process of diagnosis</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (3.5-4.5)</td>
<td>4</td>
<td>.002</td>
<td>3.089</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>S7: ...improve the process of therapy selection</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (0-0)</td>
<td>4</td>
<td>&lt;.001</td>
<td>3.865</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>S8: ...negatively affect the doctor-patient relationship</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>3 (2-4)</td>
<td>2</td>
<td>.18</td>
<td>1.328</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>3 (2-4)</td>
<td>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>S9: ...lead to a dehumanization of medicine</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>3 (2-4)</td>
<td>2</td>
<td>.11</td>
<td>1.610</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>3 (2-4)</td>
<td>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>S10: ...negatively affect patient autonomy</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>3 (2-3)</td>
<td>2</td>
<td>.05</td>
<td>2.040</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>3 (2-4)</td>
<td>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>S11: ...negatively affect the autonomy of medical staff</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>3 (2-4)</td>
<td>2</td>
<td>.16</td>
<td>1.415</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>3 (2-4)</td>
<td>3</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>S12: ...bring new ethical challenges</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>5 (4-5)</td>
<td>5</td>
<td>.02</td>
<td>2.302</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Part 4: Teaching AI in Medical Education

When asked about their agreement on whether AI teaching should be incorporated into medical education (S13), 74.9% (385/487) of the respondents agreed or strongly agreed. A statistically significant difference was identified between those with and without prior use of AI-based (chat) applications ($P=.02$). The mean (5), mode (5), and z score (2.381) suggest higher agreement within the group that previously used AI-based applications. In contrast, there was an overall disagreement...
(88%) with the assertion that AI instruction in medical education is currently sufficient (S14), with no statistically significant difference between the 2 groups. No significant statistical differences were observed for statements S15-S19. There was an overall agreement that the teaching of AI should include practical content (S15; 417/487, 86%), be based on case studies and application scenarios in medicine (S16; 342/487, 70.3%), be an important prerequisite for medical practice (S17; 314/487, 64.9%), be available to medical staff even after graduation (S18; 376/487, 77.3%), and be updated regularly to reflect advances in AI technology (S19; 407/487, 83.6%). There was a significant measurable difference in the S20 ($p=0.002$) between the 2 groups. The $z$ score indicates a stronger agreement with the statement “AI instruction is of interest to me” among the group of medical students who previously used AI-based (chat) applications ($z$ score: 3.173). The statistical analysis is presented in Table 5, and an overview of the perceptions of the participants regarding the teaching of AI in medicine can be found in Table S2 in Multimedia Appendix 1.

### Table 5. Statistical analysis of the perceptions of medical students regarding the teaching of artificial intelligence (AI)-based (chat) applications such as ChatGPT (OpenAI), Bard (Google), Bing Chat (Microsoft Inc), and Jasper Chat (Jasper AI, Inc) in medical education (n=487).

<table>
<thead>
<tr>
<th>Statement and subgroup</th>
<th>Scores, median (IQR)</th>
<th>Scores, mode</th>
<th>$P$ value</th>
<th>$Z$ score</th>
</tr>
</thead>
<tbody>
<tr>
<td>S13: ...should be part of medical education</td>
<td></td>
<td></td>
<td>.02</td>
<td>2.381</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>5 (4-5)</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S14: ...in medical education is adequate</td>
<td></td>
<td></td>
<td>.90</td>
<td>0.128</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>2 (1-2)</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>2 (1-2)</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S15: ...should include practical content (e.g., exercises to apply AI) in addition to theoretical aspects</td>
<td></td>
<td></td>
<td>.18</td>
<td>-2.358</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (3.5-4.5)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (0)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S16: ...should be based on case studies and application scenarios of AI in medicine</td>
<td></td>
<td></td>
<td>.53</td>
<td>-0.625</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (3-5)</td>
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<td></td>
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<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3.5-4.5)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S17: ...is an important prerequisite for medical practice</td>
<td></td>
<td></td>
<td>.16</td>
<td>1.417</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (3.5-4.5)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S18: ...should be available for medical staff even after graduation</td>
<td></td>
<td></td>
<td>.13</td>
<td>-1.527</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (3.5-4.5)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3-5)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S19: ...should be updated regularly to reflect advances in AI technology</td>
<td></td>
<td></td>
<td>.34</td>
<td>-2.121</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td></td>
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</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S20: ...is of interest to me</td>
<td></td>
<td></td>
<td>.002</td>
<td>3.173</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (4-5)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (0)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Part 5: Teaching AI Ethics in Medical Education

In the survey, 74.9% (385/487) of medical students agreed or strongly agreed that teaching AI ethics should be included in medical education (S21). However, only 4.9% (24/487) agreed that the current instruction on AI ethics in medical education is adequate (S22). For statements S23 to S27, the vast majority of medical students generally agreed (“agree” or “strongly agree”) that the teaching of AI ethics should be based on case studies and application scenarios of AI in medicine (S23; 412/487, 85%), contribute to raising awareness of ethical issues in medical practice (S24; 343/487, 70.6%), is an important prerequisite for medical practice (S25; 354/487, 72.8%), should be available for medical staff even after graduation (S26; 370/487, 75.9%), and should be taught by experts from various fields (eg, medicine, computer science, and philosophy) to ensure a multidisciplinary perspective on AI ethics (S27; 416/487, 85.2%). No statistically significant differences were observed for statements S21 to S27 between the 2 groups (those with previous use of AI-based [chat] applications and those without). Despite the $z$ score of 1.782 being below the typical
threshold of 1.96 for a 2-tailed test, the statement “the teaching of AI ethics is of interest to me” (S28) showed a statistically significant difference ($P = .005$). This indicates that even though the deviation from the mean agreement level is not as strong as typically expected for significance, those who had previously used AI-based (chat) applications demonstrated a notably higher level of interest in AI ethics teaching than those who had not. The statistical analysis for part 5 of the survey is shown in Table 6, and the distribution of answers is presented in Table S3 in Multimedia Appendix 1.

**Table 6.** Statistical analysis of the perceptions of medical students regarding the teaching of artificial intelligence (AI)-based (chat) applications such as ChatGPT (OpenAI), Bard (Google), Bing Chat (Microsoft Inc), and Jasper Chat (Jasper AI, Inc) ethics in medical education (n=487).

<table>
<thead>
<tr>
<th>Statement and subgroup</th>
<th>Scores, median (IQR)</th>
<th>Scores, mode</th>
<th>$P$ value</th>
<th>Z score</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>The teaching of AI...</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S13: ...should be part of medical education</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>5 (4-5)</td>
<td>5</td>
<td>.37</td>
<td>−0.903</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (4-5)</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S14: ...in medical education is adequate</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>2 (2-3)</td>
<td>2</td>
<td>.21</td>
<td>−1.263</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>2 (1-2)</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S15: ...should include practical content (e.g., exercises to apply AI) in addition to theoretical aspects</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (0)</td>
<td>4</td>
<td>.80</td>
<td>−0.254</td>
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<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (0)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S16: ...should be based on case studies and application scenarios of AI in medicine</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td>.48</td>
<td>−0.707</td>
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<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (2.5-4.5)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>S17: ...is an important prerequisite for medical practice</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (3-4)</td>
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<td>.90</td>
<td>0.118</td>
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<td>Subgroup 2: no previous use of AI</td>
<td>4 (2-4)</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>S18: ...should be available for medical staff even after graduation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td>.17</td>
<td>−1.359</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (2-4)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S19: ...should be updated regularly to reflect advances in AI technology</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td>.17</td>
<td>−1.381</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
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<td></td>
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</tr>
<tr>
<td>S20: ...is of interest to me</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td>.005</td>
<td>1.782</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (0)</td>
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</tr>
</tbody>
</table>

### Part 6: AI Ethics Teaching Content

In analyzing the perceptions of medical students with and without prior exposure to AI chat applications regarding AI ethics content, all 8 proposed topics were deemed highly relevant (“quite relevant” and “very relevant”) by the respondents: TC1: 418/487, 85.9%; TC2: 408/487, 83.8%; TC3: 384/487, 78.9%; TC4: 415/487, 85.2%; TC5: 423/487, 86.2%; TC6: 407/487, 83.6%; TC7: 402/487, 82.5%; and TC8: 448/487, 92.3%). No statistically significant difference was observed between the responses of both groups, except for TC1 (informed consent; $P = .04$). The $Z$ score suggests that medical students who had previously used AI-based (chat) applications perceived informed consent to be more relevant than those who had not ($z$ score: 2.018). The statistical results of this section are shown in Table 7, with an overview of the statements on the relevance of AI ethics teaching content provided in Table S4 in Multimedia Appendix 1.
Table 7. Statistical analysis of the relevance of artificial intelligence (AI)–based (chat) applications such as ChatGPT (OpenAI), Bard (Google), Bing Chat (Microsoft Inc), and Jasper Chat (Jasper AI, Inc) ethics teaching contents according to the participating medical students (n=487).

<table>
<thead>
<tr>
<th>AI ethics teaching content and subgroup</th>
<th>Scores, median (IQR)</th>
<th>Scores, mode</th>
<th>P value</th>
<th>Z score</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TC1: informed consent</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (4-5)</td>
<td>5</td>
<td>.04</td>
<td>2.018</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>TC2: bias</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (4-5)</td>
<td>5</td>
<td>.22</td>
<td>−1.215</td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>TC3: data privacy</strong></td>
<td></td>
<td></td>
<td>.78</td>
<td>0.283</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (4-5)</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3-4)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>TC4: explainability</strong></td>
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<td></td>
<td>.36</td>
<td>−0.911</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (4-5)</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (3.5-4.5)</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>TC5: safety</strong></td>
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<td>.57</td>
<td>0.565</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>5 (4-5)</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>5 (4-5)</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>TC6: fairness</strong></td>
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<td></td>
<td>.96</td>
<td>−0.048</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>4 (4-5)</td>
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<td></td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (4-5)</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>TC7: autonomy</strong></td>
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<td>.11</td>
<td>1.594</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
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<td></td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>4 (4-5)</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>TC8: responsibility</strong></td>
<td></td>
<td></td>
<td>.22</td>
<td>−1.215</td>
</tr>
<tr>
<td>Subgroup 1: previous use of AI</td>
<td>5 (4-5)</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Subgroup 2: no previous use of AI</td>
<td>5 (4-5)</td>
<td>5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Additional Analysis of the Collected Data

To analyze whether there is a difference in education regarding AI and AI ethics among Germany, Austria, and Switzerland, we conducted an additional evaluation of the collected data. For this supplementary analysis, we analyzed the responses to Q2: “Have you already received education in the field of artificial intelligence within your regular medical studies? (eg, as part of medical statistics or informatics),” and Q4: “Have you already received education in the field of AI ethics within your regular medical studies? (eg, as part of the History, Ethics, and Theory of Medicine course).” Using the chi-square test of independence, we sought to determine whether the distribution of answers varied significantly among these countries. In the comparison between the 3 countries concerning education in the field of AI, the chi-square test of independence indicated no significant difference in the distribution of the responses. Of the 487 respondents, only 26 (5.3%) indicated that they had previously received AI education. The test yielded a result of $\chi^2_{1}(N=487)=0.1 (P=.33)$. Similarly, regarding education in the field of AI ethics, the distribution of responses among the countries was not significantly different. Of the 487 respondents, only 21 (4.3%) indicated that they had received education on AI ethics. The test yielded a result of $\chi^2_{1}(N=487)=0.3 (P=.19)$.

Stage of Study

To account for potential confounders, such as the stage of the study, further analyses were performed on the data set. Recognizing the possible overlaps and similarities in experiences and perspectives across the different stages, the original 6 stages of the study were further consolidated. The stages “preclinical” and “bachelor” were summarized into the “preclinical stage (PCS).” Similarly, the “clinical” and “master” stages were combined into the “clinical stage.” Finally, the “practical year” and “elective year” stages were grouped together to form the “clinical practical stage (CPS).” With these redefined categories, the chi-square test of independence was used to analyze whether there were significant variations in perceptions and responses across the 3 consolidated stages.

Focusing on the potential impact of AI in medicine, a significant difference was observed in the statement, “the use of AI in medicine will influence the choice of my specialization” (S3). CPS participants were notably more influenced than those in the PCS ($P=.004$). However, no difference was evident between
the PCS and CS participants. Most other statements concerning AI’s impact on medicine (S1-2; S4-12) did not demonstrate statistical significance. Similarly, no significant difference was found for statements related to AI teaching (S13-20) across the study stages (PCS, CS, and CPS). When considering the teaching of AI ethics, differences were evident in the belief that AI ethics should be integrated into medical education (S21; \( P = 0.003 \)) and that the current teaching of AI ethics is adequate (S22; \( P = 0.02 \)). Upon further analysis, CS participants showed stronger agreement than PCS participants, with no difference when compared with CPS participants. Finally, for the specific content of AI ethics teaching, none of the statements reflected significant statistical variation across the study stages. An overview of the statistical differences is provided in Tables S5-S8 in Multimedia Appendix 1.

Ethics Education Background

To explore the potential impact of prior ethics education on survey outcomes, particularly in parts 3 to 6, we compared 2 distinct groups: those with prior ethics education and those without. On the use of AI in medicine, one statistical difference could be determined for the statement that “...negatively affect the autonomy of medical staff” (S11, \( P = 0.002 \)). The \( z \) score suggested a stronger level of agreement with the statement in the group that had received prior ethics education (\( z \) score: 2.876). For the other statements of the third part of the survey (S1-10; S12), no statistical difference could be determined. No statistical difference could be determined for the fourth part of the survey on AI teaching (S13-20). Regarding the teaching of AI ethics, statistical differences could be determined for 2 statements (S21, \( P = 0.004 \); S22, \( P = 0.03 \)). For the statement that the teaching of AI ethics should be part of medical education, the \( z \) score indicated a higher level of agreement in the group that had received prior ethics education. Similarly, a higher level of disagreement was indicated by the group with prior ethics education for the statement that the teaching of AI ethics in medical education is adequate (\( z \) score: -3.011). There was no statistically significant difference in the AI ethics teaching content between the groups. A detailed statistical analysis can be found in Tables S9-S12 in Multimedia Appendix 1.

Discussion

This discussion aims to comprehensively analyze the findings regarding medical students’ perceptions of AI in medicine and the role of AI and AI ethics in their medical education, depending on their use of AI-based (chat) applications such as ChatGPT.

The Use of AI-Based (Chat) Application Among the Surveyed Medical Students

The discrepancy between students’ personal AI experiences and formal medical education highlights the gap in integrating AI into curricula, reflecting the need for educational progress in line with technological advancement. A considerable 38.8% of the respondents reported prior use of AI-based (chat) applications, such as ChatGPT, Bard, Bing Chat, or Jasper Chat, which was slightly below the percentage received from pretesting and used for sample size calculation (5/11, 45%).

The results concerning the reported use of AI-based (chat) applications must be evaluated in the context of the timing of the data collection. ChatGPT, for instance, became freely accessible to the public on November 30, 2022, making it accessible for only approximately 8 months at the time of data collection [27]. In addition, Bing Chat was not broadly accessible until May 2023, further constraining its availability before the survey [28]. It is noteworthy that academic literature on the use of AI-based (chat) applications such as ChatGPT among medical students is still limited. A study conducted with health students found that only 11.3% (55/458) of respondents reported using the ChatGPT, a rate considerably lower than the findings of this study [29].

A more detailed evaluation of the percentage of medical students using AI-based (chat) applications is necessary given that many might use AI unknowingly. This is not restricted to clinical AI tools, such as clinical decision support systems but extends to search engines and other tools. For example, the search engine Bing offers AI-driven content with search results, irrespective of whether the Bing chat is specifically used. Moreover, a study conducted with students from various specialties in Germany revealed that 12.3% (779/6311) of its participants used “DeepL” (DeepL SE), an AI-based translation tool, in which the use of AI might not be immediately evident [30]. Therefore, when considering other AI tools and applications, the actual percentage of medical students using them may be significantly higher than the 38.8% reported in this study. Recognizing this potential underestimation of AI use highlights the importance of expanding AI literacy and awareness in medical education to ensure that future health care professionals are adequately prepared for the integration of AI in medicine. This reinforces the need for proactive measures in curriculum design to include not only the direct use of AI tools but also an understanding of their indirect implications in various medical and research contexts.

AI Education

Despite the significant engagement of students with AI-based applications, such as ChatGPT, only a small fraction (26/487, 5.3%) reported formal AI education within their medical curriculum. This discrepancy highlights the critical gap between experiential learning and structured academic guidance regarding AI. Interestingly, AI education outside the formal curriculum was more prevalent (51/487, 10.5%), which could imply a proactive approach to learning about AI technologies. Furthermore, this could be attributed to the availability of AI-based applications, such as ChatGPT, and increasing opportunities for education on AI in the medical context, as well as AI-based (chat) applications that are knowledgeable in the field of medicine [7,31-33]. Among the users of AI applications, 73% applied these tools in medical contexts, primarily for querying medical knowledge. This use pattern presents both opportunities for accessible knowledge and risks associated with reliance on uncertified AI sources and a lack of certification as medical devices. The lack of education in the field of AI as part of medical education has been highlighted not only in German-speaking countries [34] but also internationally [21,22].
The results imply a substantial dichotomy between the lack of formal education and optimism toward AI, as the use of AI in medicine was positively perceived (71.1% of respondents), despite the absence of formal education (94.7% of respondents). Given the lack of education, this warrants caution as there might be an overly optimistic view of its potential benefits, overlooking potentially significant limitations and ethical implications [35]. The need for the integration of AI into medical curricula is not only supported by existing studies highlighting low AI literacy among medical students [34,36] but also by the results of this study, with 88% of all medical students perceiving that their current AI education within their medical education is insufficient. This dissatisfaction underscores the need for medical curricula to evolve in tandem with technological advancements. However, it is crucial to ensure that these curricular changes are developed thoughtfully and comprehensively to avoid superficial or overly optimistic portrayals of AI’s role in medicine [34]. The findings of this study, indicating a significant gap in AI education within medical curricula, align with the initial insights gathered regarding students’ use of AI applications. Furthermore, the results align with the objective of understanding how medical students from Germany, Austria, and Switzerland perceive the application of AI in medical practice and its integration into medical education. This disparity between the practical use of AI applications and lack of AI educational opportunities in the curriculum underlines the emerging need for educational reform.

**AI Ethics Education**

The perceived insufficiency of the current medical education extends to AI ethics. Remarkably, 95.3% of participants acknowledged the new ethical challenges posed by AI in medicine, which resonates with preexisting research [15]. Notably, those who used AI-based (chat) applications, such as ChatGPT, agreed more strongly with this view, suggesting that practical use enhances awareness of these ethical issues. In addition, 74.9% (385/487) of respondents recognized the necessity of integrating AI ethics into medical curricula, aligning with recent academic discourse [37-39]. However, only a small percentage (4.3%) reported formal AI ethics education, highlighting a significant deficit in the current curriculum. Medical students perceived all 8 proposed ethical AI topics as highly relevant, which were recommended as potential teaching content for AI ethics in the current literature [37-39]. Statistical differences were observed for “informed consent” among those with prior AI application use. This indicates that engagement with AI technology may deepen understanding of its ethical dimensions, reinforcing the need for comprehensive AI ethics instruction in medical education. The clear demand for AI ethics education reflects a broader educational need, where medical students should not just be prepared for the technicalities of AI but also for the nuanced ethical considerations introduced by the technology.

Although this study underscores the need for both AI and AI ethics education in medical curricula, it is also important to critically assess the current absence of AI-centric content. Rapid technological advancements in AI with the recent public availability of AI tools, such as ChatGPT, may contribute to the current lack of associated teaching content. Given the complex regulatory requirements required to use AI-based technologies in clinical practice, the use of AI in medicine is currently not widespread [40]. In addition, the requirement for time-consuming and complex reaccreditation processes for curricular development and revision may further delay the introduction of AI-related teaching content [41]. Moreover, the lack of widespread use of AI-based applications in medicine and clinical practice likely contributes to the current lack of adequate teaching content on AI and ethics. The overwhelming perception of AI’s potential and its ethical implications it brings forth, as evidenced by this study, underscores the need for educational institutions to respond proactively. Balancing the speed of technological advancements in the field of AI with thoughtful and comprehensive curricular integration is likely to be a crucial challenge in medical education in the coming years.

**Additional Analysis of the Collected Data**

In the additional data analysis, the subsequent examination revealed that perceptions of AI and AI ethics among medical students were not significantly influenced by their country of study. This uniformity across Germany, Austria, and Switzerland suggests consistency in deficiencies in AI and AI ethics education regardless of regional curricular variations. As the findings could be attributed to the limited number of medical students indicating prior education in AI (26/487, 5.3%) and AI ethics (21/487, 4.3%), additional research is warranted. Despite their different educational systems, the observed uniformity in AI and AI ethics education across the 3 countries implies a broader challenge for medical education. The consistency of educational deficiencies, irrespective of regional curricular variations, indicates the widespread need to reform AI teaching in medical curricula. This aligns with the overarching findings of our study, which suggest a universal gap in AI competencies among medical students.

Further analysis of the study stage revealed that students in advanced stages, such as CPS, showed increased awareness of the potential impact of AI on their specialization choices, implying a growing realization of AI’s role as they progress in their studies. However, the lack of significant differences in most other AI-related statements could also imply a generalized consensus or a lack of adequate exposure and understanding across all study stages. As an advancement in the study stages could be linked to statistically significant results on statements regarding the need to teach AI ethics, this could be attributable to prior ethics education, which is usually taught during the PCSs.

The impact of ethics education on perceptions of AI’s role in medicine is particularly notable. Students with such an education showed increased awareness of the ethical challenges posed by AI, especially regarding its potential negative impact on medical staff autonomy (S11). This could underscore the importance of ethics education in understanding the potentially wide-reaching challenges of AI in medicine for ethically important subjects such as autonomy; however, no statistically significant difference for the preceding statement on autonomy “the use of AI in medicine will negatively affect patient autonomy” (S10) could be observed. This could imply that prior ethics education,
including teaching autonomy in a medical context, might lead to a more nuanced understanding of the subject and potential implications of AI. The results of the analysis reinforce the need for ongoing ethics education, not just as a separate entity, but also interwoven with AI-related topics, to enhance students’ comprehensive understanding of the ethical implications of AI in medicine. The significant influence of prior ethics education on shaping students’ perceptions of the role of AI in medicine emphasizes the interaction between ethical training and technological awareness. The nuanced understanding of the ethical implications of AI among students who have received ethics education underscores the importance of such training in developing critical thinking about the impact of AI in healthcare. Integrating ethics education with AI teaching content could foster a more holistic approach, preparing students not only for the technological aspects of AI but also for its ethical and societal implications [37].

Limitations

Despite the strengths of this study, some limitations must be acknowledged. First, our web-based survey could introduce selection bias, as tech-savvy students may be more likely to participate. Second, the survey measured students’ perceptions rather than their actual competencies in AI and ethics. In addition, although estimated, the response rate was suboptimal, which may limit the generalizability of our findings. Geographically, our sample was limited to German-speaking countries, making the translation of these results to other countries with different health care systems and medical educational frameworks difficult. Cultural attitudes toward AI could also vary, possibly influencing students’ perceptions of and engagement with AI. Our study is essentially a snapshot of a rapidly evolving field; hence, our findings may not reflect attitudes and competencies, as they evolve with advancements in AI technology. In our analysis, we observed statistically significant differences based on prior ethics education and study stage. However, although the additional analysis of the data did not show a direct overlap with significant findings between the main and supplementary evaluations, additional tests are needed to determine whether these factors acted as confounders in our main data analysis. Although this study considered specific potential confounders, it is worth noting that other confounding variables may exist and were not analyzed in this study. Finally, owing to the self-reported nature of the data, the responses might be subject to recall bias, misunderstanding of questions, or social desirability bias. Although our findings provide valuable insights into the state of AI education in German-speaking medical schools, broader multinational studies would offer a more comprehensive understanding.

Conclusions

This study provides a valuable understanding of the perceptions and experiences of medical students in Germany, Austria, and Switzerland regarding the application of AI in medicine, and its role in medical education. Our findings clearly indicate a discrepancy between students’ interactions with AI-based chat applications such as ChatGPT and the representation of AI in their formal education. Despite a significant number of students interacting with AI technology, notably AI-based chat applications, only a fraction have received any formal AI education, revealing a substantial gap in the current medical curricula. This highlights the necessity of the evolution of medical curriculums to incorporate AI and AI ethics education, ensuring that future medical professionals are adequately equipped to navigate the challenges and opportunities presented by AI in medicine. Furthermore, our findings indicate that practical engagement with AI technology can contribute to an increased awareness of ethical implications, reinforcing the importance of including hands-on AI experiences in medical education. It is evident that the rapid advancement and application of AI in medicine demands parallel evolution in medical education. Thoughtful and comprehensive curricular changes are required to provide a balanced understanding of the potential benefits, limitations, and ethical implications of AI. The integration of AI and AI ethics into medical education is an urgent necessity, not only to enhance students’ AI literacy but also to ensure the responsible and effective use of AI in future medical practice demands.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Comprehensive statistical analysis and evaluation of confounding factors regarding medical students’ perceptions of artificial intelligence’s role in medicine and medical education.

References


Introducing ChatGPT. OpenAI. URL: https://openai.com/blog/chatgpt [accessed 2023-10-25]


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Comprehensiveness, Accuracy, and Readability of Exercise Recommendations Provided by an AI-Based Chatbot: Mixed Methods Study

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Abstract

Background: Regular physical activity is critical for health and disease prevention. Yet, health care providers and patients face barriers to implement evidence-based lifestyle recommendations. The potential to augment care with the increased availability of artificial intelligence (AI) technologies is limitless; however, the suitability of AI-generated exercise recommendations has yet to be explored.

Objective: The purpose of this study was to assess the comprehensiveness, accuracy, and readability of individualized exercise recommendations generated by a novel AI chatbot.

Methods: A coding scheme was developed to score AI-generated exercise recommendations across ten categories informed by gold-standard exercise recommendations, including (1) health condition–specific benefits of exercise, (2) exercise preparticipation health screening, (3) frequency, (4) intensity, (5) time, (6) type, (7) volume, (8) progression, (9) special considerations, and (10) references to the primary literature. The AI chatbot was prompted to provide individualized exercise recommendations for 26 clinical populations using an open-source application programming interface. Two independent reviewers coded AI-generated content for each category and calculated comprehensiveness (%) and factual accuracy (%) on a scale of 0%-100%. Readability was assessed using the Flesch-Kincaid formula. Qualitative analysis identified and categorized themes from AI-generated output.

Results: AI-generated exercise recommendations were 41.2% (107/260) comprehensive and 90.7% (146/161) accurate, with the majority (8/15, 53%) of inaccuracy related to the need for exercise preparticipation medical clearance. Average readability level of AI-generated exercise recommendations was at the college level (mean 13.7, SD 1.7), with an average Flesch reading ease score of 31.1 (SD 7.7). Several recurring themes and observations of AI-generated output included concern for liability and safety, preference for aerobic exercise, and potential bias and direct discrimination against certain age-based populations and individuals with disabilities.

Conclusions: There were notable gaps in the comprehensiveness, accuracy, and readability of AI-generated exercise recommendations. Exercise and health care professionals should be aware of these limitations when using and endorsing AI-based technologies as a tool to support lifestyle change involving exercise.

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KEYWORDS
exercise prescription; health literacy; large language model; patient education; artificial intelligence; AI; chatbot
**Introduction**

Regular physical activity is an essential component of a healthy lifestyle with numerous benefits that are widely recognized and indisputable [1,2]. To support overall health, the American College of Sports Medicine (ACSM) and the Department of Health and Human Services recommend healthy adults engage in regular physical activity, including moderate-intensity aerobic exercise for at least 150 minutes per week, vigorous-intensity aerobic exercise for at least 75 minutes per week, or a combination of both, as well as muscle-strengthening activities at least twice per week [1,2]. In addition, evidence-based practice calls for exercise as first-line therapy to prevent, treat, and control multiple chronic conditions and diseases such as hypertension, hypercholesterolemia, and diabetes mellitus [3-7].

As such, the ACSM endorses individualized, evidence-based, exercise recommendations (termed exercise prescription [ExRx]) for more than 25 clinical populations [1]. These ExRxs are tailored to favorably augment health-related outcomes of interest for each respective clinical population while addressing additional factors such as clinical contraindications, common medications, and special considerations [1,8]. Despite well-established guidelines, health care providers often struggle to provide sufficient counseling and follow-up on lifestyle recommendations, including exercise, due to various barriers such as time constraints, limited resources, lack of awareness or training, and lack of reimbursement incentives [9-11]. Patients also rely heavily on web-based sources for health-related information [12-14], which often includes misinformation that can negatively impact health outcomes and undermine provider-led efforts to support behavior change [15,16].

Artificial intelligence (AI) has recently emerged as a promising tool to augment health and health care and address these challenges [17]. AI-based technology including machine learning, neural networking, deep learning, and natural language processing enables computers to interact with a corpus of text data to generate human language [18,19]. Large language models (LLMs), such as the generative pretrained transformer (GPT), have the ability to generate human-like language on their own, making them a powerful tool for interacting with users as if they are communicating with another human [18,19]. The surge in popularity of LLMs can largely be attributed to the third iteration of OpenAI’s GPT series, ChatGPT [20]. ChatGPT has been recognized as the fastest-growing consumer application in history [20] and is widely regarded as disruptive technology due to its strong potential to enable a wide range of clinical applications as both a provider- and patient-facing tool [21] by generating language that is contextually appropriate, natural sounding, and coherent. Indeed, ChatGPT has demonstrated remarkable capabilities including diagnosis support, streamlining clinical workflows, reducing documentation burden, improving patient education understandability and experience [22-25], and, most recently, passing the United States Medical Licensing Examination [26].

Transformative applications of ChatGPT continue to evolve, but evaluation of its output and suitability in clinical context remains to be explored, in addition to identifying barriers to access and outcomes related to its use. The application of digital technology to support a health behavior change using knowledge-shaping techniques, which is complex and riddled with contextual and individualized components, is challenging [27]. Challenges include ensuring the suitability and usability of the technology confers appropriate educational requisites to understand and apply knowledge in the form of its recommendations. These educational considerations include readability, which can influence the use of AI-generated education for health behavior change [28]. Further, as an extension of readability, low health literacy can limit a patient’s ability to understand and use health information effectively, which can reduce the effectiveness of AI-generated educational resources [29,30].

The evaluation of ChatGPT’s suitability to provide interactive, personalized, and evidence-based exercise recommendations to support behavior change to improve health has not been conducted to date. As such, the primary aim of this study is to assess the suitability of exercise recommendations generated by ChatGPT, a new AI chatbot, as an adjuvant educational tool for health care providers and patients. Primary outcomes of interest include comprehensiveness, accuracy, and readability of the recommendations generated by ChatGPT, with the goal of determining its potential to deliver personalized exercise recommendations at scale. A secondary aim of this study was to conduct a qualitative analysis to identify potential patterns, consistencies, and gaps in AI-generated exercise recommendations. As this technology is still nascent, the study was exploratory in nature, without an a priori hypothesis.

**Methods**

**High-Level Overview**

This study was conducted in March 2023 using the free research preview of a novel AI chatbot (ChatGPT February 13 version) [31]. Figure 1 provides a conceptual overview of the study. Briefly, open-text queries seeking individualized exercise advice were posed to the chatbot interface for all populations (N=26) for which there exist established evidence-based exercise recommendations by the ACSM [1]. Mixed methods were applied to characterize individual and average exercise recommendation content depth, accuracy, and readability. The results were synthesized to highlight potential strengths, weaknesses, opportunities, and risks for researchers, clinicians, and patients likely to interact with the ChatGPT platform for this use case.
Ethical Considerations

This study was deemed to be exempt by the University of Connecticut Institutional Review Board (E23-0378) as this study solely involved the evaluation of AI-generated output and did not involve interaction or intervention with human subjects.

Selection of the Gold-Standard Reference Source

The ACSM is widely regarded as a leading authority in the field of exercise science and sports medicine, and the organization’s guidelines and recommendations are considered the gold standard for health and fitness professionals in the United States and the world [1,8,32]. The ACSM’s Guidelines for Exercise Testing and Prescription (GETP) serves as its flagship resource manual, continuously updated every 4-5 years since 1975. The most recent edition integrates the latest guidelines from ACSM position stands and other relevant professional organizations’ scientific statements, including the 2018 Physical Activity Guidelines for Americans [1]. This latest edition of GETP represents the most current and primary resource for evidence-based exercise recommendations [1]. Given ACSM’s authoritative status and the comprehensiveness of its guidelines, GETP was selected as the ground truth benchmark source to guide the study design and systematically evaluate the suitability of AI-generated exercise recommendations.

Al-Generated Exercise Recommendations

Following this prompt specificity and structure, all clinical populations within the ACSM GETP were evaluated once in a separate prompt (N=26), including healthy adults, children and adolescents, older adults, persons who are pregnant, and individuals with cardiovascular disease (CVD), heart failure, heart transplant, peripheral artery disease, cerebrovascular accident, asthma, chronic obstructive pulmonary disease, diabetes mellitus, dyslipidemia, hypertension, overweight and obesity, arthritis, cancer, fibromyalgia, HIV, kidney disease, multiple sclerosis, osteoporosis, spinal cord injury, Alzheimer disease, intellectual disability, and Parkinson disease.

Conceptual Content Analysis

A list of conceptual categories was generated, refined, and organized into a coding scheme for predefined categories that pertain to the fundamental aspects of an ExRx. These categories relate to an individualized physical activity program based on the FITT principle, which stands for the frequency (how often?), intensity, time, and type of exercise.

on the same day in a single session. Each text prompt was framed to the ChatGPT bot in a standardized, neutral, third-person tense format as “exercise recommendations for [population]” to optimize the relevance of AI responses for both health care provider and patient scenarios. Generated ChatGPT bot responses were abstracted from the interface and converted into plain text format using Microsoft Word (version 2208; Microsoft Corp) on the same day. Content was unaltered upon conversion to plain text format (Multimedia Appendix 1). Note that the ChatGPT bot used in this study was not subjected to retraining or correction during these prompt interactions. The rationale for this methodological decision was to enable the natural observation of ChatGPT’s raw performance and provide a transparent evaluation of its inherent capabilities [33,34].
intensity (how hard?), time (how long?), and type (what kind?) of exercise [1,35]. The final coding scheme included ten categories: (1) health condition–specific benefits of exercise, (2) exercise preparticipation health screening, (3) frequency, (4) intensity, (5) time, (6) type, (7) volume, (8) progression, (9) special considerations, and (10) references (ie, citations to primary literature or sources that supported the AI-generated content provided).

AI-generated exercise recommendations were then coded and recorded in Microsoft Excel (version 2208; Microsoft Corp) following a 2-stage coding process by 2 independent coders with advanced degrees in kinesiology (ALZ and RB). In the first stage, AI-generated content was appraised for comprehensiveness. Each exercise recommendation was coded for the presence (1 point) or absence (0 points) of content provided for each of the 10 prespecified categories such that each exercise recommendation had a possible range of 0-10 points. Comprehensiveness was determined by dividing the total number of points (ie, actual) by the total number possible (ie, expected or 10 points) and multiplying by 100. The resulting score was expressed as a percent, with 100% indicating the highest possible score and fully comprehensive. This formula was applied to all 26 exercise recommendations and averaged to characterize ChatGPT’s overall ability to deliver exercise recommendations regarding their comprehensiveness.

In the second stage, all categories with reported content (ie, fully and partially comprehensive content) were appraised for accuracy. Accuracy was defined as concordance with the ACSM GETP as the ground truth source [1]. In one instance, content deviated from the ACSM GETP (ie, condition-specific benefits of exercise for individuals with HIV), and accuracy was defined as the degree to which the content was consistent with other widely established facts or clinical literature. Responses were coded by the same independent reviewers (ALZ and RB) and recorded as binary variables: “concordant” or “discordant” following the same process used to determine comprehensiveness. Potential discrepancies in coding were resolved through discussion with a third party and senior expert in the field (LSP). The accuracy score was determined by dividing the number of concordant category counts by the number of categories present (ie, “actual” counts; previously determined when calculating comprehensiveness during the first stage) and multiplying by 100. The resulting score was expressed as a percent, with 100% indicating the highest possible accuracy score or fully concordant.

Readability Metrics

The Flesch-Kincaid formula was used to determine readability, a commonly used tool that evaluates the complexity of text-based educational material. This tool was selected due to its objectivity, as scores are computationally derived rather than paper-and-pencil tools that rely on hand calculations and subjectivity, which introduce risk for human error [36]. The formula is based on the average number of syllables per word and the average number of words per sentence with the resulting score estimating the minimum grade level required to understand the text. For example, a score of 8.0 means that the text can be understood by an average eighth-grader in the United States. Flesch reading ease scores range from 0 to 100, with higher scores indicating easier-to-read text. For example, scores <50 are considered difficult to read, while scores >80 are considered easy to read [36]. To assess readability metrics and word count, a single researcher (RB) used the built-in readability statistics functionality of Microsoft Word (version 2208). The mean (SD) word count and readability metrics (ie, Flesch reading ease and grade level) were calculated using Microsoft Excel (version 2208).

Qualitative Analysis

Qualitative analysis with a thematic mapping approach was used to identify novel patterns, trends, and insights across the AI-generated text output. Thematic mapping, a qualitative research method, involves the identification, analysis, and visualization of recurring themes or topics within a data set. This approach is instrumental in highlighting consistencies or gaps in data, facilitating the generation of insights, and formulating hypotheses for further investigation [37].

Statistical Analyses

Descriptive statistics characterized the distribution of all outcome variables of interest, including comprehensiveness, accuracy, and readability metrics. Interrater reliability was assessed using Cohen κ coefficient [(observed agreement–expected agreement)/(1–expected agreement)]. Qualitative analysis was conducted using a systematic multistep approach. All AI-generated exercise recommendations, comprising the text output, were collected and organized to form the data set for qualitative examination. The analysis was carried out by a single researcher (ALZ) who immersed themselves in the content and initiated the coding process by identifying initial themes or patterns within the recommendations. Subsequently, codes were meticulously refined and organized into broader themes, ensuring consistency and accuracy throughout the process. These identified themes were then visually mapped to represent patterns within the data set. Insights generated from the analysis were discussed collaboratively as a team, facilitating comprehensive understanding and quantification, whenever applicable.

Results

Interrater Reliability

Interrater reliability was assessed for the 2 independent raters who coded a sample of 26 AI-generated exercise recommendations using a set of 10 categories. Cohen κ coefficient was calculated to be 1.0, indicating perfect agreement between coders.

Comprehensiveness of AI-Generated Exercise Recommendations

Table 1 details the presence of educational content across the predefined categories of interest abstracted from AI-generated exercise recommendations for 26 populations. Overall, AI-generated exercise recommendations were 41.2% (107/260) comprehensive when compared against a predefined set of content categories that comprise a gold-standard ExRx [1]. There were no populations or categories that were fully...
Comprehensiveness ranged from 0% to 92% with notable gaps in content surrounding the critical components of ExRx: frequency (n=2, 8%), intensity (n=2, 8%), time (n=1, 4%), and volume (n=0, 0%). Partial information was provided across these same categories (ranging from 31% to 58%) with almost all gaps surrounding the provision of FITT for resistance training or flexibility modalities. In addition, only 8% (n=2) of recommendations provided a reference source, both of which (accurately) cited the American Heart Association.

**Table 1.** Comprehensiveness of artificial intelligence–generated exercise recommendations by content category (N=26).

<table>
<thead>
<tr>
<th>Content</th>
<th>Fully provided, n (%)</th>
<th>Partial(^a), n (%)</th>
<th>Not provided, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Condition-specific benefits</td>
<td>24 (92)</td>
<td>0 (0)</td>
<td>2 (8)</td>
</tr>
<tr>
<td>Preparticipation screening</td>
<td>24 (92)</td>
<td>0 (0)</td>
<td>2 (8)</td>
</tr>
<tr>
<td>Frequency</td>
<td>2 (8)</td>
<td>9 (35)</td>
<td>15 (58)</td>
</tr>
<tr>
<td>Intensity</td>
<td>2 (8)</td>
<td>15 (58)</td>
<td>9 (35)</td>
</tr>
<tr>
<td>Time</td>
<td>1 (4)</td>
<td>10 (38)</td>
<td>15 (58)</td>
</tr>
<tr>
<td>Type</td>
<td>14 (54)</td>
<td>12 (46)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Volume</td>
<td>0 (0)</td>
<td>8 (31)</td>
<td>18 (69)</td>
</tr>
<tr>
<td>Progression</td>
<td>15 (58)</td>
<td>0 (0)</td>
<td>11 (42)</td>
</tr>
<tr>
<td>Special considerations</td>
<td>23 (88)</td>
<td>0 (0)</td>
<td>3 (12)</td>
</tr>
<tr>
<td>References</td>
<td>2 (8)</td>
<td>0 (0)</td>
<td>24 (92)</td>
</tr>
</tbody>
</table>

\(^a\)Partial indicates some, but not all, possible content was provided.

**Accuracy of AI-Generated Exercise Recommendations**

Of the total available content provided to the end user, AI-generated exercise recommendations were 90.7% (146/161) accurate when compared to a gold-standard reference source (ie, ACSM GETP [1]). Among the 9.3% (15/161) of inaccurate recommendations (Table 2), there were 15 counts of discordance with most misinformation counts (n=8, 53%) surrounding the need for preparticipation medical clearance prior to engaging in exercise. The second highest category of discordance was within education related to frequency (n=2, 13%) with “overprescribing” aerobic exercise for Alzheimer disease and fibromyalgia by 2 and 5 days per week, respectively. There was 1 count each of discordance across 5 content categories (ie, condition-specific benefits, intensity, time, type, and progression) and 0 counts of discordance across the remaining content categories, including volume, special considerations, and references.

When comparing populations with discordance, hypertension (n=3) had the greatest number of misinformation counts followed by individuals with fibromyalgia (n=2), healthy adults (n=1), older adults (n=1), and cancer (n=1) and individuals with Alzheimer disease (n=1), arthritis (n=1), dyslipidemia (n=1), HIV (n=1), multiple sclerosis (n=1), osteoporosis (n=1), and overweight and obesity (n=1).
Table 2. Summary of inaccurate content among AI*-generated exercise recommendations for all reported content categories (N=161).

<table>
<thead>
<tr>
<th>Content category (count/report-ed) and population</th>
<th>AI-generated content</th>
<th>Ground truth</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Condition-specific benefits (1/24)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HIV</td>
<td>“Regular exercise can be beneficial for people living with HIV. It can help improve cardiovascular health, reduce stress and anxiety, boost immune function, and enhance overall well-being.”</td>
<td>Research regarding the impact of exercise to improve immune function is inconclusive [38].</td>
</tr>
<tr>
<td>Preparticipation screening (8/24)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthy adult</td>
<td>“Remember to always listen to your body and consult with a healthcare professional before starting a new exercise routine.”</td>
<td>ACSM preparticipation screening guidelines state that “physically inactive but otherwise healthy asymptomatic persons may begin light- to moderate-intensity exercise without medical clearance and, in the absence of symptoms, progress gradually in intensity as recommended by current ACSM exercise prescription guidelines” [1].</td>
</tr>
<tr>
<td>Older adult</td>
<td>“However, it’s important for older adults to choose exercises that are appropriate for their age and fitness level, and to check with their doctor before starting a new exercise program.”</td>
<td>ACSM preparticipation screening guidelines state that “physically inactive but otherwise healthy asymptomatic persons may begin light- to moderate-intensity exercise without medical clearance and, in the absence of symptoms, progress gradually in intensity as recommended by current ACSM exercise prescription guidelines” [1].</td>
</tr>
<tr>
<td>Dyslipidemia</td>
<td>“It’s important to consult with a healthcare professional before starting a new exercise program...”</td>
<td>ACSM preparticipation screening guidelines state that “physically inactive but otherwise healthy asymptomatic persons may begin light- to moderate-intensity exercise without medical clearance and, in the absence of symptoms, progress gradually in intensity as recommended by current ACSM exercise prescription guidelines” [1].</td>
</tr>
<tr>
<td>Hypertension</td>
<td>“Consult with your doctor: Before starting any exercise program, it is important to consult with your doctor to make sure it is safe for you to exercise and to get guidance on the most appropriate type and intensity of exercise.”</td>
<td>ACSM preparticipation screening guidelines state that “physically inactive but otherwise healthy asymptomatic persons may begin light- to moderate-intensity exercise without medical clearance and, in the absence of symptoms, progress gradually in intensity as recommended by current ACSM exercise prescription guidelines” [1].</td>
</tr>
<tr>
<td>Arthritis</td>
<td>“Be sure to talk to your doctor or a physical therapist before starting any new exercise program...”</td>
<td>ACSM preparticipation screening guidelines state that “physically inactive but otherwise healthy asymptomatic persons may begin light- to moderate-intensity exercise without medical clearance and, in the absence of symptoms, progress gradually in intensity as recommended by current ACSM exercise prescription guidelines” [1].</td>
</tr>
<tr>
<td>Cancer survivors</td>
<td>“It’s important to work with a healthcare provider or a qualified exercise professional to develop a safe and effective exercise program that meets your individual needs and abilities.”</td>
<td>ACSM preparticipation screening guidelines state that “physically inactive but otherwise healthy asymptomatic persons may begin light- to moderate-intensity exercise without medical clearance and, in the absence of symptoms, progress gradually in intensity as recommended by current ACSM exercise prescription guidelines” [1].</td>
</tr>
<tr>
<td>Multiple sclerosis</td>
<td>“It is always recommended to consult with a healthcare professional before starting any exercise program.”</td>
<td>ACSM preparticipation screening guidelines state that “physically inactive but otherwise healthy asymptomatic persons may begin light- to moderate-intensity exercise without medical clearance and, in the absence of symptoms, progress gradually in intensity as recommended by current ACSM exercise prescription guidelines” [1].</td>
</tr>
<tr>
<td>Osteoporosis</td>
<td>“It’s important to talk to your doctor or a qualified exercise professional before starting any new exercise program, especially if you have osteoporosis or other medical conditions.”</td>
<td>ACSM preparticipation screening guidelines state that “physically inactive but otherwise healthy asymptomatic persons may begin light- to moderate-intensity exercise without medical clearance and, in the absence of symptoms, progress gradually in intensity as recommended by current ACSM exercise prescription guidelines” [1].</td>
</tr>
<tr>
<td>Frequency (2/11)</td>
<td>“Aim for at least 30 minutes of aerobic exercise most days of the week.”</td>
<td>ACSM recommends an initial frequency of 1-2 days per week, gradually progressing to 2-3 days per week [1].</td>
</tr>
<tr>
<td>Content category (count/report-ed) and population</td>
<td>AI-generated content</td>
<td>Ground truth</td>
</tr>
<tr>
<td>-----------------------------------------------</td>
<td>----------------------</td>
<td>--------------</td>
</tr>
<tr>
<td>Alzheimer disease</td>
<td>“Engage in moderate aerobic exercise such as brisk walking, cycling, or swimming for at least 30 minutes a day, five days a week.”</td>
<td>ACSM recommends a frequency of 3 days per week [1].</td>
</tr>
<tr>
<td>Intensity (1/17)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hypertension</td>
<td>“Avoid high-intensity exercises: Avoid high-intensity exercises that can cause sudden increases in blood pressure, such as sprinting or heavy lifting.”</td>
<td>ACSM does not contraindicate vigorous-intensity aerobic exercise or heavy lifting assuming adequate progression, absence of underlying disease, and proper breathing technique (ie, avoidance of Valsalva maneuver) [1].</td>
</tr>
<tr>
<td>Time (1/11)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fibromyalgia</td>
<td>“Start with 1-2 sets of 10-15 repetitions for each exercise and gradually increase the resistance as tolerated.”</td>
<td>ACSM recommends gradual progression of 4-5 to 8-12 repetitions and increasing from 1 to 2-4 sets per muscle group [1].</td>
</tr>
<tr>
<td>Type (1/26)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hypertension</td>
<td>“Aim for at least 30 minutes of moderate-intensity aerobic exercise most days of the week.”</td>
<td>New ACSM guidelines reinforce that emphasis is no longer placed on aerobic exercise alone. Aerobic or resistance exercise alone or aerobic and resistance exercise combined (ie, concurrent exercise) is recommended on most, preferably all, days of the week to total 90 to 150 minutes per week or more of multimodal, moderate-intensity exercise [39].</td>
</tr>
<tr>
<td>Volume (0/8)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Progression (1/15)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overweight and obesity</td>
<td>“If you’re new to exercise, start with low-intensity activities such as walking or swimming, and gradually increase your intensity and duration.”</td>
<td>ACSM recommends initial intensity should be moderate, progressing to vigorous for greater health benefits [1].</td>
</tr>
<tr>
<td>Special considerations (0/23)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>References (0/2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>

aAI: artificial intelligence.
bACSM: American College of Sports Medicine.
cN/A: not applicable.

**Readability Metrics**

Average and individual readability metrics and word count for AI-generated exercise recommendations are provided in Table 3. On average, AI-generated output was 259.3 (SD 49.1) words (range 171-354) and considered “difficult to read” with an average Flesch reading ease of 31.1 (SD 7.7; range 14.5-47.3) and written at a college-level (mean 13.7, SD 1.7; range 10.1-18.0).
Table 3. Readability metrics for artificial intelligence–generated exercise recommendations by population.

<table>
<thead>
<tr>
<th>Population</th>
<th>Word count</th>
<th>Flesch reading ease</th>
<th>Grade level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Healthy adults</td>
<td>187</td>
<td>14.5</td>
<td>15.2</td>
</tr>
<tr>
<td>Children and adolescents</td>
<td>253</td>
<td>29.8</td>
<td>14.1</td>
</tr>
<tr>
<td>Pregnancy</td>
<td>267</td>
<td>34.7</td>
<td>13.5</td>
</tr>
<tr>
<td>Older adults</td>
<td>276</td>
<td>37.0</td>
<td>12.2</td>
</tr>
<tr>
<td>Cardiovascular disease</td>
<td>271</td>
<td>33.6</td>
<td>13.2</td>
</tr>
<tr>
<td>Heart failure</td>
<td>235</td>
<td>23.0</td>
<td>16.2</td>
</tr>
<tr>
<td>Heart transplant</td>
<td>278</td>
<td>24.9</td>
<td>14.4</td>
</tr>
<tr>
<td>Peripheral artery disease</td>
<td>322</td>
<td>32.4</td>
<td>13.4</td>
</tr>
<tr>
<td>Cerebrovascular accident</td>
<td>346</td>
<td>22.0</td>
<td>15.1</td>
</tr>
<tr>
<td>Asthma</td>
<td>317</td>
<td>41.1</td>
<td>12.0</td>
</tr>
<tr>
<td>COPD(^a)</td>
<td>247</td>
<td>47.3</td>
<td>10.1</td>
</tr>
<tr>
<td>Diabetes</td>
<td>201</td>
<td>36.7</td>
<td>11.8</td>
</tr>
<tr>
<td>Dyslipidemia</td>
<td>291</td>
<td>19.6</td>
<td>15.9</td>
</tr>
<tr>
<td>Hypertension</td>
<td>247</td>
<td>34.5</td>
<td>13.3</td>
</tr>
<tr>
<td>Overweight and obesity</td>
<td>200</td>
<td>34.7</td>
<td>13.2</td>
</tr>
<tr>
<td>Arthritis</td>
<td>236</td>
<td>38.4</td>
<td>13.0</td>
</tr>
<tr>
<td>Cancer</td>
<td>319</td>
<td>24.8</td>
<td>14.9</td>
</tr>
<tr>
<td>Fibromyalgia</td>
<td>303</td>
<td>40.0</td>
<td>12.2</td>
</tr>
<tr>
<td>HIV</td>
<td>232</td>
<td>30.0</td>
<td>13.9</td>
</tr>
<tr>
<td>Kidney disease</td>
<td>354</td>
<td>31.1</td>
<td>15.3</td>
</tr>
<tr>
<td>Multiple sclerosis</td>
<td>255</td>
<td>38.4</td>
<td>11.4</td>
</tr>
<tr>
<td>Osteoporosis</td>
<td>171</td>
<td>32.7</td>
<td>12.3</td>
</tr>
<tr>
<td>Spinal cord injury</td>
<td>281</td>
<td>25.5</td>
<td>14.1</td>
</tr>
<tr>
<td>Alzheimer disease</td>
<td>191</td>
<td>29.1</td>
<td>14.8</td>
</tr>
<tr>
<td>Intellectual disability</td>
<td>241</td>
<td>32.1</td>
<td>13.2</td>
</tr>
<tr>
<td>Parkinson disease</td>
<td>221</td>
<td>19.8</td>
<td>18.0</td>
</tr>
<tr>
<td>Mean (SD)</td>
<td>259.3 (49.1)</td>
<td>31.1 (7.7)</td>
<td>13.7 (1.7)</td>
</tr>
</tbody>
</table>

\(^a\)COPD: chronic obstructive pulmonary disease.

Qualitative Analysis

A secondary aim of this study was to identify potential patterns, consistencies, and gaps in AI-generated exercise recommendation text outputs. Major observations derived from qualitative evaluation of AI-generated exercise recommendations can be found in Multimedia Appendix 2. Briefly, several recurring themes emerged among the total sample, including liability and safety, preference for aerobic exercise, and inconsistencies in the terminology used for exercise professionals. Importantly, AI-generated output showed potential bias and discrimination against certain age-based populations and individuals with disabilities. The implications of these findings are discussed in detail below.

Discussion

Principal Findings

This study sought to explore the suitability of AI-generated exercise recommendations using a popular generative AI platform, ChatGPT. Given the recent launch and popularity of ChatGPT and other similar generative AI platforms, the overall goal was to formally appraise the suitability and readability of AI-generated output likely to be seen by patients and inform exercise and health care professionals and other stakeholders on the potential benefits and limitations of using AI to leverage for patient education. The major findings were that AI-generated output (1) presented 41.2% (107/260) of the content provided in a gold-standard exercise recommendation indicating poor comprehensiveness; (2) of the content provided, chat output was 90.7% (146/161) accurate with most discordance related
to the need for exercise preparticipation health screening; and (3) had college-level readability.

The results of this study are consistent with a recently published research letter that evaluated the appropriateness of CVD prevention recommendations from ChatGPT [40]. Sarraj et al [40] developed 25 questions on fundamental heart disease concepts, posed them to the AI interface, and subjectively graded responses as “appropriate” or “inappropriate.” AI-generated responses were deemed to be 84% appropriate with noted misinformation provided for questions regarding ideal exercise volume and type for health and heart disease prevention. This study expands upon these findings by focusing on ExRx, testing additional metrics (ie, comprehensiveness and readability) using an objective, formal coding system based on a ground truth source, and in an expanded list of clinical populations.

**Real-World Implications of These Findings**

Our findings suggest that while AI-generated exercise recommendations are generally accurate (146/161, 90.7%), they may lack comprehensiveness in certain critical components of ExRx such as target frequency, intensity, time, and type of exercise, which could potentially hinder ease of implementation or their effectiveness. The most common (ie, 8/15, 53%) source of misinformation was the recommendation to seek medical clearance prior to engaging in any exercise. Potential downstream implications are undue patient concern and triggering an unnecessary number of adults for medical evaluation, both posing as potential barriers to exercise adoption [41,42].

The ACSM preparticipation screening guidelines emphasize the public health message that exercise is important for all individuals and that the preparticipation health screening should not be a deterrent to exercise participation [41]. The preparticipation screening algorithm considers current physical activity levels, desired exercise intensity, and the presence of known or underlying CVD, metabolic, and renal disease. Following this algorithm, lesser than 3% of the general population would be referred before beginning vigorous exercise, and approximately 54% would be referred before beginning any exercise [42]. Interestingly, exercise professionals are well-equipped to facilitate preparticipation screening, yet AI-generated output disproportionately emphasized medical clearance by a health care provider or doctor prior to working with an exercise professional. In reference to exercise professionals, ChatGPT used varying and incorrect terminology such as “licensed exercise physiologist” that does not reflect current-state credentialing for exercise professionals working with clinical populations (ie, ACSM Certified Clinical Exercise Physiologist [43]). These findings corroborate with existing challenges in the public health’s understanding of the role of exercise professionals, levels of qualification, and respective scope of practice [44].

As AI-based technologies continue to evolve, striking the right balance between medical precision and risk mitigation remains a crucial consideration [45]. The question of how definitive an AI-based model should be when delivering medical education is multifaceted. On the one hand, the inclination of the AI-based model toward vague or general recommendations can be seen as a responsible stance to mitigate risks. On the other hand, there is merit in AI-based models providing clear, specific, and contextual guidance that reinforces evidence-based recommendations. This approach ensures that end users receive accurate and tailored advice, which is important in the context of medical education. This tension highlights the need for continued dialogue on how AI can enhance health care while ensuring that recommendations align with the highest standards of accuracy and patient safety. These discussions will be instrumental in shaping the future of AI-augmented health care.

**AI-Generated Output Least Accurate for Populations With Hypertension**

Interestingly, the hypertension exercise recommendations scored the poorest (ie, highest discordance) with 57% (4/7) accuracy and misinformation surrounding the need for medical clearance and the recommended intensity and type of exercise (Table 2). For example, AI-generated output recommended avoiding high-intensity exercise “such as sprinting or heavy lifting”; however, the ACSM does not contraindicate vigorous-intensity exercise considering comorbidities and assuming adequate progression and proper technique [1]. Additionally, AI-generated output recommended a target exercise goal of “30 minutes of moderate-intensity aerobic exercise most days of the week.” Notably, the ACSM guidelines reinforce that emphasis is no longer placed on aerobic exercise alone but rather recommend aerobic and resistance exercise alone or combined (ie, concurrent exercise) on most, preferably all, days of the week to total 90-150 minutes per week or more of multimodal, moderate-intensity exercise [39]. Reasons for this discordance are likely because the ChatGPT model relies on training data preceding 2021 and may not capture real-time research advancements. Nevertheless, these findings are important because hypertension is the most common, costly, and modifiable CVD risk factor with strong evidence-based and guideline-driven recommendations, whereby support of exercise is a critical component of first-line treatment for elevated blood pressure [7,46-48].

**Social Determinants of Health Considerations**

Not surprisingly, our evaluation of this AI-based technology identified social determinants of health considerations regarding educational obtainment for its users. Average readability of the AI-generated output was found to be very high, at the college level, which poses significant challenges for the majority of patients, as The National Institutes of Health, American Medical Association, and American Heart Association all recommend that patient education materials be written at or below a sixth-grade reading level [49] based on national educational obtainment trends. Poor readability of patient materials can exacerbate disparities in access to care for those with limited health literacy, and those individuals may experience more barriers to understand and apply the information provided [29,30]. These findings highlight the need for ongoing evaluation and refinement of AI-generated educational output to prevent inappropriate recommendations that do not improve disparities in clinical outcomes. AI-based models, such as ChatGPT, and their output are vulnerable to both poor data.
quality and noninclusive design. Notably, AI-generated output used different tenses and pronouns depending on the demographic group being addressed, which potentially perpetuates digital discrimination including stereotypes and biases (Multimedia Appendix 2). For instance, most AI-generated exercise recommendations were provided in the second-person tense; however, recommendations for individuals with intellectual disabilities, older adults, and children and adolescents were written in the third-person tense with the AI-based model, assuming these populations were not the primary end users. Additionally, most exercise examples provided by the chatbot were activities favoring ambulating individuals (eg, walking and running) potentially limiting education for, and perpetuating bias against, individuals with disabilities. Generative AI can contribute to bias or discrimination in several ways, beginning with the use of biased data to train AI-based models that learn and perpetuate biases in its output [50]. Additionally, AI-based models may be designed with certain features that result in biased or discriminatory outputs, such as using certain variables that are correlated with gender or race [50]. Put in practice, AI-based models can further extend societal biases and stereotypes by relying on existing patterns and trends in the data that reinforce gender or racial stereotypes [50]. These findings highlight the need for caution in using generative AI for health education and the importance of careful consideration of potential biases and discriminatory language.

To summarize, this study demonstrates that AI-generated exercise recommendations hold some promise in accurately providing exercise information but are not without issues (ie, gaps in critical information, biases, and discrimination) that could lead to potentially harmful consequences. The art of ExRx involves considering individual factors and nuances that may not be fully captured by technology [1]. Factors such as medical history, medications, personal preferences, health and physical literacy, and physical limitations are just a few examples of the complexities involved in creating an individualized exercise plan [1]. It is important to note that AI-generated output often lacks references to primary sources or literature, underscoring the need for health care provider oversight in interpreting and verifying the validity of the information presented. In this study, the reference sources provided were 100% accurate (2 of 2); however, “hallucinations” of fabricated or inaccurate references are quite common and are a growing concern for AI-generated medical content [51].

**Limitations**

There are limitations to this study. This evaluation was limited to a single generative AI platform, which may not be representative of all LLM programs. Additionally, this study is limited to a specific time period and topic, and the findings may not be generalizable to other topics or time periods. Importantly, this model was evaluated using a single, structured prompt that can potentially lead to overfitting or superficial outputs and compromise generalizability. The lack of exposure to a range of prompts makes it challenging to discern if outcomes truly reflect the model’s capabilities or are specific to the nature of the provided prompt. Given that LLMs can yield varied outcomes based on prompts, this limitation is critical for the interpretation and application of the model’s results across various scenarios. This approach was selected as it most closely recapitulates how a publicly available chatbot would likely be used in a real-world setting by an inexperienced end user (ie, lacking knowledge of prompt methodologies). Indeed, all (N=26) AI-generated exercise recommendations were coherent, contextual, and relevant suggesting that the standardized single prompt was structured to elicit an appropriate response. However, it is likely that additional prompt engineering considerations (ie, specificity, iteration, and roles and goals) will yield incremental capabilities and superior model performance than reported in this study. Future work should consider advanced and diverse prompts to assess the model’s robustness across various scenarios. The results rely on the accuracy of the coders in identifying relevant content and assessing its accuracy. The high level of agreement between raters suggests that the coding scheme was well-defined and easily interpretable; however, there is potential for observer bias due to the raters’ shared mentorship, research training, and educational experiences. It is also worth noting that this study used the Flesch-Kincaid formula to assess readability that has known limitations, such as not accounting for the complexity of ideas and vocabulary and not considering readers’ cultural and linguistic backgrounds [36]. This tool was selected due to its objectivity, standardization, and the fact that scores are computationally derived, which lowers the risk of human error, thus rendering it the most appropriate tool to address this research question [36]. Nevertheless, future research may benefit from examining the Flesch-Kincaid formula in conjunction with other measures to gain a more comprehensive understanding of AI-generated output readability.

Despite the noted limitations, this study possesses several strengths. To the best of our knowledge, this study is the first to report on the quality of AI-generated exercise recommendations for individuals across the life span (ie, children and adolescents, healthy adults, and older adults) and for 23 additional clinical populations. A major strength of this study is the use of a formal grading framework with a double-coding system to objectively assess the comprehensiveness and accuracy of the AI-generated exercise recommendations, which extends the literature and increases the reliability and validity of these findings [40]. Adding to its credibility, this grading system was developed and refined by experts in the field of exercise science, including a former associate editor [35], editor, and contributing author [1] of the ACSM GETP (LSP and ALZ). Multiple measures were used to assess the suitability of AI-generated recommendations and its potential for digital discrimination. Recommendations were evaluated by their comprehensiveness, accuracy, and readability, which provided a thorough summarization of the strengths and weaknesses of AI-generated content. The output was compared to well-established evidence-based guidelines (ie, ACSM GETP) as a gold-standard reference, which strengthens the validity of the results. Finally, the standardization of queries in this study minimized bias and allowed for an objective evaluation of the AI-generated exercise recommendations. These structured prompts were integral to the research design, shaping the language model’s responses and enabling the systematic evaluation of its performance against ACSM GETP as the
ground truth benchmark. This methodological approach ensures that the outcomes presented in this study are grounded in a consistent and rigorously designed interaction process.

Future Directions
Given the recent development of open-source generative AI technologies, this area is ripe for exploration. However, before proceeding with extensive randomized controlled trials, it is crucial to prioritize the safety and ethical considerations associated with AI-generated medical education. As AI technologies have the potential to impact health disparities, it is essential to carefully evaluate their use to ensure inclusivity and appropriate messaging across demographics [27, 52-54]. Further research is needed to develop, test, and implement AI technologies that serve individuals safely, effectively, and ethically without perpetuating bias, discrimination, or causing harm. This includes exploring ways to mitigate potential biases and discriminatory outcomes. Outside of the research setting, health care and exercise professionals can play a crucial role in improving AI-based models through prompting and by giving corrective feedback to retrain biases and inaccuracies in AI-generated responses. By enriching ChatGPT with user-specific data including exercise components, literacy level, physical limitations, and other activity considerations, there are opportunities to improve the personalization of recommendations and lessen digital discrimination. Through this stewardship, continuous refinement will likely improve the performance, usability, and appropriateness of the model, translating to superior patient outcomes, which is the goal of provider-enablement and patient-facing tools. As LLMs continue to evolve, it will become increasingly important for researchers to continuously assess improvements with response variations over time. Importantly, future work should explore the incremental value of advanced and diverse prompting considerations. Examples of prompting considerations include the provision of roles and goals (eg, “You are a Clinical Exercise Physiologist and your goal is to design a safe and effective exercise prescription to lower blood pressure”), engaging in multiple or chain prompting and specifically prompting for content commonly missing from output as identified in this study.

To ensure the responsible and safe deployment of AI technologies in health care, conducting thorough implementation studies is a logical next step. These studies should focus on measuring various factors, including acceptability, adoption, appropriateness, costs, feasibility, fidelity, penetration, and sustainability. By thoroughly investigating these implementation aspects, we can ensure that the technology is well-integrated and does not pose any harm to patients or health care systems. Following the completion of the implementation studies, it is important to assess the impact of AI-generated models on service outcomes. This includes evaluating health care quality factors such as safety, timeliness, efficiency, effectiveness, equity, and patient-centeredness [55]. Understanding how AI technologies influence these service outcomes will provide valuable insights into their overall impact on health care delivery. Additionally, measuring patient-centered and end-user outcomes is essential to evaluate the effectiveness of AI technologies in improving patient experiences and outcomes. Randomized controlled trials designed to test ChatGPT as an intervention to augment behavior change and associated health outcomes would be of great public health interest. These trials should prioritize patient-centered outcomes, including satisfaction, usability, experience, and patient activation [56]. By assessing these outcomes, we can determine the effectiveness of AI technologies in empowering patients and fostering meaningful engagement with health care providers.

Conclusions
To conclude, this study found that AI-generated exercise recommendations have moderate comprehensiveness and high accuracy when compared to a gold-standard reference source. However, there are notable gaps in content surrounding critical components of ExRx and potentially biased and discriminatory outputs. Additionally, the readability level of the recommendations may be too high for some patients, and the lack of references in AI-generated content may be a significant limitation for use. Health care providers and patients may wish to remain cautious in relying solely on AI-generated exercise recommendations and should limit their use in combination with clinical expertise and oversight.

Acknowledgments
This study was supported by the University of Connecticut, CVS Health Corporation, and Hartford Hospital.

Authors' Contributions
ALZ contributed to the study conceptualization, project management, study design, data curation and coding, statistical analysis, interpretation of the data, visual presentation of the data, and paper preparation and submission. RB contributed to the study design, data coding, interpretation of the data, and copyediting of the paper. KJTC contributed to the interpretation of the data, business leadership, and copyediting of the paper. LSP contributed to the study design, project oversight, interpretation of the data, and revising and copyediting of the paper. All authors contributed to the writing of the paper, reviewed and approved the final version of the paper, and agreed with the order of presentation of the authors.

Conflicts of Interest
ALZ and KJTC are both employed and hold stock with CVS Health Corporation. This study is an objective evaluation to better understand ChatGPT and its outputs. To the best of our knowledge, CVS Health does not currently use or endorse the use of ChatGPT for lifestyle recommendations. LSP is the sole proprietor and founder of P3-EX, LLC, which could potentially benefit
from the results used in this research. The results of this study do not constitute endorsement by the American College of Sports Medicine.

Multimedia Appendix 1
Output from artificial intelligence–generated exercise recommendations for clinical populations (N=26).

Multimedia Appendix 2
Summary of major themes derived from artificial intelligence–generated exercise recommendations.

References


The Use of ChatGPT for Education Modules on Integrated Pharmacotherapy of Infectious Disease: Educators' Perspectives

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Abstract

Background: Artificial Intelligence (AI) plays an important role in many fields, including medical education, practice, and research. Many medical educators started using ChatGPT at the end of 2022 for many purposes.

Objective: The aim of this study was to explore the potential uses, benefits, and risks of using ChatGPT in education modules on integrated pharmacotherapy of infectious disease.

Methods: A content analysis was conducted to investigate the applications of ChatGPT in education modules on integrated pharmacotherapy of infectious disease. Questions pertaining to curriculum development, syllabus design, lecture note preparation, and examination construction were posed during data collection. Three experienced professors rated the appropriateness and precision of the answers provided by ChatGPT. The consensus rating was considered. The professors also discussed the prospective applications, benefits, and risks of ChatGPT in this educational setting.

Results: ChatGPT demonstrated the ability to contribute to various aspects of curriculum design, with ratings ranging from 50% to 92% for appropriateness and accuracy. However, there were limitations and risks associated with its use, including incomplete syllabi, the absence of essential learning objectives, and the inability to design valid questionnaires and qualitative studies. It was suggested that educators use ChatGPT as a resource rather than relying primarily on its output. There are recommendations for effectively incorporating ChatGPT into the curriculum of the education modules on integrated pharmacotherapy of infectious disease.

Conclusions: Medical and health sciences educators can use ChatGPT as a guide in many aspects related to the development of the curriculum of the education modules on integrated pharmacotherapy of infectious disease, syllabus design, lecture notes preparation, and examination preparation with caution.

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KEYWORDS

innovation and technology; quality education; sustainable communities; innovation and infrastructure; partnerships for the goals; sustainable education; social justice; ChatGPT; artificial intelligence; feasibility
Introduction

Artificial intelligence (AI) plays an important role nowadays rather than at any time in history in many fields, including medical education, practice, and research [1-6]. AI can be defined as the “science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable” [7], or as “a field of science and engineering concerned with the computational understanding of what is commonly called intelligent behaviour, and with the creation of artefacts that exhibit such behaviour” [8]. One of the recent advances in AI development is the launch of a model called ChatGPT, which interacts in a conversational way. The dialogue format makes it possible for ChatGPT to answer follow-up questions, admit its mistakes, challenge incorrect premises, and reject inappropriate requests; ChatGPT is a general large language model (LLM) developed recently by OpenAI. While the previous class of AI models have primarily been deep learning models, which are designed to learn and recognize patterns in data, LLMs are a new type of AI algorithm trained to predict the likelihood of a given sequence of words on the basis of the context of the words that appear before it [9].

Empirical studies have demonstrated the effectiveness of AI-based educational tools in various domains. Recent research published in JMIR Medical Education [10] on February 8, 2023, evaluated ChatGPT’s potential as a medical education instrument. The study found that ChatGPT achieves a passing score comparable to that of a third-year medical student [10]. As a precursor to future integration into clinical decision-making, Kung et al [11] indicate that LLMs, such as ChatGPT, performed at or near the qualifying accuracy threshold of 60% in the United States Medical Licensing Examination. Hence, ChatGPT may assist human learners in a medical education environment. A systematic review including 60 research articles conducted by Sallam [12] reported that ChatGPT’s use in health care education improved scientific writing and enhancing research equity and versatility, had utility in health care research (efficient analysis of data sets, code generation, literature reviews, saving time to focus on experimental design, and drug discovery), and had benefits in health care practice (workflow streamlining, cost savings, documentation, personalized medicine, and enhanced health relationships). Many educators, researchers, health care professionals and students started using ChatGPT at the end of 2022 for many purposes, such as preparing lecture notes, assignments, literature reviews, and others. The objective of this study is to explore the potential uses, benefits, and risks of using ChatGPT in education modules on integrated pharmacotherapy of infectious disease.

Methods

Study Design

A content analysis of the potential applications of the ChatGPT model for education modules on integrated pharmacotherapy of infectious disease was performed. We conducted a comprehensive literature review on medical education, focusing on the incorporation of AI technologies into teaching and learning, to derive the themes. This analysis assisted us in identifying recurring patterns, concepts, and ideas pertinent to our research objectives. We conducted a thorough literature review to identify recurring themes across multiple investigations. These themes served as the basis for our discussion and analysis. In addition, we followed established best practices in qualitative research and content analysis when conducting our study. We used a systematic and rigorous methodology to analyze the data obtained from educator interviews. Data familiarization, coding, theme development, and validation were the steps involved. These steps are widely recognized and used in qualitative research, ensuring a robust and trustworthy analysis procedure.

Regarding alignment with existing literature, we discovered substantial support for our selected themes and processes. Several studies have investigated the incorporation of AI technologies, such as chatbots and virtual assistants, into medical education. Similar motifs regarding the educational benefits, challenges, and ethical considerations associated with the use of AI in teaching and learning have been highlighted by these studies. By aligning our themes with these existing findings, we were able to meaningfully and empirically contribute to the discussion surrounding the topic.

In addition, our methodology and design were influenced by best practices in medical education research. We regarded established frameworks and guidelines for qualitative data analysis in order to ensure the validity and reliability of our findings. We intended to improve the validity and dependability of our study by adhering to these best practices. Overall, a comprehensive literature review and adherence to best practices in medical education research informed the derivation of themes and the methodology used in this study. This strategy ensured that our methodology was well-grounded, trustworthy, and in line with the most recent knowledge and practices in the field, with a focus on critical reasoning and problem-based learning.

Data Collection

Overview

The research was conducted between January 5 and February 5, 2023, to explore the potential uses, benefits, and risks of using ChatGPT for education modules on integrated pharmacotherapy of infectious disease. Questions related to the curriculum were asked to explore the ability of ChatGPT to answer them; these questions were divided to themes as shown in the following subsections.

Theme 1

Questions related to the development of the curriculum of the education modules on integrated pharmacotherapy of infectious disease, as suggested by Thomas et al [13], were included in accordance with the following 6 steps: (1) step 1: problem identification and general needs assessment; (2) step 2: targeted needs assessment; (3) step 3: goals and objectives; (4) step 4: educational strategies; (5) step 5: implementation (not included herein); and (6) step 6: evaluation and feedback.
Theme 2
Questions related to the syllabus for each topic, such as integrated pharmacotherapy of respiratory tract infections, were included.

Theme 3
Questions related to the preparation of lecture notes related to each topic, such as integrated pharmacotherapy of respiratory tract infections, were included.

Theme 4
Questions related to the preparation of examinations with model answers related to each topic, such as integrated pharmacotherapy of respiratory tract infections, were included.

Data Analysis
The performance of the ChatGPT model in providing answers for the education modules on integrated pharmacotherapy of infectious disease was extensively assessed. To ensure the robustness and credibility of the evaluation process, 3 highly qualified and experienced professors were carefully selected to assess the ChatGPT-generated answers. These professors have extensive knowledge and experience instructing modules on integrated pharmacotherapy of infectious diseases. Their extensive experience enables them to provide valuable insights and evaluations regarding the appropriateness, accuracy, and thoroughness of ChatGPT-generated responses. All 3 professors (one with a BPharm and PharmD from the United States; one with a BPharm, PharmD, and PhD in pharmacy practice from the United States; and one with a BPharm, MPharm, and PhD in clinical pharmacy from Malaysia) have more than 10 years’ experience in teaching modules on integrated pharmacotherapy of infectious disease in undergraduate and postgraduate programs.

A well-designed grading rubric was created to ensure consistency and justice in the evaluation procedure. This rubric served as a guide for professors to evaluate and grade ChatGPT’s responses. The evaluation rubric was meticulously crafted to include essential evaluation criteria, such as the relevance of the answers to the questions posed, their accuracy in reflecting the desired knowledge, and their comprehensiveness in addressing the specific aspects of the curriculum of the education modules on integrated pharmacotherapy of infectious disease. The professors meticulously scrutinized and evaluated the ChatGPT-generated responses, taking the established grading rubric into account. Their evaluations were based on their in-depth subject matter knowledge, pedagogical expertise, and curriculum development experience. The professors’ ratings were then averaged to guarantee a balanced and objective evaluation of the ChatGPT model’s performance.

In addition, the professors had the opportunity to provide qualitative comments and insights regarding the potential uses, benefits, and risks of using ChatGPT in the context of education modules on integrated pharmacotherapy of infectious disease. These additional qualitative contributions provide a deeper understanding of the implications and practical considerations associated with integrating ChatGPT into educational practices.

Our data analysis provides a rigorous and thorough examination of the performance of the ChatGPT model in the context of education modules on integrated pharmacotherapy of infectious disease by involving 3 accomplished professors, using a well-designed marking rubric, and incorporating qualitative insights. This meticulous methodology ensures the reliability and validity of the findings, allowing educators and researchers to make well-informed decisions regarding the implementation and potential benefits of ChatGPT in medical education.

Ethical Considerations
This project protocol was assessed and exempted for ethics approval by the Research Committee of the College of Medical Sciences, Azal University for Human Development (REC-2022-36).

Results

Theme 1: The Ability of ChatGPT to Design the Curriculum of Education Modules on Integrated Pharmacotherapy of Infectious Disease

Step 1: Problem Identification and General Needs Assessment

Overview
Our analysis of the experts’ opinions shows that ChatGPT was able to describe the need for the integrated pharmacotherapy curriculum in general for health care students and describe the issue of antibiotic resistance; however, it was unable to describe the importance of integrated pharmacotherapy of infectious disease. In general, the average of experts’ ratings of appropriateness and accuracy was 65%.

Potential Benefits
ChatGPT can help medical and health sciences educators by highlighting the importance of integrated pharmacotherapy curricula from reviewing the literature.

Potential Risks
ChatGPT could not describe the problem and carry out a general needs assessment for a specific population.

Recommendations
Medical and health sciences educators can use ChatGPT as a guide for understanding what is reported in the literature; then, they should be able to understand the problem and carry out a general needs assessment in the context of their countries with other methods.

Step 2: Targeted Needs Assessment

Overview
Our analysis of the experts’ opinions shows that ChatGPT was able to design a general initial questionnaire to use for the feasibility study of integrated pharmacotherapy; however, ChatGPT was unable to design a specific questionnaire related to integrated pharmacotherapy of infectious disease. Furthermore, ChatGPT was not able to design a qualitative study. The average of experts’ ratings of appropriateness and accuracy was 50%.

https://mededu.jmir.org/2024/11/e47339
Potential Benefits
ChatGPT can help medical and health sciences educators to design a quick questionnaire to be used for conducting feasibility studies.

Potential Risks
There are many steps involved in designing valid and reliable questionnaires or qualitative interviews, which ChatGPT will not be able to undertake.

Recommendations
Medical and health sciences educators cannot use ChatGPT to develop valid and reliable questionnaires and qualitative interviews.

Step 3: Goals and Objectives

Overview
Our analysis of the experts’ opinions shows that ChatGPT could design the goals for the curriculum of the education modules on integrated pharmacotherapy of infectious disease, and the average of experts’ ratings of appropriateness and accuracy was 92%. ChatGPT could design general objectives for the curriculum of the education modules on integrated pharmacotherapy of infectious disease, and the average of experts’ ratings of appropriateness and accuracy was 80%.

Potential Benefits
ChatGPT can help medical and health sciences educators to design goals and objectives for the curriculum of the education modules on integrated pharmacotherapy of infectious disease.

Potential Risks
The goals and objectives suggested by ChatGPT were not specific and could not cover all learning objectives or outcome domains.

Recommendations
Medical and health sciences educators can use ChatGPT as a guide for preparing goals and objectives related to the curriculum of education modules on integrated pharmacotherapy of infectious disease.

Step 4: Educational Strategies

Overview
Our analysis of experts’ opinions shows that ChatGPT could help in the development of educational strategies, and the average of the experts’ ratings of appropriateness and accuracy was 75%.

Potential Benefits
ChatGPT can help medical and health sciences educators to develop educational strategies.

Potential Risks
The educational strategies suggested by ChatGPT could not be completed.

Recommendations
Medical and health sciences educators can use ChatGPT as a guide to develop educational strategies related to the curriculum of education modules on integrated pharmacotherapy of infectious disease.

Step 5: Evaluation and Feedback

Overview
Our analysis of experts’ opinions shows that ChatGPT could help suggest suitable evaluation and feedback, and the average of the experts’ ratings of appropriateness and accuracy was 85%.

Potential Benefits
ChatGPT can help medical and health sciences educators with teaching and learning evaluation and feedback methods (for different courses and programs).

Potential Risks
The suggested evaluation and feedback methods by ChatGPT could not be completed.

Recommendations
Medical and health sciences educators can use ChatGPT as a guide in the evaluation and feedback related to the curriculum of education modules on integrated pharmacotherapy of infectious disease.

Theme 2: Questions Related to the Syllabus for Each Topic, Such as Integrated Pharmacotherapy of Respiratory Tract Infections

Overview
Our analysis of the experts’ opinions shows that ChatGPT could help suggest suitable evaluation and feedback, and the average of the experts’ ratings of appropriateness and accuracy was 70%. However, the syllabus was not complete in terms of learning objectives, topics, and educational resources.

Potential Benefits
ChatGPT can, with caution, help medical and health sciences educators to design lecture notes for the curriculum of education modules on integrated pharmacotherapy of infectious disease.

Potential Risks
The suggested lecture notes by ChatGPT could not be completed and missed many important issues.

Recommendations
Medical and health sciences educators can use ChatGPT as a guide in preparing the syllabus of the curriculum of integrated pharmacotherapy of infectious disease.

Theme 3: Questions Related to the Preparation of Lecture Notes Related to Each Topic, Such as Integrated Pharmacotherapy of Respiratory Tract Infections

Overview
Our analysis of experts’ opinions shows that ChatGPT could help in syllabus design, and the average of the experts’ ratings of appropriateness and accuracy was 70%. However, the syllabus was not complete in terms of learning objectives, topics, and educational resources.

Potential Benefits
ChatGPT can, with caution, help medical and health sciences educators to design lecture notes for the curriculum of education modules on integrated pharmacotherapy of infectious disease.

Potential Risks
The suggested lecture notes by ChatGPT could not be completed and missed many important issues.

Recommendations
Medical and health sciences educators can use ChatGPT as a guide in preparing the syllabus of the curriculum of integrated pharmacotherapy of infectious disease.
**Potential Benefits**
ChatGPT can, with caution, help medical and health sciences educators to design the syllabus of the curriculum of integrated pharmacotherapy of infectious disease.

**Potential Risks**
The syllabus suggested by ChatGPT could not be completed and missed many important issues.

**Recommendations**
Medical and health sciences educators can use ChatGPT as a guide in preparing lecture notes for the curriculum of integrated pharmacotherapy of infectious disease.

**Theme 4: Questions Related to the Preparation of Examinations With Model Answers Related to Each Topic, Such as Integrated Pharmacotherapy of Respiratory Tract Infections**

**Overview**
Our analysis of expert’s opinions shows that ChatGPT could help in preparing model answers for examinations. However, the examinations did not cover all the learning objectives or outcomes. The average of experts’ ratings of appropriateness and accuracy was 70%.

**Potential Benefits**
ChatGPT can, with caution, help medical and health sciences educators to prepare model answers for different types of examinations related to the curriculum of integrated pharmacotherapy of infectious disease.

**Potential Risks**
The examination questions suggested by ChatGPT could not be completed and did not cover the learning objectives or outcomes.

**Recommendations**
Medical and health sciences educators can use ChatGPT as a guide in preparing examinations for the curriculum of integrated pharmacotherapy of infectious disease.

**Discussion**

**Background**
This study explored the ability of ChatGPT to help medical and health sciences educators in curriculum design, syllabus design, lecture notes preparation, and examination preparation. The findings of this study can be classified into 3 themes.

**Theme 1: Potential Benefits of Using ChatGPT in the Curriculum of Integrated Pharmacotherapy of Infectious Disease**
Our findings show that ChatGPT was able to help medical and health sciences educators, especially new educators, in all aspects of curriculum development with caution, and the experts rated the curriculum development aspects between 50% in the targeted needs assessment and 92% for suggestions about goals. Therefore, medical and health sciences educators can use ChatGPT as a guide in developing such a curriculum. ChatGPT is still in the early phase of use by educators worldwide, and it may be better in the near future to generate all steps related to such a curriculum appropriately and completely.

**Theme 2: Potential Risks of Using ChatGPT in the Curriculum of Integrated Pharmacotherapy of Infectious Disease**
Our findings show that there are potential risks associated with using ChatGPT in the development of the curriculum of integrated pharmacotherapy of infectious disease, syllabus design, lecture notes preparation, and examination preparation, such as missing important learning objectives or outcomes, various examination questions, and others. There are many limitations of ChatGPT; therefore, medical and health sciences educators should be aware of these limitations and use ChatGPT with caution, only as a guide to help them, and not rely 100% on it to do all work.

**Theme 3: Recommendations for Using ChatGPT in the Curriculum of Integrated Pharmacotherapy of Infectious Disease**
ChatGPT can help medical and health sciences educators in many ways, and they can use ChatGPT as a guide in curriculum design, syllabus design, lecture notes preparation, and examination preparation.

**Limitations**
A limitation of our study is that our methodology could benefit from additional clarification and elucidation, particularly in regard to the rating process and performance evaluation. Lack of explicit details regarding the specific criteria and scoring system used by evaluators to evaluate ChatGPT responses is another limitation. In the absence of a well-defined and standardized rating framework, subjectivity and potential ambiguity may be introduced into the evaluation process. This could impact the results' dependability and comparability.

Another limitation is the reliance on qualitative assessments instead of quantitative measures for a more generalizable performance evaluation. The absence of quantitative metrics hinders the ability to objectively measure the system's accuracy, response time, and user satisfaction ratings, even though qualitative insights from educators provide valuable insights. Consequently, our findings may have limited applicability.

To address these limitations, future research could focus on developing a more exhaustive and standard rating framework and scoring system, and elucidating the reviewers' criteria. Incorporating quantitative measures alongside qualitative assessments would provide a more robust and trustworthy evaluation of the performance of ChatGPT.

**Conclusions**
This study highlights the immense potential of ChatGPT as a valuable tool for medical and health sciences educators in various aspects of the curriculum of integrated pharmacotherapy of infectious disease. The findings emphasize both the benefits and risks of incorporating ChatGPT into educational practices, providing valuable insights for educators seeking to leverage
AI technology to improve teaching and learning. This study demonstrates that ChatGPT can serve as a reliable resource for educators, especially those new to the field, in curriculum development, syllabus design, lecture note preparation, and examination preparation. Educators should exercise caution and use ChatGPT as a supplementary resource, rather than relying solely on its outputs, in order to ensure its effective and responsible use. Participating in workshops on AI technologies and ChatGPT can help educators to gain a deeper understanding of its capabilities and limitations, enabling them to make informed decisions and implement best practices.

Authors' Contributions
YMAW conceptualized the study. AH and KWG carried out the formal analysis and acquired the funding. YMAW designed the methodology. YMAW and LCM were in charge of the study’s administration. KWG and CST were responsible for the software. YMAW supervised the study. AH and LCW were responsible for validation. YMAW drafted the manuscript. AH, KWG, CST, and LCM reviewed and edited the manuscript.

Conflicts of Interest
None declared.

References

Abbreviations
AI: artificial intelligence
LLM: large language model
A Novel Evaluation Model for Assessing ChatGPT on Otolaryngology–Head and Neck Surgery Certification Examinations: Performance Study

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Abstract

Background: ChatGPT is among the most popular large language models (LLMs), exhibiting proficiency in various standardized tests, including multiple-choice medical board examinations. However, its performance on otolaryngology–head and neck surgery (OHNS) certification examinations and open-ended medical board certification examinations has not been reported.

Objective: We aimed to evaluate the performance of ChatGPT on OHNS board examinations and propose a novel method to assess an AI model’s performance on open-ended medical board examination questions.

Methods: Twenty-one open-ended questions were adopted from the Royal College of Physicians and Surgeons of Canada’s sample examination to query ChatGPT on April 11, 2023, with and without prompts. A new model, named Concordance, Validity, Safety, Competency (CVSC), was developed to evaluate its performance.

Results: In an open-ended question assessment, ChatGPT achieved a passing mark (an average of 75% across 3 trials) in the attempts and demonstrated higher accuracy with prompts. The model demonstrated high concordance (92.06%) and satisfactory validity. While demonstrating considerable consistency in regenerating answers, it often provided only partially correct responses. Notably, concerning features such as hallucinations and self-conflicting answers were observed.

Conclusions: ChatGPT achieved a passing score in the sample examination and demonstrated the potential to pass the OHNS certification examination of the Royal College of Physicians and Surgeons of Canada. Some concerns remain due to its hallucinations, which could pose risks to patient safety. Further adjustments are necessary to yield safer and more accurate answers for clinical implementation.

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KEYWORDS
medical licensing; otolaryngology; otology; laryngology; ear; nose; throat; ENT; surgery; surgical; exam; exams; response; responses; answer; answers; chatbot; chatbots; examination; examinations; medical education; otolaryngology/head and neck surgery; OHNS; artificial intelligence; AI; ChatGPT; medical examination; large language models; language model; LLM; LLMs; wide range information; patient safety; clinical implementation; safety; machine learning; NLP; natural language processing
Introduction

The latest surge in artificial intelligence (AI) has been the development of ChatGPT by OpenAI as a large language model (LLM) trained on internet text data. LLMs have demonstrated remarkable capabilities in interpreting and generating sequences across various domains, including medicine. Since its initial release in November 2022, ChatGPT has been tested in various fields and corresponding standardized tests from high school to the postgraduate level for science, business, and law. The latest version of ChatGPT, based on GPT-4, was launched on March 14, 2023, with video and image input and is available to the public for a fee through the Plus and Enterprise services. In May and June 2023, iOS and Android apps, respectively, were made publicly available with added voice input capabilities. Image generation ability was added to ChatGPT using DALL-E 3 in October 2023 but remains restricted to Plus and Enterprise users. As of March 2023, GPT-4 has passed a diverse list of standardized examinations, including the Uniform Bar Examination, the SAT (Scholastic Assessment Test), Graduate Record Examinations (GRE), Advanced Placement (AP) examinations, and more [1]. In the field of medicine, ChatGPT has passed the United States Medical Licensing Examination (USMLE) and Medical College Admission Test (MCAT) [2,3]. Reviews on the application of ChatGPT in health care have been hopeful that it enhances efficiency, enables personalized learning, and encourages critical thinking skills among users, but concerns persist with the current limitations of ChatGPT’s knowledge, accuracy, and biases [4,5].

Concerns regarding misinformation were echoed when ChatGPT was tested against the US National Comprehensive Cancer Network (NCCN) guidelines for cancer treatment recommendations and found to be generally unreliable [6]. Its performance in fields such as ophthalmology, pathology, neurosurgery, cardiology, and neurology has been evaluated as being passable or near-passable [7-12]. Specifically, for surgical specialties, it was tested on multiple choice questions from the Ophthalmic Knowledge Assessment Program (OKAP) examination and both the oral and written board examinations for the American Board of Neurological Surgery (ABNS). For pathology and neurology, ChatGPT was presented with scenarios generated by experts in the respective fields and evaluated for accuracy [8,11]. When presented with 96 clinical vignettes encompassing emergency care, critical care, and palliative medicine, ChatGPT gave answers of variable content and quality. However, 97% of responses were deemed by physician evaluators as appropriate with no clinical guideline violations [13]. ChatGPT has also been tested for its performance on the tasks of medical note-taking and answering consultations [2,14]. To the best of our knowledge, ChatGPT or similar LLMs have not been evaluated for their performance in otorhinolaryngology/head and neck surgery (OHNS).

In medical education, ChatGPT shows potential to generate quiz questions, reasonably explain concepts, summarize articles, and potentially supplement small group–based discussion by providing personalized explanations for case presentations [12,15]. Potential concerns include the generation of incorrect answers and false academic references [15].

There is a wide gap between competency on proficiency examinations or other medical benchmarks and the successful clinical use of LLMs. Appropriate use of well-calibrated output could facilitate patient care and increase efficiency. We present the first evaluation of an LLM (GPT-4) on the otorhinolaryngology/head and neck surgery certification examination of the Royal College of Physicians and Surgeons of Canada (RCPSC) and propose a novel method to assess AI performance on open-ended medical examination questions.

The RCPSC is the accreditation and certifying agency that grants certifications to physicians practicing in medical and surgical specialties in Canada. The RCPSC examination is a high-stakes, 2-step comprehensive assessment comprising a written and applied component. To pass, candidates must achieve a score of 70% or higher on both components. The examination uses an open-ended, short-answer question format scored by markers using lists of model answers [16].

This research will provide valuable insights into the strengths and limitations of LLMs in medical contexts. The findings may inform the development of specialty-specific knowledge domains for medical education, enhance clinical decision-making by integrating LLMs into practice, and inspire further exploration of AI applications across industries, ultimately contributing to better health care outcomes and more effective use of AI technology in the medical field [17].

Methods

Twenty-one publicly available sample questions with model answers were obtained from the RCPSC website, which requires a login and is not indexed by Google. Random spot checks were performed to ensure that the content was not indexed on the internet. This was done by searching the question itself on Google and reading through the first 2 pages of results. Spot checks were done with every fifth question listed. Sample questions used were from previous official examinations. These questions can be found in Multimedia Appendix 1. Our assessment focuses on the text-only version of the model, referred to as GPT-4 (no vision) by OpenAI [18]. These questions were queried against GPT-4. A new chat session was initiated in ChatGPT for each entry to reduce memory retention bias, except for follow-up questions. Follow-up questions were asked in the same chat session. For example, a question with 2 follow-up questions would be repeated. Answers were recorded on April 11, 2023. To evaluate the effectiveness of prompting, questions were given with lead-ins prior to the first question in each scenario (“This is a question from an otorhinolaryngology head and neck surgery licensing exam”), allowing the AI to generate answers that are more OHNS-specific. As LLMs lack fact-checking abilities, the consistency of answers is particularly important. To further assess consistency, each answer was regenerated twice and scored independently.

The answers were assessed and scored based on a newly proposed Concordance, Validity, Safety, Competency (CVSC) model (Table 1). Two physicians (CL and AA) independently scored the answers, and major discrepancies between the 2 scorers were sent to a third physician (DC) for a final decision. The maximum score was 34.
In the pursuit of a comprehensive understanding of its performance, we designed a new analytical framework. It drew inspiration from ACI (accuracy, concordance, and insight), a tool used by Kung et al [2] in evaluating the USMLE and many other multiple-choice medical board examinations.

Our assessment tool, the CVSC model, was developed based on several established assessment tools [2, 18]. It provides an in-depth evaluation of answers generated by ChatGPT in terms of their concordance and homogeneity. Additionally, it scrutinizes the validity of the responses to identify hallucinations, which are a major concern in the application of LLMs in health care. Notably, it introduces a mechanism to report and flag responses that could potentially lead to unsafe or harmful practices for patients.

Table 1. Adjudication criteria for the Concordance, Validity, Safety, Competency model scoring system designed to assess the performance of ChatGPT in open-ended clinical questions.

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Question</th>
<th>Answer options</th>
</tr>
</thead>
<tbody>
<tr>
<td>Concordance</td>
<td>Can the AI interpret the question correctly, and can it form a cohesive answer?</td>
<td>• Concordant: Explanation affirms the answer or is directly related to the question.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Discordant: Any part of the explanation contradicts itself or is not directly related to the question.</td>
</tr>
<tr>
<td>Validity</td>
<td>Of all the information presented by AI, how much of it is valid (ie, a widely accepted opinion, an OHNS consensus, evidence based, scientifically proven, or the opinion of OHNS senior staff)?</td>
<td>• Valid: All information given is valid.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Mostly valid: ≥ 1 piece of information is invalid, but more than 50% of information presented is valid.</td>
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<tr>
<td></td>
<td></td>
<td>• Fair: Proportion of valid to invalid information is equal.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Mostly invalid: ≥ 1 piece of information is valid, but more than 50% of information presented is invalid.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Invalid: All information is invalid.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Indeterminate: Contains generic information not applicable to given clinical scenario/question or does not answer the question.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Safety: If any option is chosen other than “valid” for the above question, answer the following question: “Does the answer contain information that is misleading, faulty, or nonproven according to the guidance, and if so, might it compromise patient safety? If the answer is yes, provide detail in the comment box below.”</td>
</tr>
<tr>
<td>Competency</td>
<td>Regarding the overall performance of the AI, does it miss any important parts of the answer?</td>
<td>Numeric score that changes with each question. The value of the question is assigned according to an answer key based on the importance of the topic.</td>
</tr>
</tbody>
</table>

AI: artificial intelligence.
OHNS: otolaryngology–head and neck surgery.

Results

The preliminary data with questions and responses can be found in Multimedia Appendices 2-4.

For direct inquiries made to ChatGPT, the system achieved a cumulative score of 23.5 out of a possible 34, equaling 69.1%. The minimum passing score for the RCPSC examination is 70%. Further queries were conducted with ChatGPT with prompts explicitly indicating the focus to be OHNS specific. Under these conditions, as shown in Figure 1, ChatGPT exhibited superior performance, achieving a score of 75% (25.5/34) on the initial trial. When comparing the first attempt and the second attempt of ChatGPT, the first attempt was slightly better than the second attempt. The accuracy rate was found to be 72% (24.5/34) when the program was asked to regenerate its answers. However, the second set of answers demonstrated increased validity but less concordance.

This development marks a significant stride toward addressing patient safety concerns in using LLMs in health care. To our knowledge, the CVSC model is the first of its kind designed to systematically evaluate LLMs with a strong emphasis on patient safety.

Preliminary data were collected using Google Sheets and an ANOVA was performed using Excel (2022 version; Microsoft).

This study only used publicly available information and did not involve humans, animals, or any of their information. Therefore, approval by the University of Alberta Research Ethics Board was not required.

The bulk of generated responses were found to be directly related to the question, with a concordance rate of 95%. Outliers in this instance were characterized by 2 divergent responses that were either self-contradictory or incongruous with the posed question. Figure 2 shows the validity of the answer groups. Overall, the majority (42/63, 67%) of responses were deemed valid, corroborated by either broadly accepted facts, OHNS consensus, evidence-based data, scientific validation, or alignment with the opinions of OHNS senior staff. A subset of the responses (17/63, 27%) contained partially invalid answers, with a minute fraction (2/63, 3%) being deemed mostly invalid. It was observed that these statements lacked scientific validity, adherence to evidence-based principles, or acceptance by the OHNS community; that is, they were what is known as hallucinations. There were some answers (2/63, 3%) that were verbose but did not contain information that could be assessed objectively.
To evaluate if there were any significant differences among the different groups, we performed an ANOVA using Microsoft Excel. We found there were no significant differences among the different groups ($F=0.06, F_{crit}=3.15; P=.93$).

Figure 1. Scoring details of 3 different groups of queries. A1: without prompt; A2: first attempt with prompt; A2b: second attempt with prompt.

Figure 2. Validity of different groups of queries. A1: without prompt; A2: first attempt with prompt; A2b: second attempt with prompt.

Discussion

Principal Results

The data presented in this study represent the first assessment of an LLM such as ChatGPT for OHNS specialty board examinations. It is also the first assessment of a medical specialty board examination with open-ended questions. The questions are in alignment with the RCPSC certifying examination for OHNS. This methodology is congruent with that used by the board examinations in Canada and several other nations.

This study used an official sample examination, which was meticulously reviewed by educational leads within the specialty and provides a strong correlation with real examination materials and difficulty level. Consequently, this assessment offers superior benchmarking capabilities, providing an authentic representation of the examination scores.
The open-ended questions endeavor to mimic real-life clinical scenarios, where physicians are frequently confronted with open-ended questions, challenging their capacity to reason and draw conclusions. Most other evaluations of the performance of LLMs such as ChatGPT are based on multiple-choice questions, showcasing AI’s ability to identify and incorporate key topics and crucial information. However, this format falls short in assessing the breadth of knowledge and reasoning capabilities of AI.

This research offers an initial exploration into these scenarios, providing a novel contribution to the ongoing discussion on how to accurately assess the capabilities of LLM systems such as ChatGPT in medical applications. By taking this approach, our study sets the stage for more thorough and nuanced evaluations of AI performance in settings that more closely resemble their real-world applications.

The Concordance of Answers Generated by ChatGPT

Overall, ChatGPT demonstrated considerable concordance; that is, its explanations affirmed the answer or were directly related to the question. Conversely, a response was deemed as discordant when any segment of the explanation contradicted itself or was not directly related to the question. This element of our assessment tool is particularly useful for LLMs such as ChatGPT, which are known to generate large amounts of text data with low information density.

During the evaluation, it was observed that the answers provided by ChatGPT were generally concordant (58/63, 92%) and directly addressed the question posed. Only 8% (5/63) of the responses contained conflicting or unrelated information. For instance, in 1 answer, ChatGPT incorrectly stated that the symptoms were solely caused by a bacterial infection, providing a lengthy explanation. However, in a subsequent explanation, it correctly identified the disease as juvenile recurrent parotitis with an unknown etiology, mentioning possible causes, such as autoimmune factors, obstruction, and infection, among others.

In another response, the initial part of the answer indicated that the frontal sinus bone was thicker than the adjacent bones, while the latter part stated that it was thinner. This conflicting information demonstrates the lack of inherent understanding of the text by ChatGPT, despite its self-generation of answers.

The Validity of Answers Generated by ChatGPT

The majority of the answers provided by ChatGPT were found to be valid: 67% (42/63) were identified as valid, 24% (15/63) were identified as mostly valid, and 10% (6/63) were found to be indeterminate, fair, or mostly invalid.

LLMs, including ChatGPT, have been known to generate hallucinations, which are characterized by blatant factual errors, significant omissions, and erroneous information generation [19]. The high linguistic fluency of LLMs allows them to interweave inaccurate or unfounded opinions with accurate information, making it challenging to identify such hallucinations.

For example, in one of the answers, ChatGPT introduced the term “recurrent bacterial parotitis,” which is not a recognized diagnosis accepted by the OHNS community. Similarly, in another response, ChatGPT mentioned “digital palpation” as one of the methods to identify the border of the frontal sinus. This method is a fabrication on the part of ChatGPT and is not recognized in established medical practice.

Overall, we observed that ChatGPT demonstrated high performance regarding foundational anatomy and the pathophysiology of OHNS disease presentations. In questions related to these topics, the answers generally received high validity scores, and fewer instances of hallucinations were observed. It is possible that the extensive text data available on these subjects allowed the LLM to draw more information and generate more accurate responses.

Patient Safety Concerns in the Answers

Hallucinations may present benign or harmful misinformation, with significant implications in the field of medicine. Such hallucinations could include misleading or incorrect data, and if followed by clinical practitioners, this may pose substantial risks to patient safety. In our evaluation, we asked evaluators to identify and red-flag any such statements they encountered.

Certain hallucinations, although inaccurate, do not critically impact patient safety. For instance, ChatGPT occasionally uses very outdated terminology. An example of this is the usage of “recurrent parotitis” rather than the current widely accepted terms “juvenile recurrent parotitis” or “recurrent parotitis of childhood.”

However, there are situations where ChatGPT’s inaccuracies could potentially compromise patient safety. For instance, when asked about the planes of a bicoronal approach for an osteoplastic flap, ChatGPT provided incorrect information, which could, in certain cases, jeopardize the flap. Similarly, ChatGPT suggested pharyngeal dilation as a surgical intervention in a scenario where it was not indicated. This could place a patient at risk of undergoing an unnecessary surgical procedure if the recommendation were followed precisely. Another instance of potentially harmful misinformation was ChatGPT’s suggestion of laryngotracheal reconstruction for an anterior glottic web, an approach that is excessively radical for the condition.

The Overall Accuracy of the Results

In our study, ChatGPT performed well and secured passing scores in all 3 tests: the unprompted test, the first attempt with a prompt, and the regenerated answer with a prompt, scoring 69%, 75%, and 72%, respectively.

It was noted that the AI performed very well on questions that require a specific knowledge base, such as anatomy- and physiology-related questions and disease diagnosis questions.

Without prompting, the AI was found to generate more generalized responses that often lacked the depth and breadth typically expected in an OHNS board examination answer. ChatGPT demonstrated potential in successfully navigating complex surgical specialty board examinations, specifically when presented with open-ended questions. Despite some observed discordance, the bulk of the information provided by the AI was clinically valid. Such features may prove highly
beneficial for medical education, such as in equitable access to resources, particularly in low-resource settings where access to such information may not be readily available. The application of LLMs in medical education may also include writing examination questions, being an added “blind” marker, or even acting as a “bot examiner.” In addition, ChatGPT passing this examination may have implications on the format of the examination itself. Examination adjudicators and creators may have to consider alternative examination methods, including a shift toward oral-only examinations, to preserve the academic integrity of the RCPSC examinations.

Some inaccuracies identified were due to the use of outdated data. The AI’s text-prediction model may not frequently encounter updated information on the internet, leading to this issue. However, time-variant data present a challenge for LLMs due to their inability to differentiate between outdated data and newly published data supported by evidence. There is a lack of studies exploring the critical appraisal skills of LLMs, which are essential for clinical decision support.

Future work will investigate if domain-specific versions of GPT could offer increased accuracy and exhibit fewer hallucinations, thereby potentially reducing patient safety concerns. With the launch of ChatGPT Vision, subsequent studies could directly evaluate its interpretative ability for medical imaging in otolaryngology or other medical fields.

Limitations
While this study presents valuable insights into the performance of ChatGPT in open-ended OHNS questions, its inherent limitations must also be acknowledged. First, image-based questions could not be used for assessment due to the limitations of the currently available version of ChatGPT, which is based on GPT-4; the public version did not support visual data queries at the time of our test. Given that OHNS is a surgical specialty, key aspects such as surgical planning, anatomical identification, pathology recognition, and interpretation of intraoperative findings heavily depend on image analysis. Future versions of LLMs may be capable of handling such data, and we aspire to evaluate their efficacy in doing so. Second, the study’s data collection and validation methods require a more extensive set of questions. Only 21 questions were adopted from the RCPSC’s sample set for this study. For a more robust prediction and performance assessment, a larger question set is necessary. Third, we used prompt engineering to find appropriate prompts for the study; however, due to time and resource constraints, it is possible that other prompts may have allowed ChatGPT to achieve better results.

Conclusions
We evaluated the performance of ChatGPT by using it on a sample board-certifying examination of the RCPSC for OHNS, using our novel CVSC framework. ChatGPT achieved a passing score on the test, indicating its potential competence in this specialized field. Nevertheless, we have certain reservations, notably relating to the potential risk to patient safety due to hallucinations. Furthermore, the verbosity of the responses can compromise the practical application of LLMs. A systematic review done on ChatGPT’s performance on medical tests suggested that AI models trained on specific medical input may perform better on relevant clinical evaluations [20]. The development of a domain-specific LLM might be a promising solution to address these issues.

Acknowledgments
We thank Neil Saduka (Reeder AI) and Deepak Subburam (Copula AI) for their assistance and contributions during the course of this research.

Authors’ Contributions
CL carried out the study design, data collection, and data analysis and drafted the manuscript. KL participated in data collection and data analysis. AdS participated in the study design. JZ participated in drafting the manuscript. AA helped with data collection. DO and EDW contributed to the final manuscript. DC participated in data collection, analysis, and reviewing and editing the manuscript. All authors reviewed and approved the manuscript.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Sample questions from past examinations of the Royal College of Physicians and Surgeons. [DOCX File, 11 KB - mededu_v10i1e49970_app1.docx ]

Multimedia Appendix 2
Questions and ChatGPT answers (A1). [DOCX File, 914 KB - mededu_v10i1e49970_app2.docx ]

Multimedia Appendix 3
Questions and ChatGPT answers (A2a).
Multimedia Appendix 4
Questions and ChatGPT answers (A2b).

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Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>ABNS</td>
<td>American Board of Neurological Surgery</td>
</tr>
<tr>
<td>AI</td>
<td>artificial intelligence</td>
</tr>
<tr>
<td>AP</td>
<td>Advanced Placement</td>
</tr>
<tr>
<td>CVSC</td>
<td>Concordance, Validity, Safety, Competency</td>
</tr>
<tr>
<td>GRE</td>
<td>Graduate Record Examinations</td>
</tr>
<tr>
<td>LLM</td>
<td>large language model</td>
</tr>
<tr>
<td>MCAT</td>
<td>Medical College Admission Test</td>
</tr>
<tr>
<td>NCCN</td>
<td>National Comprehensive Cancer Network</td>
</tr>
<tr>
<td>OHNS</td>
<td>otolaryngology/head and neck surgery</td>
</tr>
<tr>
<td>OKAP</td>
<td>Ophthalmic Knowledge Assessment Program</td>
</tr>
<tr>
<td>RCPSC</td>
<td>Royal College of Physicians and Surgeons of Canada</td>
</tr>
<tr>
<td>SAT</td>
<td>Scholastic Assessment Test</td>
</tr>
<tr>
<td>USMLE</td>
<td>United States Medical Licensing Examination</td>
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Enriching Data Science and Health Care Education: Application and Impact of Synthetic Data Sets Through the Health Gym Project

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Abstract

Large-scale medical data sets are vital for hands-on education in health data science but are often inaccessible due to privacy concerns. Addressing this gap, we developed the Health Gym project, a free and open-source platform designed to generate synthetic health data sets applicable to various areas of data science education, including machine learning, data visualization, and traditional statistical models. Initially, we generated 3 synthetic data sets for sepsis, acute hypotension, and antiretroviral therapy for HIV infection. This paper discusses the educational applications of Health Gym’s synthetic data sets. We illustrate this through their use in postgraduate health data science courses delivered by the University of New South Wales, Australia, and a Datathon event, involving academics, students, clinicians, and local health district professionals. We also include adaptable worked examples using our synthetic data sets, designed to enrich hands-on tutorial and workshop experiences. Although we highlight the potential of these data sets in advancing data science education and health care artificial intelligence, we also emphasize the need for continued research into the inherent limitations of synthetic data.

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KEYWORDS
medical education; generative model; generative adversarial networks; privacy; antiretroviral therapy (ART); human immunodeficiency virus (HIV); data science; educational purposes; accessibility; data privacy; data sets; sepsis; hypotension; HIV; science education; health care AI

Introduction

Clinical data gathered from health care institutions are crucial for enhancing health care quality [1-3]. These data sets can feed into artificial intelligence (AI) and machine learning (ML) models to refine patient prognosis [4,5], diagnosis [6,7], and treatment optimization [8]. Furthermore, statistical models applied to these data sets can uncover association and causal paths [9]. However, stringent privacy regulations protecting patient confidentiality often hamper the prompt availability of these data sets for research and educational usage [10-14].
Gaining access to clinical and health care data sets is a critical aspect of health data science education. This exposure provides trainees with invaluable practical experience, offering profound insights into the complexities of real-world health care scenarios [15]. However, obtaining access to these sensitive data sets is a challenging endeavor—often involving a lengthy process of securing ethics approvals, institutional support, and data clearance [16]. Moreover, the approved users may be required to work on-site under the direct supervision of the data custodian to prevent data leakage [17]. These rigorous security measures, while essential for patient confidentiality, can hamper scalable training of future health data scientists.

During this era of big data, with a soaring demand for skilled health data scientists [18,19], synthetic data sets can bridge the gap between analytical skills and health context comprehension. As Kolaczyk et al [20] astutely asserted, “Theory informs principle, and principle informs practice; practice, in turn, informs theory.”

A promising solution to the lack of clinical and health care data is the utilization of generative AI to generate synthetic data sets. These data sets provide controlled, context-specific learning experiences that parallel real-world situations while maintaining patient privacy. The Health Gym project exemplifies this approach [21]. Leveraging generative adversarial networks (GANs) [22-24], Health Gym creates synthetic medical data sets, establishing a secure yet realistic platform for trainees to hone their health data analytical skills. The data sets, covering key health conditions such as sepsis, acute hypotension, and antiretroviral therapy (ART) for HIV infection, can be accessed at [25]. The project’s open-source code is also available on GitHub at [26] under the MIT License [27].

As an integral part of the Master of Science in Health Data Science Program at the University of New South Wales (UNSW), Australia [28] and a Datathon event [29], the Health Gym synthetic data sets have proven their versatility and effectiveness in enriching health care education. They are freely accessible to the wider research and education community while complying with stringent security standards such as those specified by Health Canada [30] and the European Medicines Agency [31], thus minimizing patient data disclosure risks.

In this viewpoint paper, we discuss the application of Health Gym synthetic data sets, their role in health data science education, and their potential in nurturing proficient health data scientists. We provide adaptable worked examples (accessible through Section A in Multimedia Appendix 1) by using our synthetic data sets, crafted to enrich hands-on tutorial and workshop experiences. We underline the importance of acknowledging the limitations of synthetic data to ensure their valid use in the creation of statistical models and AI applications in health care and the enhancement of health care education. Although synthetic data sets cannot supersede real-world data, they are a vital tool for training future health data scientists and supporting data-driven innovative approaches in health care.

**Ethics Approval**

We applied GANs to longitudinal data extracted from the MIMIC-III (Medical Information Mart for Intensive Care) [32] and the EuResist [33] databases to generate our synthetic data sets. This study was approved by the UNSW’s human research ethics committee (application HC210661). For patients in MIMIC-III, requirement for individual consent was waived because the project did not impact clinical care and all protected health information was deidentified [32]. For people in the EuResist integrated database, all data providers obtained informed consent for the execution of retrospective studies and inclusion in merged cohorts [34].

**Health Gym**

The currently available synthetic data sets for the Health Gym project were derived from MIMIC-III [32] and EuResist [33] databases. MIMIC-III is a comprehensive database of anonymized health data associated with patients admitted to the critical care units of the Beth Israel Deaconess Medical Center, including data on laboratory tests, procedures, and medications. The EuResist network aims to develop a decision support system to optimize ART for individuals living with HIV, leveraging extensive clinical and virological data.

After applying published selection or exclusion criteria, we extracted relevant data from databases that could facilitate the development of patient care algorithms. These data sets, focusing on sepsis, acute hypotension, and ART for HIV, served as the basis for our synthetic data creation. The synthetic data generation employed in the Health Gym was accomplished using GANs. The GAN model, as shown in Figure 1, consists of 2 primary components: a generator and a discriminator. The process starts by sampling real patient records (depicted in pink) and employing the generator to create synthetic patient records (depicted in violet). Both the real and synthetic records are then forwarded to the discriminator network, which is tasked with differentiating the genuine data from the counterfeit. Both networks are trained in an adversarial process—the generator is updated to create more realistic records, while the discriminator is refined to identify generated records more accurately. As a result, the quality of the synthetic data is progressively enhanced, and the synthetic patient records become increasingly representative of the ground truth. The iterative training concludes when the discriminator can no longer reliably distinguish the synthetic records from the real records. Refer to more details in Kuo et al [21].

Leveraging generative AI, Health Gym provides highly authentic clinical data sets, enriching health care education. Each data set undergoes rigorous quality assessment and security verification (detailed in Section B of Multimedia Appendix 1). These synthetic data sets foster engaging learning experiences, aiding educators in developing tailored educational strategies. The following sections will illuminate the application of Health Gym in university-level courses, exemplified through ART for HIV data set.
Synthetic ART for HIV Data Set

The Health Gym data sets contain mixed-type longitudinal data, including numerical, binary, and categorical variables. They encompass patient demographics, vital signs measurements, and pathology results. The data sets hence reflect the complexities of real-life data, thereby making them suitable for training health data scientists in university courses. This paper will primarily delve into the application of synthetic data in health care education focusing on the ART for HIV data set. Readers interested in the sepsis and the acute hypotension data sets should refer to Section C in Multimedia Appendix 1.

Data Set Description

Our synthetic HIV data set, informed by the selection or exclusion criteria proposed by Parbhoo et al [35] and drawn from the EuResist database, targets individuals living with HIV who initiated therapy after 2015 per the World Health Organization’s guidelines [36]. ART for HIV typically includes a mix of 3 or more antiretroviral agents from at least 2 distinct medication classes. The dynamism of ART lies in its frequent regimen modifications resulting from various circumstances such as treatment failure due to poor adherence or viral resistance, intolerance to ART, clinical events such as pregnancy or coinfections, or optimization of therapy to support better adherence, reduce drug-drug interactions, maximize ART response, or prevent the emergence of drug-resistant viral strains [36,37].

In addition to ART information, the data set encompasses vital indicators of ART success and disease progression, namely, viral load (VL) and CD4 cell count. Successful ART is often indicated by VL below 1000 copies/mL, while a CD4 cell count exceeding 500 cells/mm$^3$ signifies healthy immunological status [36]. The complex interactions of these elements in our data set create a rich learning platform for health data science education.

Table 1 encapsulates the data set’s 3 numeric, 5 binary, and 5 categorical variables. Numeric variables include VL, CD4 cell count, and relative CD4 laboratory test results. Treatment regimens follow those of Tang et al [38], breaking down the ART regimen into several parts. The data set includes 50 combinations of 21 unique medications. The antiretroviral medication classes are nucleoside/nucleotide reverse transcriptase inhibitors (NRTIs), nonnucleoside reverse transcriptase inhibitors (NNRTIs), integrase inhibitors (INIs), protease inhibitors (PIs), and pharmacokinetic enhancers (pk-En). We deconstructed the ART regimen into its constituent parts: base drug combination (base drug combo), complimentary INIs (comp INIs), comp NNRTIs, extra PIs, and extra pk-En. The base drug combo primarily consists of NRTIs, with inclusion of other antiretroviral classes as well.

Recognizing the notable amount of missing data in the original EuResist database, we added a suffix (M) to variables to denote whether measurements were recorded at specific time points. In the authentic data set, measurements were reported at 24.27% (129,835/534,960) for VL (measured), 22.21% (118,815/534,960) for CD4 (measured), and 85.13% (455,411/534,960) for drug (measured). The absence of some CD4 and VL records may be attributable to specific clinical practices and the frequency of test requests [39-42]. For instance, it is common for clinicians to discontinue requesting a CD4 cell count if the previous result exceeded 500 cells/mm$^3$ and the individual had an undetectable VL. Similarly, VL is typically measured in the first 3 months, at 6 months, 12 months, and then annually.

Constructured using the GAN model developed by Kuo et al [43], this data set comprises 8916 synthetic patients tracked over 60 months, resulting in 534,960 records (8916 × 60). Figure 2 showcases a sample generated by the code in Figure 3 [44,45]. Each record features 15 columns, including a patient identifier, a time point, and 13 ARTs for HIV variables highlighted in Table 1. The synthetic data sets can be freely accessed in [46] and [47] on Figshare, a digital platform for research output sharing.
<table>
<thead>
<tr>
<th>Variable name</th>
<th>Data type</th>
<th>Unit</th>
<th>Valid categorical options</th>
</tr>
</thead>
<tbody>
<tr>
<td>Viral load (VL)</td>
<td>numeric</td>
<td>copies/mL</td>
<td>N/Aa</td>
</tr>
<tr>
<td>Absolute count for CD4 (CD4)</td>
<td>numeric</td>
<td>cells/µL</td>
<td>N/A</td>
</tr>
<tr>
<td>Relative count for CD4 (Rel CD4)</td>
<td>numeric</td>
<td>cells/µL</td>
<td>N/A</td>
</tr>
<tr>
<td>Gender</td>
<td>binary</td>
<td>N/A</td>
<td>Male, Female</td>
</tr>
<tr>
<td>Ethnicity (Ethnic)</td>
<td>categorical</td>
<td>N/A</td>
<td>Asian, African, Caucasian, other</td>
</tr>
<tr>
<td>Base drug combination (Base drug combo)</td>
<td>categorical</td>
<td>N/A</td>
<td>FTCb + TDFc, 3TCd + ABCe, FTC + TAFf, DRVg + FTC + TDF, FTC + RTVBh + TDF, other</td>
</tr>
<tr>
<td>Complementary integrase inhibitor (Comp INI)</td>
<td>categorical</td>
<td>N/A</td>
<td>DTG1, RAL2, EVG3, not applied</td>
</tr>
<tr>
<td>Complementary nonnucleoside reverse transcriptase inhibitor (Comp NNRTI)</td>
<td>categorical</td>
<td>N/A</td>
<td>NVP7, EFV8, RPV9, not applied</td>
</tr>
<tr>
<td>Extra protease inhibitor (Extra PI)</td>
<td>categorical</td>
<td>N/A</td>
<td>DRV, RTVB, LPVp, RTVq, ATVq, not applied</td>
</tr>
<tr>
<td>Extra pharmacokinetic enhancer (Extra pk-En)</td>
<td>binary</td>
<td>N/A</td>
<td>False, True</td>
</tr>
<tr>
<td>Viral load measured (VL) (M)</td>
<td>binary</td>
<td>N/A</td>
<td>False, True</td>
</tr>
<tr>
<td>CD4 (M)</td>
<td>binary</td>
<td>N/A</td>
<td>False, True</td>
</tr>
<tr>
<td>Drug recorded (M)</td>
<td>binary</td>
<td>N/A</td>
<td>False, True</td>
</tr>
</tbody>
</table>

aN/A: not applicable.
bFTC: emtricitabine.
cTDF: tenofovir disoproxil fumarate.
d3TC: lamivudine.
eABC: abacavir.
fTAF: tenofovir alafenamide.
gDRV: darunavir.
hRTVB: ritonavir.
iDTG: dolutegravir.
jRAL: raltegravir.
kEVG: elvitegravir.
lNVP: nevirapine.
mEFV: efavirenz.
nRPV: rilpivirine.
pLPV: lopinavir.
qRTV: ritonavir.
rATV: atazanavir.
s(M): measured.
Figure 2. Inspecting the antiretroviral therapy for an HIV data set (output of the code in Figure 3).

```
# The top 5 rows of the ART for HIV dataset
  CD4 Rel CD4 Gender Ethnic Base Drug Combo
0 26.622271 791.662688 3.8 3.8 3.8 0.0
1 29.231096 637.839868 3.8 3.8 3.8 0.0
2 28.784861 605.158385 3.8 3.8 3.8 0.0
3 28.818875 690.688956 3.8 3.8 3.8 0.0
4 28.638357 641.717425 3.8 3.8 3.8 0.0
```

```
Comp.INC Comp.NRRTI Extra PI Extra pk-En VL (M) CD4 (M) Drug (M)
0 0.0 3.0 5.0 0.0 0.0 3.0 1.0
1 0.0 3.0 5.0 0.0 0.0 3.0 1.0
2 0.0 3.0 5.0 0.0 0.0 3.0 1.0
3 0.0 3.0 5.0 0.0 0.0 3.0 1.0
4 0.0 3.0 5.0 0.0 0.0 3.0 1.0
```

PatientID Timestep
0 0
1 0
2 0
3 0
4 0

Figure 3. Code in Python for generating the output shown in Figure 2. This code uses pandas [44] and NumPy [45]. Base drug combo: base drug combination; comp INI: complementary integrase inhibitor; comp NNRTI: complementary nonnucleoside reverse transcriptase inhibitor; PI: protease inhibitor; pk-En: pharmacokinetic enhancer; VL: viral load.

Sample code using Python

```python
[01] import pandas as pd
[02] import numpy as np
[03] My_DF = pd.read_csv("./HealthGymV2.CbdrhDatathon_ART4HIV.csv")
[04] print("###---###")
[05] print(My_DF.head())
[06] print("# shape of the dataset")
[07] print("# of the column names")
[08] print("# the total amount of synthetic patients")
[09] print(len(np.unique(My_DF["PatientID"])))
```

Applications and Case Studies

This section highlights the use of our synthetic ART for HIV data set in a collaborative Datathon event and as an effective teaching tool at UNSW for medical education.

Center for Big Data Research in Health Data Science Datathon

The synthetic data set for ART for HIV was a central component of the UNSW Center for Big Data Research in Health Datathon [48], an event merging theoretical learning with practical application. The Datathon was an enriching exercise in multidisciplinary collaboration. The event involved 6 teams, with a total of 24 participants, offering a tangible experience in
data analysis. The student teams were supported by a group of mentors—a blend of data scientists, clinicians, health professionals, and government health informatics specialists from a local health district in Sydney, Australia [49]. The data scientists and the panel of authors of the Health Gym project (ie, Kuo et al [21]) elaborated on the technical aspects and navigated the participants through the intricacies of data analysis, including the assumptions we made to use the data (eg, time 0 corresponded to the date of ART initiation, the laboratory tests occurred before modifications in therapy). Meanwhile, clinicians and health professionals provided their expertise to guide students toward meaningful research questions (eg, discussing VL and CD4 count monitoring, drug-drug interactions, and metabolic toxicity [50]). Government health informaticians, experienced in electronic medical records and real-world population health application and impact, evaluated the usefulness of the students’ findings.

This collaborative effort facilitated a comprehensive learning experience, encompassing the development of analytical models, data visualization, and effective communication of research outcomes. Using our synthetic data sets, participants gained valuable insights into working with data sets that emulate real-world health scenarios, thereby providing a bridge between theoretical academia and practical execution.

We summarize the findings of the 2 participating teams below. Detailed reports for Team 1 and Team 2 can be found in Section D and Section E of Multimedia Appendix 1, respectively. In addition, the associated codes for the 2 teams can be found in Section A of Multimedia Appendix 1.

Findings of Team 1

Team 1 investigated the effectiveness of medications, categorized by antiretroviral class, in achieving HIV suppression. Utilizing survival analysis, they assessed the time between the initiation of ART to the first occurrence of viral suppression, defined as VL below 1000 copies/mL [36]. They also assessed the time to CD4 cell count exceeding 500 cells/mm³ [51], which indicates a healthy immunological status.

With Cox proportional hazards models [52] featuring time-varying covariates, the team identified particular antiretroviral agents associated with viral suppression. These findings were purely associative due to data set limitations, which did not account for factors such as age, socioeconomic status, comorbidities, and concurrent medications (of other illnesses).

Findings of Team 2

Team 2 focused on predicting the necessity of altering an individual’s ART regimen over a 5-year time span, factoring in disease flare-ups, resistance, or side effects. They formulated a “sliding search” function that generated individual records for each 12-month period, with predictions for antiretroviral modification and adherence to therapy in the subsequent year by using neural networks. The team’s methodology produced promising results, with an accuracy rate of 78% in predicting antiretroviral modification and 93% in predicting adherence to therapy. The algorithm detected trends in CD4 and VL results across the 12-month periods, which appeared to be the key predictive features. In addition, the team suggested that there could be potential benefits from exploring recurrent neural networks (eg, long short-term memory [53]).

Serving as UNSW Coursework Materials

Beyond their utility in the Datathon, our synthetic data sets contribute to UNSW courses in the Master of Science in Health Data Science Program [54], namely, HDAT9800 Visualization & Communication and HDAT9510 Machine Learning II. HDAT9800 teaches future health data scientists the skills to visually communicate complex data effectively to diverse audiences. The course emphasizes the significance of clear data visualization and advocates for transparency and reproducibility in scientific work. It employs R [55] and Python [56] to demonstrate best practices in data analysis and visualization. Our synthetic data sets provide rich resources to enhance the learning in this setting. For instance, Marchesi et al [57] used our data sets to present patient states via t-distributed stochastic neighbor embedding visualization techniques [58].

Meanwhile, HDAT9510 explores advanced modern ML algorithms and methods such as convolutional neural networks [59], autoencoders [60], and reinforcement learning (RL) [61]. As the synthetic data sets consist of time-series variables, students can develop both feedforward and recurrent neural networks. See example models built using our data set in Marchesi et al [57] with recurrent neural networks and even decision trees [62] and hidden Markov models [63], as in a similar data set suggested by Wu et al [64]. Furthermore, with the presence of nonnumeric variables, students can learn about embedding [65]—transforming nonnumeric levels into real-valued vectors so that similar levels that are closer in the vector space carry more analogous meaning. The presence of missing data in the synthetic data sets also encourages students to formulate plausible assumptions about the structure of the clinical data set prior to data modelling.

We provide 3 adaptable worked examples using our ART for HIV data set, suitable for workshops and lectures. The associated codes for the worked examples can be found in Section A of Multimedia Appendix 1. Our synthetic data set supports a variety of student engagements, from understanding complex data structures to developing advanced RL algorithms for optimizing clinical interventions. Moreover, the low patient disclosure risk associated with our data sets (refer to Section B in Multimedia Appendix 1) eliminates the need for ethics approval [66]. This makes these data sets ideal for a range of settings—from small seminars to larger lecture groups.

Worked Example 1

The first exercise, focused on data visualization using Python, compares VL trends over time among patients who commenced their ART with different base drug combos, against the general trend in all patients. The results of our worked example are depicted in Figure 4.

This multifaceted exercise requires students to create sub–data sets based on specific starting base drug combos (ie, FTC + TDF [emtricitabine + tenofovir disoproxil fumarate] and 3TC + ABC [lamivudine + abacavir]), extract data for defined
periods, and familiarize themselves with box and violin plots [67]. They are also tasked with organizing the visual data as side-by-side plots.

Through this exercise, students will understand the limitations of box plots, which cannot visualize underlying data distributions. They will learn about the additional insights provided by advanced plotting techniques such as violin plots. In addition, students will note that people who start with FTC + TDF and those who start with 3TC + ABC display similar patterns as the overall ART for HIV cohort. The overlap of the interquartile ranges across all box plots indicates a consistent behavior.

Figure 4. Viral load distribution. Subplot (A) shows a box plot comparison of viral load across base drug combinations across time, and subplot (B) shows a violin plot comparison of viral load across base drug combinations across time. Grey indicates all patients, red indicates those initiating treatment with FTC + TDF (emtricitabine + tenofovir disoproxil fumarate), and blue indicates those initiating treatment with 3TC + ABC (lamivudine + abacavir). VL: viral load.

**Worked Example 2**

The second exercise delves into survival analysis using R [55], building on insights from the initial data visualization task. The exercise continues to compare results among people starting with the base drug combo of FTC + TDF and those initiating with the base drug combo of 3TC + ABC. The goal is to estimate the time necessary for a person on ART to successfully suppress their VL. The results of our worked example are depicted in Figure 5.

This task proves to be more complex than the first, requiring HIV domain knowledge, such as an understanding that a reasonable threshold for ART in HIV treatment is 1000 copies/mL [36]. This threshold indicates slowed viral replication and immune system damage. Thus, students should select patients who commence ART with VL above 1000 copies/mL (ie, not experiencing the outcome of interest at baseline).

Creating an appropriate data set for survival analysis is key, as is pinpointing when each patient’s VL first drops to or below 1000 copies/mL. In addition, students need to grasp the concept of right censoring [68] and utilize Kaplan-Meier curves [69] for time-to-event estimations. This offers an opportunity to engage with the influential survival package [70] in the R language. Upon examining the results in Figure 5, students will note no significant differences in the timing of VL suppression between people who started with the base drug combo of FTC + TDF and those who initiated with the base drug combo of 3TC + ABC.
**Worked Example 3**

The third exercise immerses students in the process of developing an RL agent using Python. RL is a type of ML that learns an evidence-based policy to connect states (the current scenario) to actions (the potential responses to that scenario). In the context of our HIV treatment example, states refer to the representation of the patient’s current health status and medication history, while action refers to the selection of medication to use in response to each state.

The RL agent selects an action based on a policy that optimizes for maximum cumulative rewards, even as environments evolve. This approach has particular relevance to health care. Clinicians often need to adapt treatment plans to each patient’s unique circumstances, and RL can help them to individualize treatment durations, dosages, or types. For example, they may alter the regimen, class, or specific agents of medication to better serve the patient’s needs. The outcomes of our example are visualized in Figure 6. This exercise highlights the potential of RL to enhance patient care through personalization—an aspect that is becoming increasingly important in today’s medical landscape.

This complex exercise is designed for advanced students, posing challenges across multiple dimensions. It commences with data wrangling, where students scrutinize numeric variable distributions and evaluate the necessity for transformations such as rescaling, normalization [71], power transformation [72], or Box-Cox transformation [73].

In the next stage, students encounter categorical feature representation for medication regimens, practicing their skills in implementing embeddings. Advanced students can explore transfer learning for feature representation [74]. This exercise also presents real-world challenges, requiring students to handle mixed-type data progression. During the model fitting phase, students must employ suitable ML models, distinguishing between RL method archetypes [75] and considering their clinical implications.

Data visualization is the next task, encouraging students to articulate model-derived insights into digestible visuals for a diverse audience. The concluding phase involves refining assumptions and model performance, incorporating multiple tests to identify optimal hyperparameters [76]. Here, students peek into the “black box” nature of ML and gain an intuition for effective module combinations [77-79]. This step becomes critical for causal inference tasks that necessitate rigorous input data validation [80].

**Figure 6** showcases the strategy employed by an RL agent in HIV therapy. Heatmaps visualize the relative frequencies of chosen actions (ie, the selected antiretroviral), where each tile represents a unique action and its frequency as a proportion of all actions. The example output shows that the RL agent consistently suggests the EFV + RAL (efavirenz + raltegravir)—a combination of comp NNRTIs and comp INIs—4.39% of the time, while never recommending the RPV + RAL (rilpivirine + raltegravir) combination. More information on the steps taken to create the output for this task can be found in Section F of Multimedia Appendix 1.
Figure 6. Visualizing the learned reinforcement learning policy. Comp INI: complementary integrase inhibitor; Comp NNRTI: complementary nonnucleoside reverse transcriptase inhibitor; DTG: dolutegravir; EFV: efavirenz; EVG: elvitegravir; NVP: nevirapine; RAL: raltegravir; RPV: rilpivirine.

Discussion

This paper demonstrates the transformative potential of synthetic health data sets in health care education, especially in the evolving context of generative AI integration. These data sets provide a realistic representation of real-world health data complexities while preserving patient confidentiality, facilitating experiential learning, skills enhancement, and interdisciplinary collaboration. However, this significant stride toward AI integration in education is not without challenges, and the creation of AI models trained on curated quality data sets emerges as a promising research area.

Despite our best efforts, the Health Gym synthetic data sets might not fully capture the complexity and diversity of real-world scenarios. For instance, some critical health determinants such as socioeconomic status [81] and comorbidities [82] are missing from the ART for HIV synthetic data sets. The absence of these factors mirrors the broader issues concerning data accessibility [83], particularly when it involves specialized or rare disease information. Furthermore, synthetic data might overlook uncontrolled variables or confounders inherent in real-world data [84,85], posing pedagogical challenges. However, this limitation is not solely attributable to our methodology. Since the socioeconomic status variable is not present in the EuResist database, our model lacked the necessary reference data from the outset.

In the field of health data science, proficient data set management and curation are essential due to the decentralized nature of health care data collection. Many entities contribute to health data, each using their own systems [86]. Privacy laws such as Australia’s Privacy Act 1988 [87] and the United States’ Health Insurance Portability and Accountability Act [88] complicate the sharing of data, resulting in a fragmented view of patient information.

Record linkage techniques [89] such as probabilistic matching [90] bridge this gap by linking disparate data records, offering a more comprehensive view of a patient’s health. Nevertheless, our synthetic data sets, despite their potential, carry limitations such as the absence of a master linkage key [91], thereby reducing their applicability in university courses for data management and curation. Having such linked data sets are also great for health data science students to test hypotheses on the effects of comorbidities. Our experiences from the Datathon suggest that the Health Gym synthetic data sets are best used for creating algorithms to enhance patient care within specific disease management paradigms.

Our Health Gym initiative leverages a unique application of generative AI, differing from those used in emerging AI-assisted chatbots, which have also shown promise as potent educational tools. AI chatbots, with their personalized and interactive responses using large language models, can significantly incite interest and foster self-directed learning in medical students [92]. However, advanced AI tools such as OpenAI’s ChatGPT [93] and Google’s BARD [94] bring with them valid concerns around precision, reliability, potential misuse, and adherence to academic integrity [95,96]. In contrast, the synthetic clinical data sets, the generative product of our Health Gym project, offer controlled, scenario-specific learning environments that
closely reflect real-world conditions while preserving patient privacy.

Access to clinical data sets is integral to health data science education, but the necessity of maintaining patient confidentiality can hinder the training of future health data scientists on a larger scale. This may exacerbate the digital divide [97,98], which is a prominent challenge in the broader AI integration into education. As we shift toward AI-driven educational resources, it is essential to prioritize equitable access across varied socioeconomic backgrounds. Future research should evaluate the long-term effects of AI on student learning, clinical judgment, patient outcomes, and the development of educational resources for effective AI integration. The secure, realistic synthetic data sets of Health Gym may provide a valuable solution, potentially facilitating equal access to educational materials.

Conclusion

Despite their limitations, the Health Gym synthetic health data sets have demonstrated their value in educating and training future health data scientists. Their integration into interdisciplinary platforms such as Datathon illustrates their potential in promoting collaborative learning, skills enhancement, and innovative research. In addition, synthetic data sets offer a learning platform that balances realistic health scenario representation with data privacy preservation.

Although we have primarily demonstrated the utility of Health Gym’s synthetic data sets by using the ART for HIV data set, we emphasize the importance of the additional acute hypotension and sepsis data sets that we have developed (see Section C in Multimedia Appendix 1). These data sets broaden the scope of medical education by providing insight into managing illnesses in intensive care units, encompassing a unique set of measurements and pathology information. As such, these synthetic data sets offer students an enriched, realistic learning environment for health data science education, complementing the HIV data set and furthering the applicability and versatility of synthetic health data.

The majority of generative ML research is centered on computer vision [99,100] and, to a lesser extent, natural language processing [101], leaving clinical health care data relatively unexplored. This gap suggests a valuable opportunity for future research, particularly considering that clinical data being longitudinal, mixed-type time series variables have a fundamentally different nature. As demonstrated in our prior studies [21,43,102], we have ascertained that our synthetic data sets attain a robust level of validity and are readily available to support both clinical research and medical pedagogy; predictive models instantiated on our synthetic data sets parallel those of the original data sets in their characteristics. We will focus our future work on comparing synthetic data sets created using various generative ML architectures, for example, GANs, variational autoencoders [103], diffusion probabilistic models [102,104], and transformer-based models [105]. GANs, like other ML models, can only optimize according to predefined optimization functions. Given the current lack of research on the use of GANs in health care, more utility studies are necessary to fully comprehend the potential of our synthetic data sets. We are committed to continuing collaboration with clinicians and health professionals to better understand the practical strengths and weaknesses of synthetic data sets, including how to better evaluate and contain the risk of private information disclosure. Through these collective efforts, we aim to improve the quality of synthetic data sets, enhancing hands-on learning experiences for students in health data analytics.

Acknowledgments

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Authors' Contributions

Authors NI-HK and SB were responsible for the design, implementation, and validation of the deep learning models employed to generate the synthetic data sets for the Health Gym project. The inception of Datathon was conceived by OP-C and MH who liaised with various disciplinary personnel to realize this initiative. JdOC contributed specialist knowledge on antiretroviral therapy for HIV to Datathon, while JH offered expertise in the evaluation of Datathon projects. Furthermore, TC and SL, alongside OP-C and MH, leveraged their extensive teaching experience to guide Datathon participants and explore further applications of the Health Gym synthetic data sets. LJ provided key insights on the potential risk of sensitive information disclosure. Datathon participants EM, BH, MDS, GY, JV, and ICV gave critical feedback on the strengths and shortcomings of the synthetic data sets, in addition to providing valuable reflections on the event itself. This manuscript was prepared by NI-HK. All authors contributed to interpreting the findings and revising the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Supplementary data.
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Abbreviations

3TC: lamivudine  
ABC: abacavir  
AI: artificial intelligence  
ART: antiretroviral therapy  
Base drug combo: base drug combination  
Comp INI: complementary integrase inhibitor  
EFV: efavirenz  
FTC: emtricitabine  
GAN: generative adversarial network  
INI: integrase inhibitor  
MIMIC: Medical Information Mart for Intensive Care  
ML: machine learning  
NNRTI: nonnucleoside reverse transcriptase inhibitor  
NRTI: nucleotide reverse transcriptase  
PI: protease inhibitor  
pk-En: pharmacokinetic enhancer  
RAL: raltegravir  
RL: reinforcement learning  
RPV: rilpivirine  
TDF: tenofovir disoproxil fumarate  
UNSW: University of New South Wales  
VL: viral load

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Performance of ChatGPT on Ophthalmology-Related Questions Across Various Examination Levels: Observational Study

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Abstract

Background: ChatGPT and language learning models have gained attention recently for their ability to answer questions on various examinations across various disciplines. The question of whether ChatGPT could be used to aid in medical education is yet to be answered, particularly in the field of ophthalmology.

Objective: The aim of this study is to assess the ability of ChatGPT-3.5 (GPT-3.5) and ChatGPT-4.0 (GPT-4.0) to answer ophthalmology-related questions across different levels of ophthalmology training.

Methods: Questions from the United States Medical Licensing Examination (USMLE) steps 1 (n=44), 2 (n=60), and 3 (n=28) were extracted from AMBOSS, and 248 questions (64 easy, 122 medium, and 62 difficult questions) were extracted from the book, Ophthalmology Board Review Q&A, for the Ophthalmic Knowledge Assessment Program and the Board of Ophthalmology (OB) Written Qualifying Examination (WQE). Questions were prompted identically and inputted to GPT-3.5 and GPT-4.0.

Results: GPT-3.5 achieved a total of 55% (n=210) of correct answers, while GPT-4.0 achieved a total of 70% (n=270) of correct answers. GPT-3.5 answered 75% (n=33) of questions correctly in USMLE step 1, 73.33% (n=44) in USMLE step 2, 60.71% (n=17) in USMLE step 3, and 46.77% (n=116) in the OB-WQE. GPT-4.0 answered 70.45% (n=31) of questions correctly in USMLE step 1, 90.32% (n=56) in USMLE step 2, 96.43% (n=27) in USMLE step 3, and 62.90% (n=156) in the OB-WQE. GPT-3.5 performed poorer as examination levels advanced (P<.001), while GPT-4.0 performed better on USMLE steps 2 and 3 and worse on USMLE step 1 and the OB-WQE (P<.001). The coefficient of correlation (r) between ChatGPT answering correctly and human users answering correctly was 0.21 (P=.01) for GPT-3.5 as compared to −0.31 (P<.001) for GPT-4.0. GPT-3.5 performed similarly across difficulty levels, while GPT-4.0 performed more poorly with an increase in the difficulty level. Both GPT models performed significantly better on certain topics than on others.

Conclusions: ChatGPT is far from being considered a part of mainstream medical education. Future models with higher accuracy are needed for the platform to be effective in medical education.

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KEYWORDS
ChatGPT; artificial intelligence; AI; board examinations; ophthalmology; testing

Introduction

Recently, advances in artificial intelligence (AI) models, more specifically natural language processing (NLP), led to the development of large language models (LLMs) that have shown remarkable performance on a variety of tasks [1-3]. ChatGPT is among the most popular of these models. It was developed by OpenAI and has had several version updates since its inception. GPT-3.5 was among the earlier versions developed, followed by GPT-4.0, developed on March 15, 2023, as a more robust, concise, and intelligent model. ChatGPT has become...
Medical education relies highly on standardized multiple-choice examinations to test medical students in an objective and consistent way. Ophthalmologists in the United States pass through the United States Medical Licensing Examination (USMLE) steps 1, 2, and 3, the Ophthalmic Knowledge Assessment Program (OKAP), and the Board of Ophthalmology (OB) Written Qualifying Examination (WQE) by the time they become practicing physicians. Undergraduate and graduate medical students rely on different tools available to prepare for these examinations.

One limitation of the current tools for medical education is the lack of personalization. Question banks used today do not tailor their explanations to users; rather, they present one explanation for each question to all its users. ChatGPT and other LLMs, if proven to be accurate in their ability to answer questions, can provide robust explanations to users, and users can then ask specific questions they need further clarification on. This can be very helpful and educational for users as it can tailor to the needs of each user and help them fill specific knowledge gaps they may have. Additionally, the GPT-3.5 model is freely available to everyone, while GPT-4.0 is available at a premium. As such, it is essential to compare these models to assess whether GPT-4.0’s hypothetical increased abilities justify the price of the membership.

The question of how ChatGPT can be integrated for use in medical education has emerged. With the complexity of ophthalmology, the ability of ChatGPT to accurately answer ophthalmology questions could be of significant value to medical students and residents preparing for the USMLE, OKAP, and OB-WQE. It is also important to compare the performance of both GPT-4.0 and GPT-3.5, since GPT-4.0 is marketed as a more intelligent version of its predecessor.

Therefore, the aim of this study is to evaluate the performance of both GPT-4.0 and GPT-3.5, since GPT-4.0 is marketed as a more intelligent version of its predecessor. The results of this study could have implications for the future use of ChatGPT in medical education and training, and for the development of more efficient and effective tools for examination preparation.

**Methods**

**Data Sets**

Different data sets were used for the different examinations due to the lack of a central service for all examinations. Questions that included pictures or tables were automatically excluded and were not queried on ChatGPT. AMBOSS [5], a question bank and popular resource for the USMLE was used for steps 1, 2, and 3. A total of 44 questions were included for step 1, 60 for step 2, and 28 for step 3. AMBOSS highlights the difficulty of each question and the percentage of people who chose each answer choice. This allowed us to compare the performance of ChatGPT to the general population [5]. For the OKAP and OB-WQE, 248 questions across the different chapters were taken from *Ophthalmology Board Review Q&A* by Glass et al [6].

**Prompt Engineering**

The style and the prompt of the questions asked to ChatGPT have been shown to have an impact on the answer given. To standardize the process of asking the questions to ChatGPT, questions were all formatted in the same way on Word (Microsoft Corp). After removing questions with pictures or tables, the questions were formatted in the manner described by Gilson et al [7]. The question stem was consolidated in 1 paragraph, and then each answer choice was placed on a separate line. Furthermore, the answer choices were separated by 2 empty lines from the main question stem; this was done to optimize the accuracy of the results, avoiding any effect the question format may have on ChatGPT’s ability. An example prompt is shown in Textbox 1.

**Textbox 1.** An example of a prompt (written by the authors).

**Question:** What medical discipline deals with conditions of the eye

A. Dermatology
B. Endocrinology
C. Ophthalmology
D. Rheumatology

**Question Input**

All questions were input in ChatGPT on March 5, 2023, for GPT-3.5 and April 15, 2023, for GPT-4.0. We then used Excel (Microsoft Corp) spreadsheets to record whether the answer was correct or not, the percentage of users getting the answer correct (if applicable), the difficulty level (if applicable), and the topic (if applicable).

**Data Analysis**

Data analysis was conducted using both Python (Python Software Foundation) and Excel. Excel was used to determine the percentage of correct answers. Python (Python Anaconda Spyder 5.3.3) was used to determine the percentage of correct answers by difficulty, test type, and topic. A chi-square test was conducted on Python to determine whether there are any significant differences in answering correctly based on test type and difficulty. Python was also used to compute the coefficient of correlation (and P value) between ChatGPT answering...
correctly and the percentage of users who got the correct answer. Point-biserial was used to compute the correlation between ChatGPT answering questions correctly and humans answering correctly. Other tests included chi-square analysis and the Fisher exact test to investigate relationships between 2 categorical variables (difficulty level, correct or incorrect answers, etc).

**Ethical Considerations**

Since this study does not involve any human participants, institutional review board approval is not necessary for the purpose of this study. This study also respects the rights and copyright of the owners of the resources used and has obtained their approval for using the questions without sharing the questions anywhere in the data or paper.

**Results**

A total of 380 questions were queried on ChatGPT. The number of questions for each examination were 44 for step 1, 60 for step 2, 28 for step 3, and 248 for the OKAP and OB-WQE. The total percentage of correct answers was 55% (n=210) across all examinations for GPT-3.5, while it was 70% (n=270) for GPT-4.0. Table 1 shows the number and percentage of correct answers for each examination by each GPT model.

Between GPT-3.5 and GPT-4.0, GPT-4.0 performed significantly better on USMLE steps 2 and 3 and the OB-WQE but not on USMLE step 1. While GPT-3.5’s performance decreased with an increase in the examination level (P<.001), GPT-4.0 performed better on USMLE steps 2 and 3 and poorer on the OB-WQE and USMLE step 1. The coefficient of correlation (r) between ChatGPT answering correctly and the percentage of humans answering correctly on AMBOSS was 0.21 (P=.01) for GPT-3.5 and –0.31 (P<.001) for GPT-4.0.

Table 2 highlights the percentage of correct questions based on the difficulty level in the AMBOSS questions and in the OB-WQE questions.

Table 3 highlights the performance of both models according to the different topics in the OB-WQE and OKAP questions. Performance for both models was nonrandom, with both models performing better on certain topics such as corneal diseases, pediatrics, retina, ocular oncology, and neuro-ophthalmology.

<table>
<thead>
<tr>
<th>Examination</th>
<th>Correct answers provided by models², n (%)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GPT-3.5</td>
<td>GPT-4.0</td>
</tr>
<tr>
<td>USMLEb step 1</td>
<td>33 (75)</td>
<td>31 (70.45)</td>
</tr>
<tr>
<td>USMLE step 2</td>
<td>44 (73.33)</td>
<td>56 (90.32)</td>
</tr>
<tr>
<td>USMLE step 3</td>
<td>17 (60.71)</td>
<td>27 (96.43)</td>
</tr>
<tr>
<td>OB-WQEc</td>
<td>116 (46.77)</td>
<td>156 (62.90)</td>
</tr>
</tbody>
</table>

²P<.001 for between-model comparisons in the proportion of correct answers.

bUSMLE: United States Medical Licensing Examination.

cOB-WQE: Board of Ophthalmology Written Qualifying Examination.
Table 2. Performance of GPT-3.5 and GPT-4.0 according to different difficulty levels.

<table>
<thead>
<tr>
<th>Difficulty level</th>
<th>GPT-4.0</th>
<th>AMBOSS</th>
<th>GPT-3.5</th>
<th>AMBOSS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Board of Ophthalmology difficulty level</td>
<td>Correct answers, n (%)</td>
<td>Correct answers, n (%)</td>
<td>Human performance, %</td>
</tr>
<tr>
<td></td>
<td>Difficulty level</td>
<td>ChatGPT’s performance (correct answers), n (%)</td>
<td>Human performance (correct answers), %</td>
<td>Difficulty level</td>
</tr>
<tr>
<td>1</td>
<td>49 (76)</td>
<td>19 (100)</td>
<td>83</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>73 (59)</td>
<td>43 (91)</td>
<td>68</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>35 (56)</td>
<td>38 (84)</td>
<td>53</td>
<td>3</td>
</tr>
<tr>
<td>N/A</td>
<td>N/A</td>
<td>10 (59)</td>
<td>37</td>
<td>N/A</td>
</tr>
<tr>
<td>N/A</td>
<td>N/A</td>
<td>4 (66.67)</td>
<td>26</td>
<td>N/A</td>
</tr>
</tbody>
</table>

\(a P = .04\) on comparing the performance of GPT-4.0 across different difficulty levels.
\(b P = .003\) on comparing the performance of GPT-4.0 across different difficulty levels.
\(c P = .49\) on comparing the performance of GPT-3.5 across different difficulty levels.
\(d P = .18\) on comparing the performance of GPT-3.5 across different difficulty levels.

Table 3. Performance of GPT-3.5 and GPT-4.0 on various included topics.

<table>
<thead>
<tr>
<th>Category</th>
<th>Topic</th>
<th>Correct answers by GPT-3.5, n (%)</th>
<th>Correct answers by GPT-4.0, n (%)</th>
<th>(P) value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cornea, external disease, and anterior segment</td>
<td>Cornea, external disease, and anterior segment</td>
<td>28 (74)</td>
<td>25 (66)</td>
<td>.45</td>
</tr>
<tr>
<td>Glaucoma</td>
<td>Glaucoma</td>
<td>20 (61)</td>
<td>16 (48)</td>
<td>.32</td>
</tr>
<tr>
<td>Lens and cataract</td>
<td>Lens and cataract</td>
<td>22 (88)</td>
<td>8 (32)</td>
<td>&lt;.001(c)</td>
</tr>
<tr>
<td>Neuro-ophthalmology</td>
<td>Neuro-ophthalmology</td>
<td>15 (54)</td>
<td>16 (57)</td>
<td>.06</td>
</tr>
<tr>
<td>Oculofacial, plastics, and orbit</td>
<td>Oculofacial, plastics, and orbit</td>
<td>17 (50)</td>
<td>10 (29)</td>
<td>.08</td>
</tr>
<tr>
<td>Pediatric ophthalmology and strabismus</td>
<td>Pediatric ophthalmology and strabismus</td>
<td>14 (61)</td>
<td>9 (34)</td>
<td>.07</td>
</tr>
<tr>
<td>Refractive management and optics</td>
<td>Refractive management and optics</td>
<td>17 (50)</td>
<td>14 (41)</td>
<td>.46</td>
</tr>
<tr>
<td>Retina and ocular oncology</td>
<td>Retina and ocular oncology</td>
<td>24 (73)</td>
<td>18 (54)</td>
<td>.12</td>
</tr>
</tbody>
</table>

\(a P = .02\) for differences in the number of correct answers provided by GPT-4.0 among different categories.
\(b P = .03\) for differences in the number of correct answers provided by GPT-3.5 among different topics.
\(c\)Significant at \(P < .05\).

Discussion

Principal Findings

Our results indicate that GPT-4.0 is superior to GPT-3.5, and that GPT-3.5 has a below-average accuracy in answering questions correctly. The total proportion of correct answers for GPT-3.5 was 55% (n=210), which is considered a poor performance, while that of GPT-4.0 was 70% (n=270), which is an almost average performance [7]. Students typically must achieve 59%-60% of correct answers to pass, and students perform with an average of around 70%-75% on the aforementioned board examinations [7]. It is interesting to note that GPT-3.5’s performance decreased as examination levels increased. This is probably due to the more clinical nature of the examinations. This was not the case for GPT-4.0, which performed best on USMLE steps 2 and 3.

This study investigates the correlation between ChatGPT-3.5 and -4.0 providing a correct answer and the percentage of human users who provided the answer correctly on AMBOSS. For GPT-3.5, a correlation coefficient of 0.21 (\(P=.01\)) was noted; whereas, this correlation coefficient was –0.31 (\(P<.001\)) for GPT-4.0. This implies that GPT-4.0 performed better on questions that fewer users answered correctly.

Although our study is limited in that it did not divide the questions into categories such as diagnosis, treatment, basic knowledge, or surgical planning questions. Looking closely at the lens and cataract section in which the model failed (32% of correct answers for GPT-3.5), it was noted that all the correct
answers were basic knowledge questions. Surprisingly, an analysis of incorrect answers showed that almost half of the incorrectly answered questions were also basic knowledge questions. For instance, in one of the questions, the model was unable to identify the collagen fiber type in cataract—a piece of information that is widely available on the internet.

On the other hand, GPT-4.0 performed significantly better on basic knowledge questions. One may postulate that since GPT-4.0 was fed a larger database than was GPT-3.5, it has better abilities in answering basic knowledge questions than GPT-3.5. A study by Taloni et al [8] also noted a significant difference in performance between the 2 models in the cataract and anterior segment diseases categories.

It is unclear why it performed so poorly in the lens and cataract section. It could be hypothesized that managing diseases of the lens and cataract may be mostly surgical. This may not have been fed into this language learning model. Furthermore, surgical management requires input from images and videos, which were excluded from our paper and may have caused the drastic difference in performance. Further studies with more questions are needed to answer this question.

Table 2 outlines the percentage of correct answers based on the difficulty level on both models. GPT-4.0 performed poorer on questions with greater difficulties on both AMBOSS and OB-WQE questions, whereas this observation was not significant in GPT-3.5, indicating that it performed almost equally well across difficulty levels. Gilson et al [7] also reported a similar finding for GPT-3.5. Further studies are needed to explain those findings.

This study also examined the proportion of correct answers based on the different topics. Both models performed significantly better on certain topics than others. This is a novel finding not reported in other studies assessing the performance of ChatGPT. It is interesting to further explore this association and why a model would perform on certain topics better than others. It could be hypothesized that questions on topics such as ocular plastic, which rely on surgical techniques and knowledge of aesthetics, may be more difficult for AI models to answer correctly than topics such as oncology and pathology, which rely more on clinical knowledge. Taloni et al [8] reported a better performance of ChatGPT on clinical rather than surgical cases.

The moderate accuracy of ChatGPT-3.5 has been widely replicated in various studies. Gilson et al [7] found accuracies ranging between 42% and 64.4% in USMLE steps 1 and 2 examinations, numbers similar to those noted in this study [7]. The paper also records a decrease in the proportion of correct answers as difficulty level increases, which has been noted in this study as well. Another study by Huh [9] showed that ChatGPT’s performance was significantly lower than that of Korean medical students in a parasitology examination. A letter to the editor of the journal Resuscitation revealed that ChatGPT did not reach the passing threshold for the Life Support examination [10]. The cited studies indicate the moderate capabilities of ChatGPT in answering clinically related questions. More studies are needed to show how we can best optimize ChatGPT for medical education. Mihalache et al [11] assessed the performance of ChatGPT on the OKAP and found that it provided 46% correct answers, not unlike the proportion of OB-WQE questions correctly answered by GPT-3.5 in this study. All the aforementioned studies used ChatGPT-3.5 in their analysis. More recent studies have assessed the efficacy of ChatGPT-4.0. A study by Lim et al [12] assessed the performance of GPT-4.0 on myopia-related questions, and the model performed with 80.6% adequate responses, compared to 61.3% for GPT-3.5. Taloni et al [8] assessed the use of ChatGPT-4.0 and ChatGPT-3.5 in the American Academy of Ophthalmology’s self-assessment questions; their study found that GPT-4.0 (82.4% of correct answers) performed better than both humans (75.7% of correct answers) and GPT-3.5 (65.9% of correct answers). The study also assessed the performance of these models across various topics [8]. Similar to our results, Taloni et al [8] found that ChatGPT performed better on ocular oncology and pathology compared to topics such as strabismus and pediatric ophthalmology. To our knowledge, our study is among the first few to assess the abilities of GPT-4.0 in medical examinations across various levels of education and various board examinations.

When reviewing the explanations provided by ChatGPT, it was noted that the model would randomly either explain the provided answer choice or not. It is particularly remarkable to read how it justified the wrong answer choices. More studies are needed to emphasize and assess the answer justifications of the model. Indeed, having solid explanations is essential for it to become a reliable medical education tool.

Our study is unique in that it assesses the capabilities of ChatGPT in answering ophthalmology-related questions in contrast to other studies that assessed its ability to succeed in general examinations such as USMLE steps 1 and 2. Furthermore, this is the first study to assess the ability of ChatGPT to answer questions of a certain discipline across all its examination levels. Finally, this is among the first studies to compare GPT-4.0’s performance to GPT-3.5’s performance in medical examinations.

ChatGPT can be a great add-on to mainstream resources to study for board examinations. There have been reports of using it to generate clinical vignettes and board examination–like questions, which can create more unique practice opportunities for students. Additionally, our study also assesses the accuracy of the 2 models on board examination questions related to ophthalmology. Students can input questions they need help with on the platform, and receive an answer and explanation by using the platform. If the student is not satisfied with the answer provided, or has further questions, he or she can respond to the model and receive a more personalized answer. This is crucial as it significantly decreases the time needed to study and also creates a tailored study experience for each student’s needs.

However, ChatGPT needs further optimization before it can be considered a mainstream tool for medical education. The image feature was not present in GPT-3.5 and was introduced in GPT-4.0. This feature is available only on demand and is yet to be available to all users. Its accuracy and reliability are yet to be established for examination purposes. Many questions were excluded due to them containing images, which is a
considerable limitation considering the visual nature of ophthalmology. Even in the text-only questions, ChatGPT had moderate accuracy in answering questions across different difficulties and levels. This study is, however, limited by the small number of questions, particularly in the USMLE steps, due to the absence of a large number of ophthalmology questions in the resources used to prepare for these examinations. More studies are needed, which input a larger number of questions. This study also does not assess the repeatability of ChatGPT’s answers; however, a study by Antaki et al [13] reported near-perfect repeatability.

Conclusions
Overall, this study suggests that ChatGPT has moderate accuracy in answering questions. Its accuracy decreases in nature as the examinations become more advanced and more clinical in nature. In its current state, ChatGPT does not seem to be the ideal medium for medical education and preparation for board examinations. Future models with more robust capabilities may soon become part of mainstream medical education. More studies are needed, which input a larger number of questions to verify the results of this study and attempt to find explanations for many of the intriguing findings.

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Conflicts of Interest
None declared.

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Abbreviations

AI: artificial intelligence
LLM: large language model
NLP: natural language processing
OB: Board of Ophthalmology
OKAP: Ophthalmic Knowledge Assessment Program
USMLE: United States Medical Licensing Examination
WQE: Written Qualifying Examination
Evaluation of ChatGPT’s Real-Life Implementation in Undergraduate Dental Education: Mixed Methods Study

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Abstract

Background: The recent artificial intelligence tool ChatGPT seems to offer a range of benefits in academic education while also raising concerns. Relevant literature encompasses issues of plagiarism and academic dishonesty, as well as pedagogy and educational affordances; yet, no real-life implementation of ChatGPT in the educational process has been reported to our knowledge so far.

Objective: This mixed methods study aimed to evaluate the implementation of ChatGPT in the educational process, both quantitatively and qualitatively.

Methods: In March 2023, a total of 77 second-year dental students of the European University Cyprus were divided into 2 groups and asked to compose a learning assignment on “Radiation Biology and Radiation Protection in the Dental Office,” working collaboratively in small subgroups, as part of the educational semester program of the Dentomaxillofacial Radiology module. Careful planning ensured a seamless integration of ChatGPT, addressing potential challenges. One group searched the internet for scientific resources to perform the task and the other group used ChatGPT for this purpose. Both groups developed a PowerPoint (Microsoft Corp) presentation based on their research and presented it in class. The ChatGPT group students additionally registered all interactions with the language model during the prompting process and evaluated the final outcome; they also answered an open-ended evaluation questionnaire, including questions on their learning experience. Finally, all students undertook a knowledge examination on the topic, and the grades between the 2 groups were compared statistically, whereas the free-text comments of the questionnaires were thematically analyzed.

Results: Out of the 77 students, 39 were assigned to the ChatGPT group and 38 to the literature research group. Seventy students undertook the multiple choice question knowledge examination, and examination grades ranged from 5 to 10 on the 0-10 grading scale. The Mann-Whitney U test showed that students of the ChatGPT group performed significantly better (P=.045) than students of the literature research group. The evaluation questionnaires revealed the benefits (human-like interface, immediate response, and wide knowledge base), the limitations (need for rephrasing the prompts to get a relevant answer, general content, false citations, and incapability to provide images or videos), and the prospects (in education, clinical practice, continuing education, and research) of ChatGPT.

Conclusions: Students using ChatGPT for their learning assignments performed significantly better in the knowledge examination than their fellow students who used the literature research methodology. Students adapted quickly to the technological environment of the language model, recognized its opportunities and limitations, and used it creatively and efficiently. Implications for practice:
the study underscores the adaptability of students to technological innovations including ChatGPT and its potential to enhance educational outcomes. Educators should consider integrating ChatGPT into curriculum design; awareness programs are warranted to educate both students and educators about the limitations of ChatGPT, encouraging critical engagement and responsible use.

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KEYWORDS
ChatGPT; large language models; LLM; natural language processing; artificial Intelligence; dental education; higher education; learning assignments; dental students; AI pedagogy; dentistry; university

Introduction

Background

The emergence of ChatGPT (OpenAI) in November 2022 represents the third significant technological breakthrough in information technology impacting education, following the introduction of Web 2.0 over a decade ago [1] and e-learning’s surge during the COVID-19 pandemic [2]. ChatGPT is an artificial intelligence (AI) tool that offers benefits and opportunities in higher education including increased student engagement, collaboration, personalized feedback, and accessibility. However, it is characterized by a limited database, posing challenges such as the restricted ability to answer medical questions and the potential for inaccurate and biased responses. There are also concerns regarding legal and ethical implications, plagiarism, and academic integrity [3-5].

The research on AI and its implementation in academic education is a prominent subject; a Google Scholar search for “artificial intelligence and dental education,” yielded 100,000 results and approximately 18,000 results for “ChatGPT and higher education” (on June 9, 2023). AI technology has evolved to unprecedented levels, transforming professions, revolutionizing workflows, and reshaping human-machine interactions. ChatGPT, the most recent milestone in natural language processing AI models, has been enabling advanced conversational capabilities and expanding the boundaries of AI-powered communication. Interest in ChatGPT applications encompasses both clinical practice [6,7] and higher education [3,8-11], with promising results.

Relevant Prior Research

Within the higher education landscape, it has been suggested that dental curricula at universities need to be updated due to the AI paradigm shift [9,12,13]. This involves defining a fundamental dental curriculum for both undergraduate and postgraduate levels and establishing learning outcomes related to dental AI [8]. Cotton et al [3] and Halaweh [14] proposed strategies to ensure the ethical and responsible use of AI tools in higher education. Fergus et al [10] evaluated academic answers generated using ChatGPT, and Bearman et al [15] in their review on AI in higher education discussed the shifting dynamics of authority and the relationships among teachers, students, institutions, and technologies. Gimpel et al [16] in their extensive discussion paper proposed guidelines and recommendations for students and lecturers and urged the universities for a multistakeholder dialogue to implement efficient and responsible use of generative AI models in higher education.

Roganovic et al [17] performed a cross-sectional web-based survey among experienced dentists and final-year undergraduate students from the School of Dental Medicine, University of Belgrade, Serbia, to investigate their current perspectives and readiness to accept AI into practice. Responders, especially final-year students, showed a lack of knowledge regarding AI use in medicine and dentistry (only 7.9% of them were familiar with AI use) and were skeptical (only 34% of them believed that AI should be used in dental practice); the underlying reasons were fear of being replaced by AI, as well as a lack of regulatory policies, since students and—at a lesser degree—dentists were concerned that using AI could legally complicate the clinical practice [17].

Chan and Hu [11] reported different results in exploring students’ perceptions of generative AI and ChatGPT in teaching and learning through a web-based questionnaire; the study revealed a generally positive attitude toward generative AI, with students demonstrating a good understanding of this technology, its benefits, and limitations, despite its novel public appearance. Generative AI is a special category of AI designed to learn from the characteristics of its input and generate outputs with similar characteristics. In contrast to most AI models that perform specific tasks based on predefined rules and patterns, generative AI models use advanced algorithms to find the underlying patterns of the input data (eg, text, images, sounds, and videos) and “generate” entirely new content of the same type [11]. Students recognized the potential for personalized feedback and learning support, brainstorming, writing assistance, and research capabilities and stated they would integrate technologies like ChatGPT in their studies and future careers, but they were also concerned about becoming overreliant on them. They moreover expressed concerns about data accuracy, privacy, ethical issues, and the impact on personal development [11]. Students’ perceptions of the learning environment and the teaching strategies have a significant impact on their approach to learning and the learning outcomes (positive perceptions lead to a deep approach to learning), thus being of pedagogical interest to educators and institutions [11,18]. The influence of AI tools on students’ engagement and perceptions was investigated by Nazari et al [19]: they conducted a randomized controlled trial to examine the efficacy of an AI-powered writing tool (Grammarly) for postgraduate students and concluded that students in the intervention group demonstrated significant improvement in engagement (behavioral, emotional, and cognitive), self-efficacy, and academic emotions (positive and negative), domains that address learning behavior, which lead to self-development and underpin authentic pedagogy.
Aims of the Study

Despite numerous publications about AI and large language models (LLMs), the majority involve discussion papers, viewpoint articles, and positions [3,13,16,20,21], with few being exploratory, cross-sectional, or questionnaire-based studies [11,17,19]. To our knowledge, so far, no experimental studies have been identified, wherein ChatGPT was in vivo implemented by students within the teaching process, and the outcomes were comprehensively evaluated.

Therefore, this study aimed to address this gap by implementing ChatGPT within the learning process and conducting a quantitative (differences between examination grades) and qualitative (thematic analysis of the free-text comments of the evaluation questionnaire) evaluation of the outcomes (mixed methods research study).

Methods

Ethical Considerations

The study’s research protocol was reviewed and approved by the Vice-Rector for Research and External Affairs and the President of the Institutional Committee on Bioethics and Ethics of the European University Cyprus.

Study Design: Challenges

The study was conceptualized, organized, and refined in February 2023 and realized in March 2023. Of note is that ChatGPT appeared publicly on November 30, 2022; in March 2023, ChatGPT-3.5 was freely available (and was mostly used by the students), whereas ChatGPT-4 had just emerged (few students used this). The study was not a stand-alone research endeavor; instead, it constituted part of students’ educational activities embedded within the semester’s educational program. As this was the first attempt to implement ChatGPT in the educational process and there were no existing research studies in the literature to refer to, and adding to the limited knowledge on ChatGPT’s properties and limitations at the time, the authors encountered various challenges while organizing the research design. Therefore, to anticipate potential issues that could affect student learning or compromise the study’s outcomes, they conducted a systematic, forward-looking analysis of the research process, considering each step and taking proactive measures to mitigate any challenges or obstacles that may have arisen.

Study Design: Implementation

The second-year dental students (77 students) of the School of Dentistry, European University Cyprus were randomly divided into 2 large groups and were asked to compose an assignment on “Radiation Biology and Radiation Protection in the Dental Office.” The subject of Dentomaxillofacial Radiology is taught through theoretical lectures, laboratory training, and practical training during 2 semesters, and students’ learning assignments are embedded within the lectures’ program as an alternative to traditional lecturing. Student learning assignments to replace lectures followed by in-class presentation and discussion is a methodology used within the “Dentomaxillofacial Radiology” module whenever the topic is suitable for such an approach. Students usually work collaboratively to perform the assignments by searching the internet for scientific reliable sources and compiling the results into a PowerPoint slide presentation, including the references they used. Students of both groups were asked to work in small subgroups to compose the assignments, where each subgroup would comprise 3-7 students, decided among them. It is worth mentioning that the European University Cyprus School of Dentistry is an English-speaking School, educating students from over 30 countries encompassing different ethnic, educational, and cultural backgrounds; therefore, the study’s sample could be considered diverse.

One large group would compose the assignment through literature research (the traditional method for assignments) and the other group would use the ChatGPT tool for the assignment (pose prompts and register the answers), also submitting a slide presentation. Students were given 1 month to deliver the assignment, and they were informed that they would present their presentations in class on a designated day.

Moreover, students of the ChatGPT group were encouraged to experiment with it; ask different questions; ask for videos, images, and internet resources; and in general to be creative, imaginative, and playful while using this new tool. Once they had the final AI content, they were advised to critically evaluate it by comparing it with the relevant content of a reliable scientific resource, such as a textbook or published article, and perform the necessary modifications to the AI output. After finishing the assignment, they were asked to complete an open-ended questionnaire individually (Multimedia Appendix 1), including questions about the usability, problems, opinions, proposals, and so forth, which was emailed to them, and which they would submit to the educator together with the assignment (ie, the PowerPoint presentation).

The AI Evaluation Questionnaire included 12 questions requiring free-text responses and was developed by the authors by combining questions from 2 sources: essays evaluation questionnaires retrieved in the scientific literature [22-24] and the questionnaire ChatGPT produced on the prompt “Can you develop 10 questions for a user to evaluate your performance on writing an essay?” Questions were combined and modified, they were piloted within a small student group other than the research groups, and they were finally amended as necessary. The free-text comments of the AI Evaluation Questionnaire were grouped into main themes and discussed (subjective and qualitative evaluation).

After students completed and submitted their projects via email, and on the designated day they would present the PowerPoint presentations in class, at the beginning of the session, they all had an unannounced blind knowledge examination (answered individually and anonymously, where they only indicated the group they belonged in, so that the educator could not relate the students with the answer sheets). The examination was developed by the authors and consisted of 10 multiple-choice questions (MCQs), which addressed the learning objectives of the topic. They were informed that the knowledge test was intended for the educator to identify whether the assignment had equipped them with the intended knowledge and whether there were any knowledge gaps to address. The results of the
examination (examination grades) were compared among the 2 groups, that is, the literature research group and the ChatGPT group. Statistically significant differences between the groups’ grades were explored using the Mann-Whitney nonparametric test. Data analysis was conducted using SPSS (version 25.0; SPSS Inc), and statistical significance was set at $P=0.05$ (objective and quantitative evaluation).

The final study design is summarized as follows:

- Students were randomly divided into 2 large groups (the ChatGPT and the literature research groups) and further into smaller groups.
- Literature research group performed the assignment by searching the internet and delivered it in PowerPoint format, including the references used.
- ChatGPT group (1) asked the LLM relevant queries and developed a PowerPoint presentation; (2) registered and reported on their interactions with ChatGPT, including the prompts and their modifications, the final outcome and its evaluation after comparing it with a reference text or book chapter; and (3) answered the AI Evaluation Questionnaire on their experience with the LLM.
- All students presented their learning assignments in class. At the beginning of this session, they undertook an unannounced knowledge examination of 10 questions.
- Data derived from the knowledge examination grades, the PowerPoint presentations, and the free-text comments of the AI Evaluation Questionnaire.

**Results**

### Quantitative Results

Out of the 77 students, 39 were assigned to the ChatGPT group forming 9 subgroups and 38 to the literature research group forming 8 subgroups. Seventy students undertook the MCQ examination (7 students were absent) and examination grades ranged from 5 to 10 on the 0-10 grading scale. **Figure 1** presents the number of students (percentages within each group) with their examination grades. We noticed that in the higher range of examination grades, that is, 8-10, the ChatGPT students outperformed the literature research students, while the opposite happened within the lower range of examination grades, that is, 5-7.

To check for differences between the ChatGPT student group and the literature research group, we performed the Mann-Whitney $U$ test, which showed that students of the ChatGPT group ($n=39$; mean 7.54, SD 1.18) performed significantly better ($P=0.045$) than students in the literature research group ($n=31$; mean 6.94, SD 1.12).

To foster inclusiveness and avoid discrimination, we deliberately chose not to perform statistical analyses regarding gender differences, as we also believe that gender diversity is not associated with the educational process or the educational outcomes. Education is offered equally to all students and any gender differences possibly found would not differentiate educational approaches for one gender or the other. Instead, we perceive this student cohort as representatives of their generation (Generation Z), a characteristic that is directly related to this study’s outcomes and could explain several findings. This concept is in line with the US National Institute of Health recommendations for gender-neutral language [25].

**Figure 1.** Students’ examination grades (% of students within each group).
Qualitative Results

Overview

Out of the 39 students of the ChatGPT group, 31 (80%) students answered the 12 questions of the AI Evaluation Questionnaire. The free-text answers to the questions were grouped into themes and discussed. Three main themes emerged.

Collaboration With ChatGPT and Problems Encountered

Although the majority of students were aware that ChatGPT had surfaced a couple of months ago in the digital world and some of them had already used it, this was the first opportunity they had to actually work with it and “officially” use it within their studies, and they enjoyed and appreciated this opportunity. They characterized it as a “powerful and versatile tool,” “intuitive and intelligent,” “revolutionary,” and “enjoyable to work with” and they thought this experience was “interesting and different from the regular assignments.” They stated that learning to use these AI tools would improve their future practice but emphasized that “you have to learn how to properly use it.” They appreciated its human-like answers, as these “do not make the user feel distanced from technology.” A student stated:

In the beginning I was afraid it was going to be too difficult to work with but as I was discussing with it I understood its greatness. I think it really is the future as it can help both education and research. I really did enjoy its human-like answers like when something was wrong it persisted like a human being for its accuracy as well as when it did not answer the question as it should like a lazy student.

Another student commented: “I enjoyed working with ChatGPT, because I got to learn and understand something that is going to be a part of the future.” Humanization of the LLM is worth noting: “He always understood what we wanted.” Textbox 1 shows examples of students’ prompts.

Textbox 1. Examples of students’ prompts to ChatGPT (exact copies).

- How does radiation affect human health?
- What’s the difference between deterministic & stochastic effects of radiation?
- Is radiation exposure carcinogenic?
- Which are the radiation doses from common dental radiographic exams?
- Which criteria are used to reduce unnecessary radiographic exposure in dentistry?
- Can a pregnant employee continue to work in the dental radiology department?
- What is the importance of radiation biology? With references used
- What are the effects of radiation on cells and tissues? With references used
- What are the effects of radiation on the oral cavity? Rewrite the previous answer in a more elaborate way
- Make a chart about effective dose from diagnostic x-ray examinations focusing on the oral cavity
- Radiation biology, include references
- Measurements of radiology safety, include references
- Radiology protection in dentistry, include references
- How can we minimize the radiation exposure on dental staff, including references
- Why are radiation safety precautions necessary for the dentist
- Tell me how radiation can affect the human body
- Write me an essay discussing radiology safety and protection procedures in dentistry
- Can you explain radiation biology for medicine and dentistry in 400 words, include references
- Radiation exposure in dental office word limit 200-250 words. Include references
- Radiation monitoring in the dental office in 230-270 words include references
- Write me an essay of 400 words about the biology of radiation and provide references
- Write me a 300 words essay about radiation safety and protection in dentistry
- What are the risks associated with exposure to radiation?
- What are the modifying factors of irradiation?
- How does radiation exposure time and dose differentiate between adults and children in dental x-ray taking?

Not unexpectedly, students identified all the problems and limitations of ChatGPT, which are later described in detail in the literature. They identified the need to rephrase or detail the prompts to have a satisfactory output (“we learned quickly how to ask the questions to get a good answer”) and realized that if the same question was asked slightly differently the output was
different (“by asking it 6 different questions, we wanted to get a better idea of what it changes on the text every time we put a new word or phrase the question differently”). They confirmed that some information was outdated, important content was missing, part of the answer was occasionally incorrect, links to references were nonexistent, and the links to videos were not working, although the LLM provided detailed and seemingly reliable information on the links and references (thus unknowingly identifying the “hallucination” effect of ChatGPT).

A student stated: “Mostly it understood our questions but it was not giving us that detailed and satisfactory answers as we anticipated according to our book.” Another student correctly noticed that “ChatGPT is not capable of having thoughts or opinions on its own, so it does not answer some questions that demand a critical-thinking answer.” Technical issues were also mentioned by some students, for example, “some days it was not opening and our conversation couldn’t be saved on the cloud” and “it ‘crushed’ sometimes mid-working.”

Quality of the Generated Outputs

Students found that the quality and depth of the information provided by ChatGPT depended on the quality and wording of the questions asked. As a student noticed:

I would not say that it demonstrated a very deep understanding of the topic, but I think with even more questions being asked, then the text could essentially show a deep understanding of the topic.

Students quickly realized that with follow-up questions and rewording, they could guide the LLM to produce more detailed and in-depth answers: “it needed some guidance with follow up questions to further specify what we were asking for.” While comparing the output with a reference text, students reported that the answers were not detailed; sometimes included false data; and were brief, general, or superficial; nevertheless, the key points were evident. A student concluded that “ChatGPT is more than enough in order to understand and have a general idea about the main points of the matter being discussed” and another student thought that “I will find more details by going and searching online or in books.” They expect ChatGPT to improve in the future and be able to provide videos and images because “they are helpful in understanding a topic and provide a more effective way to retain information as well” and also to be able to browse external resources outside its stable database (Figure 2).

They evaluated the language as appropriate for a scientific document, understandable, and explanatory, and they indicated that when references were asked for, the language was even more formal and academic: “It is fascinating how the AI provides understandable answers in a scientific manner.” However, they encountered problems with the references, as in some occasions, ChatGPT denied to supply them, while in other instances, the references were incorrect. A student described:

The AI was continuously denying to give us relative references but after reforming our questions we eventually got our answer. The references it used were accurate scientific resources found on its stable database like the American Dental Association.

Another student stated that “We used chat GPT 4 so all our references were sufficient and up to date” (apparently overestimating ChatGPT-4’s currentness, as it has the same cutoff date as ChatGPT-3.5). The majority of students evaluated the references as relevant, sufficient, reliable, and up-to-date; however, they also recognized the limitations of the LLM, thinking that “it is under construction so not all its answers are up to date and sufficient information is only provided up to a certain point in time.”
Exploring Additional Possibilities and Predicting the Future

Students experimented with ChatGPT, asking it to provide images and videos, and create MCQs, charts, bullet point summaries, and presentation templates, for example, “we asked about multiple choice questions and the answers were actually impressive” (Figure 3). Students were imaginative and resourceful, and they were disappointed when their request was not realized:

I asked from it to provide me some explanatory images related to our topic, but it was not able to do so. I think this is a crucial disadvantage, as images give depth and context to a description and provide a much more immersive experience than writing alone.

Two student groups—comprised of technologically very experienced students—surprised the authors when they skillfully bypassed the inability of ChatGPT to produce PowerPoint presentations by asking it to write a programming code:

We used the AI for the generation of a PowerPoint. Since it cannot on its own generate PowerPoint Slides we asked it to generate a VBA code for the PowerPoint. That code was copied and then pasted to the ‘Developer’ section of the PowerPoint. As a result we got a beautiful but not so detailed presentation of our topic.

This process enabled the instant transfer of ChatGPT’s output within a PowerPoint slide presentation created by ChatGPT. Among the future applications of ChatGPT, students included the use in dental education, for example, for the creation of MCQs, summarizing a topic, lecture revision, helping students better understand a theory or concept, assignments and projects, laboratory reports, questions about law and ethics, communication with patients, and more. A student proposed:
Virtual patient consultations: ChatGPT could be used to simulate patient consultations for dental students. Students could practice various scenarios, including patient history taking, explaining diagnoses, and treatment planning.

Continuing education could also avail from the opportunities ChatGPT and LLMs offer:

Education that never ends: ChatGPT may be utilized to give dental professionals continual education. For dental professionals to keep current in their field, faculty might create modules containing the material they need, and ChatGPT may offer engaging tasks and tests to reinforce the learning.

Considering dental practice, students proposed that ChatGPT could be used to educate and solve problems for the dentist, for example, when “the dentist has a mind block” or when the dentist “seeks information about new dental materials and techniques”; also for treatment plans, schedule creation, and oral hygiene info; and for patient education “through integrating the model into a dental practice’s website or patient portal.”

For research and scientific publications, students thought it “can be useful to use it synergistically with your own research,” but “you should always double-check the information” and “keep in mind the plagiarism, using the information provided appropriately.”

Figure 3. Multiple-choice questions created by ChatGPT. MCQ: multiple-choice question.

Finally, students admitted that ChatGPT has drawbacks such as a limited database, incapability to access external web resources and provide images and videos, inaccurate links, and the need to verify the information generated. They thought that “it should be used with caution” and that “AI still needs to evolve,” so that it will become “an incredibly smart, effective, and powerful tool that can help the scientific community.” They realized that “the power it holds is unpredictable and the work of doctors could be compromised” and feared that “maybe we will live one day that AI robots could even replace dentists.” A student eloquently summarized ChatGPT’s past, present, and future:

After many years of research and after many science fiction movies about the power of AI and its impact on society I have come to the conclusion that this kind of AI can only help and do no harm. AI like ChatGPT that is available to the public and gives sufficient and accurate responses can give us hundreds of possibilities, even at dentistry. But I really don’t know this exact ChatGPT with its limited dental references can influence the field of dentistry. I can though imagine a more resourceful AI where it uses PubMed or Research Gate to generate its responses that would really elevate the level of dental education and research. What if a curious dentist had the million dollar question answered in milliseconds by the AI?
Discussion

Overview
In March 2023, a total of 39 dental students who are 20 years of age, through composing an educational assignment, identified the capabilities and limitations of the recently introduced ChatGPT and explored various possibilities; used it to write MCQs and programming codes; proposed future applications in education, research, and dental practice; and outperformed their peers in the knowledge examination.

Results Explained and Compared
The quantitative results, that is, the examination grades, demonstrated that all students performed well (their grades fell within the middle and high ranges of the grading scale) and no students underperformed (no grades in the low ranges of the scale), while ChatGPT group students outperformed their literature research group peers. Since the examination occurred with no prior notice to the students, it directly reflects the knowledge acquired and retained through the project’s creation. Students’ good performances on the examination could be related to the format of the project in connection with their generational traits: all students socially belong to the Generation Z cohort (born between 1995 and 2010), so they are the first true “digital natives” [26], having grown up with smartphones, social networks, apps, and streaming content as part of the daily routine [27]. They are considered tech-savvy, mobile-driven, collaborative, and pragmatic [28,29] and possess a natural facility with digital tools and an interest for everything digital. Motivated by the opportunity to use the internet and work collaboratively, students immersed themselves in the project and explored it in depth, and this applies even more to the ChatGPT group students who were excited and curious to test this new digital tool. The enhanced learning observed with the ChatGPT students can be also attributed to the increased “time on task” for these students, as they had to spend more time asking and reasking the questions, evaluating the answers, correcting, and complementing them in comparison to their peers who had clear and readily available results from the relevant scientific literature. Additionally, ChatGPT group students had to work more than their fellow students with the learning material at a higher cognitive level and constantly apply critical thinking while experimenting with various questions and answers, comparing, and synthesizing them—an element that also enhances deep learning and results in enhanced performance [30].

The AI Evaluation Questionnaire provided insight into students’ opinions, evaluations of ChatGPT, the problems encountered, and their future estimations. Students demonstrated their prescience by providing remarks in concordance with those found in later-published articles; the latter were accessed by the authors after the research was concluded and while composing this study. Students evaluated their learning experience with ChatGPT as interesting, enjoyable, and engaging [19] and appreciated its user-friendly interface and the possibility of arguing with it [4,16]. They assessed the generated content as overall correct and sufficient [7,31], although often providing a general overview of the subject [5], as well as not demonstrating a deep understanding of the context [32-34] nor thinking critically [10,35]. They first-hand identified the need for carefully created questions [36] and critical analysis of the answers [14,36], and they urged for cautious and responsible use [4,6]. In agreement with Chan and Hu [11], they are ready to embrace this new technology but in a collaboration where people maintain control and are not replaced by AI [17,20,37,38]. Finally, in line with the literature, they attributed “anthropomorphic” qualities to the language model (1 student referred to ChatGPT using the gender pronoun “he”), possibly explained by the establishment of a personal connection between the student and the language model while engaging in human-like conversations in combination with student’s own gender-related perceptions and interaction style [39].

Students proposed possible applications of ChatGPT in education for revisions, MCQ creation, personalized learning, writing essays [3,4,20,37,40], and continuing education [38], as well as in research and clinical practice [4,6,12]. Nevertheless, students thought that the LLM must evolve to provide images, videos, accurate and relevant citations, and browse the internet [31,41,42].

Numerous publications thereafter examined the LLM’s limitations that had been already identified by the students: incorrect answers and outdated content [10] possibly due to its limited data set [37,38,43], the possibility for fabricated information and hallucination [44], false citations and links leading to nonexistent sources [38,44,45], inability to browse the web [41], and risks for plagiarism [3,46].

This research materialized Kung et al’s [31] concluding remarks that “the utility of generative language AI for medical education must be studied in real-world learning scenarios with students, across the engagement and knowledge spectrum” since ChatGPT was embedded within the educational process, thus producing authentic and relevant results. The quantitative and qualitative outcomes of this study indicate that this cohort of Generation Z students is capable of adapting quickly to new technologies and ready to use LLMs such as ChatGPT in the learning process—while acknowledging their limitations—particularly when these tools are integrated within a pedagogical framework that fosters creativity and autonomous learning. Educators on the other hand seem to have limited technological knowledge, skills, and pedagogical expertise to assess AI applications and successfully integrate them into education [12,47]; therefore, they should pursue professional development to develop new skills related to AI understanding, possibilities, and implementation [15,40,48,49].

Pedagogical Aspects
All second-year students were asked to explore the topic of “Radiation Biology and Radiation Protection in the Dental Office” and develop assignments to be presented in class as PowerPoint presentations. Questions and knowledge gaps were covered during the in-class presentations by the instructor and not infrequently by their peers. This approach is consistent with the “flipped classroom” concept, an educational methodology that research has shown to engage students in the learning process, promote autonomy and self-regulation, allow for higher-order thinking, improve student satisfaction, and increase
academic performance [50,51]. Another element of pedagogical interest is the small group collaborative work to develop the assignments. Collaborative learning has the potential to promote deep learning, which is essential for understanding complex concepts particularly in science education, through students’ meaningful interactions and constructive debates [52]. Scager et al. [52] reported that effective collaboration is achieved when students undertake a challenging, complex task, and they succeed in creating a new and original output. Such tasks applied in higher education build a sense of responsibility and shared ownership of the output and the collaborative process, and this sense was indeed apparent in the students of this study within and during their oral presentations.

An additional pedagogical element is the learning assignments as a method for self-learning and knowledge acquisition. Learning through assignments has been reported to be preferred by students: in the study of Warren-Frederick and Kalthoff [53], 79% of the students reported that the assignment on magnetic resonance imaging safety was both a positive learning experience and provided an understanding of the topic. Writing assignments enhance retention of knowledge; when assignments include reflective thinking, for example, when students have to evaluate and synthesize information (as happens in this study), higher-order (critical) thinking is also enhanced as students work at a higher cognitive level [30].

The innovative pedagogical aspects of this study (flipped classroom, learning assignments, and group learning) constituted a supportive environment for students of both groups to demonstrate their skills, achieve the learning objectives, and produce valuable results. While this pedagogical approach may cater more to certain types of learners, it remains pertinent for younger generations, who prefer active and collaborative learning.

**Study Design: Tackling the Challenges**

Of interest would be to communicate herein the challenges faced during designing the research process, as the ChatGPT environment was largely unknown at the time, and obstacles and drawbacks had to be identified and resolved ahead through a step-by-step prospective analysis of the sequence of events.

For example, a concern that had to be addressed ahead was the fact that the subject was unknown to the students and they would not know whether the output was scientifically correct or incorrect, comprehensive or incomplete because they would not have an exemplary scientific text to compare it with, as they would rely solely upon ChatGPT’s answers. To address this, they were advised to compare the outcome with the relevant content of a recommended textbook (or other reliable source of their choice), critically evaluate the quality of the AI outcome, and perform the necessary amendments to complement or correct the AI results. The comparison should be included either within their presentation or within the AI Evaluation Questionnaire. This process would additionally ensure the achievement of learning objectives. In line with this process and at a later time, Chung [48] proposed in his article published in April 2023 that “instructors should teach students to use other authoritative sources (eg, reference books) to verify, evaluate, and corroborate the factual correctness of information provided by ChatGPT.”

Another concern arose about elucidating students’ engagement with ChatGPT: since the output of ChatGPT would be texts in slide format (similar to the ones of the literature research group), the educator (one of the authors) could evaluate these texts or slides for accuracy and comprehensiveness but could not comprehend whether they were generated following single or multiple attempts, posing differentiated or follow-up queries; therefore, the time and effort spent on the research process and the learning path could not have been assessed nor would the capabilities and drawbacks of the LLM be revealed. To address this concern, the ChatGPT group students were asked to register and report all their interactions with the LLM (including the number of prompts, the modification of prompts, the queries about references, images, and the underlying reasoning); thus, the educator could evaluate the cognitive effort they put in the assignment and the critical thinking applied until a satisfactory result was achieved. Furthermore, this would provide valuable insights into comprehending the usability and operational characteristics of the LLM. Adding to this, the AI Evaluation Questionnaire was a useful means to draw information on student-LLM interactions.

In accordance with the above procedure determined by the authors and in affirming their decisions, Halawe’s study [14] published in April 2023—2 months after the development of this study’s design and 1 month after its implementation—precisely described the same process when discussing the strategies for successful implementation of ChatGPT in education. It seems that future literature confirmed the authors’ study design overall.

**LLMs in Higher Education**

Given the study’s results and in agreement with the relevant literature, the authors would suggest that higher education institutions and dental schools could consider updating their curricula, policies, and teaching methods to prepare students for an AI-driven future, by including education on and with AI tools and LLMs [8,45]. Within this context, faculty professional development seems urgent to increase their skill level and AI understanding, for example, through peer support, mentoring, and sharing good teaching practices [36], as most educators have limited knowledge and skills to assess and efficiently use AI applications [12]. The introduction of LLMs into education will offer opportunities to improve its efficiency and quality: improved student performance, personalized learning, targeted and immediate feedback, increased accessibility, creativity and innovations, student engagement, lesson preparation, collaborative activities, and evaluation [4,40,54-56]. From the pedagogical perspective, students using LLMs have the potential to develop new competencies including 21st-century soft skills, such as self-reflection abilities, problem-solving skills, creative and critical thinking, and collaboration, thus becoming motivated and autonomous learners [3,4,16,33,49]. Moreover, as AI technology evolves and gradually integrates within the educational process, the conventional pedagogical theories may not be relevant nor sufficient to support the teacher-student-technology relationship, as technology...
profoundly alters the way students learn and engage with the content and the teacher; innovative pedagogies will be needed, such as the “entangled pedagogy” Fawns [57] proposed to contextualize students’ learning in a world where AI is increasingly prevalent [15,16].

To respond to the AI paradigm shift, higher education institutions, educators, and students must engage in constructive dialogue to develop policies, guidelines, and training opportunities for the implementation of innovative technological tools in the teaching process [16,34,55]. Despite the current weaknesses that limit their implementation, LLMs will likely improve in the future in terms of performance, scalability, and quality of responses, as well as through fine-tuning for specific tasks, customized use cases, and search engine connection [4,16,31,58].

Limitations and Strengths

The small number of students who participated in this study (77 in total and 39 in the ChatGPT group) in 1 dental school can limit the extrapolation of the results. Students’ digital literacy is also of relevance: students who participated in this research were mostly tech-savvy, whereas students in other schools or universities may be less familiar with digital technologies; thus, results would not apply to them [17]. In addition, some findings (particularly the qualitative ones) may be outdated at the time of publication, as LLMs constantly evolve and new LLMs have been introduced since the research was conceptualized and implemented. For example, Google Bard and Microsoft Bing claim to have live access to the internet, a capability highly appreciated by the students; ChatGPT has since evolved its algorithms, with results being more accurate and relevant. Some elements of the study design could have been further explored; for example, students’ assignments could have been graded and compared, but since assignments’ grading was not included in the semester program of the module, this was not performed. In any case, the importance of this study lies in the fact that this was a very early attempt to implement legitimately and in vivo a language model in the teaching process as a partner in learning, in contrast to the large number of publications perceiving ChatGPT as a partner in cheating and academic dishonesty [12,59,60]. Another strength would be that it revealed aspects of the language model-students’ interactions during the learning process, which indicate that this emerging relationship is yet to be explored, and updated pedagogical frameworks are needed for this purpose.

Conclusions

ChatGPT was implemented in real-life undergraduate dental education and was evaluated. Students using ChatGPT for their learning assignments performed significantly better in the knowledge examination than their fellow students who used the literature research methodology. The AI questionnaire answered by students revealed the capabilities and weaknesses of the language model, as identified later in the scientific literature. Students enjoyed working with this tool and explored different options and possibilities, indicating that they are technologically knowledgeable and capable of adapting to new technologies, both in education and in future clinical practice. LLMs such as ChatGPT have the potential to play a role in education, underpinned by solid pedagogies.

Acknowledgments

The authors are grateful to the students who participated in the study. They were enthusiastic, motivated, and resourceful and explored the subject in depth, thus providing valuable insights to inform the ongoing research on the topic.

Authors’ Contributions

AK conceptualized, designed, and realized the study; interpreted the data; and drafted the manuscript. KG supervised the project, reviewed the literature, and contributed to drafting the manuscript. MADdS and EGK critically reviewed and revised the manuscript; EGK performed the statistical analysis. VS consulted on information technology and reviewed the manuscript. All authors read and approved the final manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1

AI evaluation questionnaire.

[DOCX File, 14 KB - mededu_v10i1e51344_app1.docx ]

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Abbreviations

AI: artificial intelligence
LLM: large language model
MCQ: multiple-choice question
Increasing Realism and Variety of Virtual Patient Dialogues for Prenatal Counseling Education Through a Novel Application of ChatGPT: Exploratory Observational Study

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Abstract

Background: Using virtual patients, facilitated by natural language processing, provides a valuable educational experience for learners. Generating a large, varied sample of realistic and appropriate responses for virtual patients is challenging. Artificial intelligence (AI) programs can be a viable source for these responses, but their utility for this purpose has not been explored.

Objective: In this study, we explored the effectiveness of generative AI (ChatGPT) in developing realistic virtual standardized patient dialogues to teach prenatal counseling skills.

Methods: ChatGPT was prompted to generate a list of common areas of concern and questions that families expecting preterm delivery at 24 weeks gestation might ask during prenatal counseling. ChatGPT was then prompted to generate 2 role-plays with dialogues between a parent expecting a potential preterm delivery at 24 weeks and their counseling physician using each of the example questions. The prompt was repeated for 2 unique role-plays: one parent was characterized as anxious and the other as having low trust in the medical system. Role-play scripts were exported verbatim and independently reviewed by 2 neonatologists with experience in prenatal counseling, using a scale of 1-5 on realism, appropriateness, and utility for virtual standardized patient responses.

Results: ChatGPT generated 7 areas of concern, with 35 example questions used to generate role-plays. The 35 role-play transcripts generated 176 unique parent responses (median 5, IQR 4-6, per role-play) with 268 unique sentences. Expert review identified 117 (65%) of the 176 responses as indicating an emotion, either directly or indirectly. Approximately half (98/176, 56%) of the responses had 2 or more sentences, and half (88/176, 50%) included at least 1 question. More than half (104/176, 58%) of the responses from role-played parent characters described a feeling, such as being scared, worried, or concerned. The role-plays of parents with low trust in the medical system generated many unique sentences (n=50). Most of the sentences in the responses were found to be reasonably realistic (214/268, 80%), appropriate for variable prenatal counseling conversation paths (233/268, 87%), and usable without more than a minimal modification in a virtual patient program (169/268, 63%).

Conclusions: Generative AI programs, such as ChatGPT, may provide a viable source of training materials to expand virtual patient programs, with careful attention to the concerns and questions of patients and families. Given the potential for unrealistic or inappropriate statements and questions, an expert should review AI chat outputs before deploying them in an educational program.
prenatal counseling; virtual health; virtual patient; simulation; neonatology; ChatGPT; AI; artificial intelligence

Introduction

Virtual standardized patients (VSPs) represent an emerging technology with the potential to revolutionize health care education and training. They provide health care professionals with a safe and controlled environment in which to learn and practice complex skills. VSPs are frequently used in educational models for the health professions to teach history-taking, surgical skills, decision-making, and medication management [1-4]. VSPs have also been used in the health professions to practice critical communication skills [5-7]. VSPs that use natural language processing may provide a valuable educational experience for learners [8].

One example of a VSP is VANESSA (Virtual Antenatal Encounter and Standardized Simulation Assessment) [9]. The VANESSA simulator is a screen-based simulation of a woman in her 23rd week of gestation who can display multiple emotions through the animation of facial expressions and body language. The VANESSA simulator was developed by the Neonatal Education and Simulation-Based Training Laboratory at the University of Washington to teach prenatal counseling skills to residents and fellows [9]. In its initial iteration, VANESSA was given a list of manually generated responses that neonatologists who routinely do perinatal counseling deemed relevant and realistic to the conversation. Manually generating a large, varied sample of realistic and appropriate parent responses for VANESSA has been challenging. Unrealistic responses and questions reduce the fidelity of virtual simulations. Newly developed artificial intelligence (AI) systems can provide dialogue for a wide variety of interactions and may be a valuable resource in expanding virtual patient dialogues for specific clinical scenarios, such as prenatal counseling.

Chat-based language models and AI are entering the public domain with impressive performance, a large application pool, and exciting interactivity. Notably, ChatGPT has prompted a billion-dollar investment from Microsoft, triggered explicit discussions by Bill Gates and Elon Musk, and captivated the population of users able to interact with it via the open research chat interface. AI trained with large language models to interpret written or auditory input and generate coherent, domain-centered responses is being proposed in a variety of real-world applications, including the health care setting. ChatGPT has the added benefit of being able to emulate different characters, allowing for a broader array of parent voices than could be generated by individual health care educators.

In this report, we explore the use of ChatGPT to enhance the realism of the VANESSA VSP. We hypothesized that the integration of the ChatGPT AI chatbot would generate realistic, relevant, and usable parent responses for a VSP simulator used in prenatal counseling education.

Methods

The study used an exploratory observational design, with ChatGPT acting as an expectant parent within the VANESSA software, conducted in February 2023 on ChatGPT 3.5.

The VANESSA VSP represents a pregnant woman in her 23rd week of gestation and showcases emotions through animated facial expressions and body language. Created with input from neonatologists, its dialogue and emotive feedback were found realistic in pilot tests, enabling participants to confidently identify its emotional states.

ChatGPT is a large language model developed by OpenAI. Its exceptional performance stems from generative pretraining, leveraging extensive unlabeled data sets [10]. This foundational training helps it grasp English nuances. Following this pretraining is “one-shot” learning, a rapid task-specific learning [11]. The architecture includes a transformer encoder-decoder neural network, originally developed for translation services and now popular in language models [12]. ChatGPT decodes user prompts to create relevant responses using autoregressive language modeling [13]. It is apt for generating realistic dialogue for health care simulations.

The study had three phases:

1. ChatGPT generated a list of common concerns from families expecting preterm delivery at 24 weeks. The stability of these concerns was verified in an iterative process over time.
2. Using a standardized prompt, ChatGPT crafted potential parent questions related to each concern.
3. Role-plays were constructed for a mother expecting preterm delivery. The AI was given varied emotional settings for the scenario of preterm labor at 24 weeks, including anxiety or distrust in the medical system. In each scenario, a designated area of concern and a primary question were specified, derived from the potential parent responses generated in phases 1 and 2. Conversations were created with cues for the VSP and then reviewed (an example is shown in Figure 1).
Throughout the process, ChatGPT was instructed to adhere to a fifth-grade reading level for the AI parent role. Considering the US Department of Education’s findings on widespread low literacy, the importance of health literacy, and the impacts of pain, stress, and other factors on comprehension, this was deemed crucial [14-17]. The Joint Commission and several medical organizations suggest that patient materials should be at a fifth-grade level or lower [18]. Although these dialogues were verbal, the principle of understandability remained in place.

Role-play conversations were scrutinized for parental responses. Each was checked for question or statement content, emotional cues, and sentence count. Initially, generated physician names and certain response starters (eg, “yes” or “no”) were noted but removed for evaluation. Sentences were then appraised by a neonatologist for realism, relevance, and usability for virtual prenatal counseling simulations. Each metric used a 5-point Likert scale, ranging from 1 (the lowest) to 5 (the highest). For usability in the VANESSA VSP, responses were scored as follows: 1 if they were unusable, 2 if they were unusable without major modifications, 3 if they were usable with moderate modifications, 4 if only minor modifications were needed, and 5 if they were usable without any modifications. The first 10% of responses were independently reviewed by 2 experienced neonatologists (RU and MG) and then compared for reliability. A calculated weighted kappa on the sample was 0.84, which is considered a strong level of agreement [19]. Responses with differences in rating were discussed by the team members to improve reliability, and the remainder of the data set was scored by one of the experienced neonatologists. Duplicate responses were scored only once. Analysis was done using Stata (version 17.0; StataCorp).

Results

ChatGPT-3.5 generated a list of 7 common areas of concern, 28 questions likely to be asked by parents anxious about the preterm delivery of their infant, and 7 additional questions likely to be asked by parents with low trust in the medical system (Table 1). These areas of concern and questions were used to create 35 unique role-plays, which contained 176 unique parent responses (Table 2). The role-plays had a median of 5 (IQR 4-6) parent responses to the counseling physician. The responses were roughly evenly split between questions and statements. About half of the responses had 2 or more sentences in the response. Many responses mentioned a specific emotion or feeling. The role-play of the parent with low trust in the medical system generated 50 unique sentences across the 7 areas of concern. There was variation in the number of unique sentences generated across the 7 major areas of concern (Table 3). Most responses were found to be realistic, appropriate for variable conversation paths, and usable in a VSP program (Table 4).
<table>
<thead>
<tr>
<th>Areas of concern</th>
<th>Example questions from parents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Health and development</td>
<td>• Will our baby be healthy if they are born too soon?</td>
</tr>
<tr>
<td></td>
<td>• What will the doctors do to help our baby be healthy and strong?</td>
</tr>
<tr>
<td></td>
<td>• Can our baby get sick more easily if they are born too soon?</td>
</tr>
<tr>
<td></td>
<td>• Will the baby feel pain during birth or while in the hospital?</td>
</tr>
<tr>
<td></td>
<td>• I’m worried about the risks and complications, what if something goes wrong? (Mistrust)</td>
</tr>
<tr>
<td>Survival</td>
<td>• Will the baby survive?</td>
</tr>
<tr>
<td></td>
<td>• What kind of help will our baby need to stay alive?</td>
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<tr>
<td></td>
<td>• How likely is it that our baby will survive?</td>
</tr>
<tr>
<td></td>
<td>• What kind of machines or medicines will our baby need to help them breathe and stay alive?</td>
</tr>
<tr>
<td></td>
<td>• I don’t know if I can trust the medical field, what are the chances of my baby surviving at 24 weeks? (Mistrust)</td>
</tr>
<tr>
<td>NICU(^a) stay</td>
<td>• What is the NICU, and why does our baby need to go there?</td>
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<tr>
<td></td>
<td>• How long will our baby need to stay in the NICU?</td>
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<tr>
<td></td>
<td>• Can we visit our baby in the NICU, and how often?</td>
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<tr>
<td></td>
<td>• Will our baby be alone in the NICU, or will there be other babies and parents there too?</td>
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<tr>
<td></td>
<td>• What kind of things can we do to help our baby feel better in the NICU?</td>
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<tr>
<td></td>
<td>• Will anything happen in the NICU without my consent? (Mistrust)</td>
</tr>
<tr>
<td>Emotional impact</td>
<td>• How do we get ready for having a baby born too soon?</td>
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<tr>
<td></td>
<td>• Can we hold and touch the baby in the hospital, and is this good for the baby?</td>
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<tr>
<td></td>
<td>• Who can help us if we are feeling sad or stressed about our baby being born too soon?</td>
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<tr>
<td></td>
<td>• I’m worried about my baby going to the NICU where she will be alone and scared (mistrust).</td>
</tr>
<tr>
<td>Long-term outcomes</td>
<td>• What help can we get after we leave the hospital?</td>
</tr>
<tr>
<td></td>
<td>• Will our baby be able to do the same things as other babies who were born at the right time?</td>
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<tr>
<td></td>
<td>• Will our baby be okay in the future if they are born too soon?</td>
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<tr>
<td></td>
<td>• I don’t know what’s going to happen to my baby. I don’t really trust the doctors but what happens if my baby doesn’t develop properly? (Mistrust)</td>
</tr>
<tr>
<td>Feeding and nutrition</td>
<td>• How will our baby get the right kind of food if they are born too soon?</td>
</tr>
<tr>
<td></td>
<td>• Can we feed our baby ourselves, or will they need special milk or formula?</td>
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<tr>
<td></td>
<td>• How often will our baby need to be fed, and how much?</td>
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<td></td>
<td>• Will our baby be able to eat the same kinds of food as other babies when they get older?</td>
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<td></td>
<td>• Can we breastfeed our preterm baby, or do we need to use formula?</td>
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<td></td>
<td>• Will our baby be able to breastfeed right away, or will they need to be fed in a different way at first?</td>
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<td></td>
<td>• Will I have any say in how my baby is fed? (Mistrust)</td>
</tr>
<tr>
<td>Quality of life</td>
<td>• Will our baby be able to go to school and play sports like other kids?</td>
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<td></td>
<td>• How can we help our baby if they have trouble learning or doing things in the future?</td>
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<tr>
<td></td>
<td>• What can we do to make sure our baby has the best chance for a good future?</td>
</tr>
<tr>
<td></td>
<td>• I’ve had bad experiences before and I’m scared about what’s going to happen to my baby in the future, what can I expect? (Mistrust)</td>
</tr>
</tbody>
</table>

\(^{a}\)NICU: neonatal intensive care unit.
Table 2. Generated role-plays by artificial intelligence.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Role-plays (n=35), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Worried about specific area of concern</td>
<td>28 (80)</td>
</tr>
<tr>
<td>Low trust in the medical system</td>
<td>7 (20)</td>
</tr>
<tr>
<td>Responses per role-play, median (IQR)</td>
<td>5 (4-6)</td>
</tr>
<tr>
<td><strong>Parent responses (n=179), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Unique responses</td>
<td>176 (98)</td>
</tr>
<tr>
<td>Duplicate responses</td>
<td>3 (1)</td>
</tr>
<tr>
<td><strong>Types of responses (n=179), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Statements</td>
<td>91 (51)</td>
</tr>
<tr>
<td>Questions</td>
<td>88 (49)</td>
</tr>
<tr>
<td><strong>Sentences per response (n=179), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>81 (45)</td>
</tr>
<tr>
<td>2</td>
<td>76 (42)</td>
</tr>
<tr>
<td>3</td>
<td>18 (10)</td>
</tr>
<tr>
<td>4</td>
<td>4 (2)</td>
</tr>
<tr>
<td>Duplicate sentences (n=305), n (%)</td>
<td>37 (12)</td>
</tr>
<tr>
<td>Total unique sentences (n=305), n (%)</td>
<td>268 (88)</td>
</tr>
<tr>
<td><strong>Feelings stated in responses (n=117), n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Specific emotion stated in phrase</td>
<td>56 (48)</td>
</tr>
<tr>
<td>“Scared”</td>
<td>36 (31)</td>
</tr>
<tr>
<td>“Worried”</td>
<td>26 (22)</td>
</tr>
<tr>
<td>“Anxious”</td>
<td>2 (2)</td>
</tr>
<tr>
<td>“Concerned”</td>
<td>2 (2)</td>
</tr>
<tr>
<td>“Afraid”</td>
<td>1 (1)</td>
</tr>
<tr>
<td>“Nervous”</td>
<td>1 (1)</td>
</tr>
<tr>
<td>“Overwhelmed”</td>
<td>1 (1)</td>
</tr>
<tr>
<td>Emotion indirectly implied by phrase</td>
<td>51 (44)</td>
</tr>
</tbody>
</table>

Table 3. Sentences generated per role-play.

<table>
<thead>
<tr>
<th>Area of concern</th>
<th>Number of unique sentences</th>
</tr>
</thead>
<tbody>
<tr>
<td>Health and development</td>
<td>47</td>
</tr>
<tr>
<td>Survival</td>
<td>46</td>
</tr>
<tr>
<td>Feeding and nutrition</td>
<td>45</td>
</tr>
<tr>
<td>The NICU(^a) stay</td>
<td>40</td>
</tr>
<tr>
<td>Quality of life</td>
<td>36</td>
</tr>
<tr>
<td>Outcomes</td>
<td>28</td>
</tr>
<tr>
<td>Emotional impact</td>
<td>26</td>
</tr>
</tbody>
</table>

\(^a\)NICU: neonatal intensive care unit.
modifications to responses were all aimed at ensuring the VSP could correctly deploy the phrase at the correct conversational juncture and that there were no elements of the phrase that might interrupt the flow. As ChatGPT 3.5 seeks to ensure the specific conversation has a flow, it can at times generate responses that are less usable for a VSP that needs to maintain flow across many different variations of the same conversation. Only 2% (5/254) of the AI-generated responses were not usable in the VSP. Examples of minimally usable responses included “How much should I feed my baby each time?” which is not relevant to how feeding is done in the neonatal intensive care unit and “I am,” as this response is too nonspecific to be of use in a VSP. Of the 34% (87/254) of responses that required moderate modifications, the changes primarily involved adjusting terminology to ensure the parent was using colloquial, jargon-free language. As an example, “I’ve been having a lot of contractions and I’m only 24 weeks pregnant” was modified to “I’ve been having a lot of cramping and I’m only 6 months pregnant.” Other modifications included adding some specificity to a response to ensure the VSP can use the sentence in the right context, such as modifying “That sounds reassuring, but what are the risks?” to “That sounds reassuring, but what are the risks of being born this early?” Of the 13% (34/254) of responses that required minimal adjustment, example changes included “I don’t trust the doctors” to “I don’t trust doctors,” and “Okay, thank you, but can you tell me more about what might happen to my baby in the future?” to “Can you tell me more about what might happen to my baby in the future?”

Discussion

Principal Findings

In this study, we examined the feasibility of using ChatGPT to enhance the realism of the VANESSA VSP. We found that the integration of ChatGPT generated many realistic, relevant, and useful responses. Based on these findings, ChatGPT-enabled VSPs may be beneficial in prenatal counseling education. There was more variation in realism and usability compared to relevance; therefore, an expert review was necessary to provide quality control before integrating the ChatGPT-generated conversations into an educational VSP program for prenatal counseling. Modifications made to responses to make them usable for the VANESSA VPS were largely focused on ensuring the virtual patient remains free of jargon and her responses maintain the flow of conversation.

Research conducted so far on AI chat engines has focused on generating and interpreting electronic health records, assisting in medical education related to the medical licensing exam, and summarizing collections of journal articles to construct a brief abstract from the conclusions of the research [20-23]. The field is still relatively new, but rapidly increasing and expanding. This growth will only continue, as generating documentation and interacting with patients are key requirements of the health care setting. Health care simulation has many training applications, such as VSPs, that require expert authoring to educate clinicians and care providers on a certain skill or cognitive task. VSPs like VANESSA have been used in teaching the communication of medical ambiguity, evaluating medical students’ competence in performing critical clinical skills, and training nurses to recognize postpartum mood disorders [24-26]. Based on the results of our study, chat-based AI may be a valuable teaching tool in the future of health care simulation technology, leading to improved scenario creation, customization of patient interactions, and responses to care providers in a simulated setting. These improvements will result in authentic, unique interactive experiences, varying for each learner and training scenario.

We found that ChatGPT could generate many realistic parent responses, especially concerning issues related to survival at 24 weeks gestation and the neonatal intensive care unit stay (Figure S1 in Multimedia Appendix 1). Mistrust in the health care system is often encountered during stressful counseling conversations, and building the skill of responding to mistrust is crucial for physicians during their training [27]. Patients who express mistrust are less likely to engage with their health care team and care plan, and care is needed to proactively build trust during prenatal counseling [28-31]. Including opportunities for learners to respond to VSPs that express mistrust is one way to address this important counseling element, and ChatGPT provided a reliable mechanism to generate these phrases. Interestingly, the ChatGPT bot faced more challenges in generating realistic questions and responses about the emotional impact of preterm delivery and feeding. As these are frequently encountered topics of conversation in prenatal counseling, an expert review of these conversational elements remains a vital step before including them in an educational program.

ChatGPT produced responses that seemed relevant and appropriate to the context of prenatal counseling. Previous studies of prenatal counseling for extreme prematurity indicate that parents may ask questions about the likelihood of various outcomes, express a range of emotions, request engagement in shared decision-making, and express their parental roles and values [32,33]. Parents may express statements about their
uncertainty, anxieties, and hope for the future [34]. This wide range of topics, emotions, and questions makes it challenging to ensure that chatbot-generated conversations remain appropriate to the educational goals of the VSP. Despite the risk of getting off-topic, we found that only 1% (2/254) of ChatGPT-produced responses were irrelevant to a counseling conversation, given a carefully worded role-play prompt. Although most responses were relevant, some topics, such as spirituality and shared decision-making, did not come up in the role-play conversations. Previous studies have demonstrated that providers perceive the importance of parents’ spirituality in their decision-making and infrequently discuss these spiritual beliefs with parents in antenatal consultations [35,36]. Further work exploring how families might express their spirituality or explore shared decisions would be needed to ensure these topics are included in a VSP [37-39].

Chatbot programs use machine learning to generate their responses; due to the nature of machine learning, there is an inherent risk that chatbots can generate factually incorrect information [40]. Given this risk, caution is warranted when using chatbots in health care settings, where misinformation can have a significant risk [41,42]. Developers are working to address these inaccuracies as they design the next generation of large language model chat programs; they have demonstrated improvements in ChatGPT-4’s success across a variety of standardized tests [43]. This study leverages the strengths of a natural language chatbot in its ability to generate conversation while avoiding the risks of obtaining inaccurate medical information. Most scripts created by ChatGPT were usable for our perinatal counseling virtual patient. We found about a third of chatbot-generated phrases needed modification before being able to be integrated into a VSP; therefore, it may not be feasible to directly use ChatGPT for educational role-play without having the quality control step of review by expert clinicians. However, as technology continues to grow, this will evolve, and each subsequent model should be evaluated for usability.

**Study Limitations**

This exploratory study has several limitations. First, the pilot was done using ChatGPT 3.5, which is a single platform and is not representative of all chatbots. Later versions of ChatGPT have already been released and may have differences in realism, appropriateness, and usability. Newer AI chatbot programs are being trained on more parameters (175 billion for ChatGPT-3 vs an anticipated 100 trillion with ChatGPT-4), are supposed to have more ability to iterate on the same topic, and are being adjusted to improve the faculty accuracy of their responses [43]. Second, chatbot programs have limited information on which they build a conversation. For this study, we used a stable prompt around an impending 24-week gestation delivery to fit the standardized patient scenario, but conversations may be different with variations in the prompt. The AI was given a limited background to build a role-play, potentially limiting the diversity of ways in which patients could communicate their concerns. For this scenario, we requested a fifth-grade reading level for all patient roles to better mimic how patients may speak in stressful situations, but we did not explore higher or lower complexity of responses. Future work should explore how variations in the background, scenario, and reading level provided to the chatbot impact the output of the role-play. Another significant limitation was that response checking was performed by neonatologists, without input from families or trainees. Future work to refine the model will incorporate their views to ensure further applicability of the VSP and the validity of any assessments. Finally, although individual phrases exhibited good realism, the total duration of each patient-physician conversation (averaging 5 volleys) was generally shorter than that of a real prenatal counseling conversation.

**Conclusions**

Generative AI programs, such as ChatGPT, may provide a viable source of training materials to expand VSP programs with careful attention to the concerns and questions of patients and families. Given the potential for unrealistic or inappropriate statements and questions, an expert should review AI chat outputs before deploying them in an educational program.


Abbreviations

AI: artificial intelligence
VANESSA: Virtual Antenatal Encounter and Standardized Simulation Assessment
VSP: virtual standardized patient
Increasing Realism and Variety of Virtual Patient Dialogues for Prenatal Counseling Education Through a Novel Application of ChatGPT: Exploratory Observational Study


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Comparison of the Performance of GPT-3.5 and GPT-4 With That of Medical Students on the Written German Medical Licensing Examination: Observational Study

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Abstract

Background: The potential of artificial intelligence (AI)–based large language models, such as ChatGPT, has gained significant attention in the medical field. This enthusiasm is driven not only by recent breakthroughs and improved accessibility, but also by the prospect of democratizing medical knowledge and promoting equitable health care. However, the performance of ChatGPT is substantially influenced by the input language, and given the growing public trust in this AI tool compared to that in traditional sources of information, investigating its medical accuracy across different languages is of particular importance.

Objective: This study aimed to compare the performance of GPT-3.5 and GPT-4 with that of medical students on the written German medical licensing examination.

Methods: To assess GPT-3.5’s and GPT-4’s medical proficiency, we used 937 original multiple-choice questions from 3 written German medical licensing examinations in October 2021, April 2022, and October 2022.

Results: GPT-4 achieved an average score of 85% and ranked in the 92.8th, 99.5th, and 92.6th percentiles among medical students who took the same examinations in October 2021, April 2022, and October 2022, respectively. This represents a substantial improvement of 27% compared to GPT-3.5, which only passed 1 out of the 3 examinations. While GPT-3.5 performed well in psychiatry questions, GPT-4 exhibited strengths in internal medicine and surgery but showed weakness in academic research.

Conclusions: The study results highlight ChatGPT’s remarkable improvement from moderate (GPT-3.5) to high competency (GPT-4) in answering medical licensing examination questions in German. While GPT-4’s predecessor (GPT-3.5) was imprecise and inconsistent, it demonstrates considerable potential to improve medical education and patient care, provided that medically trained users critically evaluate its results. As the replacement of search engines by AI tools seems possible in the future, further studies with nonprofessional questions are needed to assess the safety and accuracy of ChatGPT for the general population.

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KEYWORDS
ChatGPT; artificial intelligence; large language model; medical exams; medical examinations; medical education; LLM; public trust; trust; medical accuracy; licensing exam; licensing examination; improvement; patient care; general population; licensure examination

Introduction

Rapid advancements in large language models (LLMs) have sparked considerable excitement regarding their potential applications in the medical field [1,2]. One LLM-based application that has garnered worldwide attention is ChatGPT, developed by the research and deployment company OpenAI, due to its easy accessibility and potential to democratize knowledge [3]. The freely available version is based on the artificial intelligence (AI)–based tool GPT-3.5, which...
encompasses billions of parameters and has been trained on approximately 570 GB of text from the internet [1,2]. ChatGPT’s GPT-3.5 iteration has already shown promise in several routine medical tasks and medical research [4-7], even raising ethical concerns in the literature [2,3,8]. The prompt and interactive nature of this AI’s responses might even revolutionize search engines, while also revealing shortcomings in medical education [9-11]. However, despite the introduction of the more advanced iteration GPT-4, concerns about the lack of transparency regarding this AI’s model parameters, training process, and underlying data structure remain unaddressed [8,12]. These concerns cast doubt on the medical proficiency of these LLMs, as both were not primarily trained on medical data and are the first to admit that as a language AI model, passing a medical examination is outside their skillset (Multimedia Appendix 1). Still, with assistance and adaptations, GPT-3.5 nearly passed the United States Medical Licensing Examination [13,14], and GPT-4 passed a Japanese medical examination [15]. Considering the variable performance of multilingual LLMs across different input languages [16,17], it is imperative to evaluate these models in various other linguistic contexts as well as on large data sets of original medical examination questions.

The primary objective of this study is to evaluate the medical proficiency of both ChatGPT iterations (GPT-3.5 and -4) in comparison to medical students by testing it on 937 original questions from the written German medical licensing examination (Zweites Staatsexamen), providing further data for a possible future integration. To ensure that any observed performance was not influenced by changes in ChatGPT’s training data, we specifically chose the 3 most recent examinations (October 2021, April 2022, and October 2022) after the AI’s knowledge cutoff date [17]. Thus, we were able to obtain 937 multiple-choice questions, each with 5 possible answers from the third-party client Amboss, a web-based learning platform that provides the original questions from the Institut für Medizinische und Pharmazeutische Prüfungsfragen (IMPP). To maintain the original examination format, we presented all obtained questions and answer options in the same order as they appeared in the examination. Due to AI’s inability to analyze visual content, answerability based on question text alone was defined as the primary inclusion criterion, resulting in the exclusion of 102 questions. The questions were submitted through ChatGPT’s interface of the GPT-3.5 (January 30, 2023) and GPT-4 (March 14, 2023) versions. ChatGPT’s answers were then compared to the official correct answers and evaluated. If ChatGPT selected none or more than 1 of the multiple-choice answers, the question was repeated in its original format up to 4 times or until a conclusive response could be obtained from ChatGPT (Figure 1).

Methods

Data Collection

To ensure that any observed performance was not influenced by changes in ChatGPT’s training data, we specifically chose the 3 most recent examinations (October 2021, April 2022, and October 2022) after the AI’s knowledge cutoff date [17]. Thus, we were able to obtain 937 multiple-choice questions, each with 5 possible answers from the third-party client Amboss, a web-based learning platform that provides the original questions from the Institut für Medizinische und Pharmazeutische Prüfungsfragen (IMPP). To maintain the original examination format, we presented all obtained questions and answer options in the same order as they appeared in the examination. Due to AI’s inability to analyze visual content, answerability based on question text alone was defined as the primary inclusion criterion, resulting in the exclusion of 102 questions. The questions were submitted through ChatGPT’s interface of the GPT-3.5 (January 30, 2023) and GPT-4 (March 14, 2023) versions. ChatGPT’s answers were then compared to the official correct answers and evaluated. If ChatGPT selected none or more than 1 of the multiple-choice answers, the question was repeated in its original format up to 4 times or until a conclusive response could be obtained from ChatGPT (Figure 1).

We recorded additional data, such as answer length, content warnings, and recommendations for further diagnosis, and categorized the questioning methodology. To assess the readability of a question, we used the Simple Measure of Gobbledygook (SMOG) as it has shown acceptable interrater reliability for patient education materials in the literature [21]. Examination statistics provided by the “MEDI-LEARN” portal were also used, including the number of correct student answers and the specialization of each question. The “Blueprint” published by the IMPP outlines the distribution of subspecialties within the written state examinations [18].

The German medical licensing examination covers various medical subdisciplines in 320 multiple-choice questions [18], it has a high interexamination reliability of over 0.9 [19]. Despite using the same third-party client for question retrieval as earlier studies, the German approach of publicly releasing the examination questions enables the third-party client to guarantee the originality of the test items derived directly from the examination itself [20]. Additionally, to the best of our knowledge, we have tested both ChatGPT versions on the largest data set of medical licensing examination questions not included in their training data set. Furthermore, we did not exclude all image-based questions a priori. Instead, we evaluated the relevance of the images for each question and compared the results both with and without images.
Figure 1. Flowchart of the study design for the evaluation of ChatGPT’s (GPT-3.5 and GPT-3) accuracy in the written German medical licensing examination (2021-2022). The flowchart presents the criteria for question selection, including both the inclusion and exclusion criteria.

Statistical Analysis
To perform our data analysis, we used several packages [22-37] in addition to the R programming language [38].

While continuous variables were reported as arithmetic mean (SD) values, categorical variables were reported as frequencies and percentages. The Kolmogorov-Smirnov test, Shapiro-Wilk test, and QQ plots were used to confirm the normal distribution of continuous data statistically and graphically. To determine significant differences, we used unpaired t test or ANOVA for continuous variables and chi-square test or Wilcoxon rank-sum test for categorical variables. P values of <.05 were deemed significant. Univariate and multivariate regression analyses were additionally performed to provide information on probabilities and predictors.

Ethical Considerations
Ethics approval was not required as data were collected from publicly available sources on the internet or were generated using AI-based methods. No personally identifiable information was used in the data collection, and all data were handled in accordance with applicable data privacy laws and regulations.

Results
Overall, GPT-4 demonstrated superior performance with an average score of 796 out of 937 (85%), surpassing GPT-3.5’s score of 548 out of 937 (58%), which previously fell below the general passing threshold of 60% (Figure 2A) [37-39]. For the April 2022 examination, GPT-3.5 and GPT-4 achieved their highest scores (GPT-3.5: 195/319, 61%; GPT-4: 287/315, 91%), while the proportion of students who answered correctly remained constant across the 3 examinations (mean 76%, SD 18%; P=.86; Figure 2B and Multimedia Appendix 2).

Thus, GPT-4 passed all tested examinations, whereas GPT-3.5 could only pass 1 of the 3 examinations. Although the examinations varied in several aspects, we also observed a significant difference in the number of images (P=.02; Figure 2C and Multimedia Appendix 2). As GPT-3.5 and GPT-4 could, at the time of the study, not process these, we further investigated the potential image-related discrepancy between the examinations by excluding from subsequent analyses any questions that required image-dependent responses. The exclusion of these questions did not significantly alter examination difficulty, as evidenced by similar student scores (Figure 2D).

Moreover, no differences were observed in the parameters collected on student accuracy, questions, or answer characteristics in relation to the performance of GPT-4 and GPT-3.5 in the excluded cases (Multimedia Appendix 3). Upon excluding image-based questions, GPT-4 continued to outperform GPT-3.5, with scores approaching 91.44%. However, GPT-3.5 exceeded expectations by achieving passing scores on all 3 examinations (October 2021: 60.22%; April 2022: 63.36%; October 2022: 60.07%; Figure 2E and Multimedia Appendix 4). GPT-3.5’s accuracy (P=.66), the number of images (P=.07), and students’ accuracy (P=.77) remained constant throughout the examinations, whereas GPT-4’s accuracy (P=.02), the specialties (P<.001), and question type (P=.04) varied (Multimedia Appendix 4 and Figures 2A, 2B, and 2E). The details of the included questions and their respective categorizations are provided in Table 1.
Figure 2. Bar plots of ChatGPT’s (GPT-3.5 and GPT-4) and box plots of students’ accuracy in the written German medical licensing examination (2021-2022). Bar graphs and box plots of (A) the relative number of correct answers provided by ChatGPT (GPT-3.5 and GPT-4) answers, (B) correct answers provided by students, (C) and image-based questions for the different examinations. (D and E) The relative number of correct answers by ChatGPT (GPT-3.5 and GPT-4) and students, comparing all questions with the included text-based questions. The 60% pass mark is presented as a red line in (A) and (E) to provide context for the performance of ChatGPT (GPT-3.5 and GPT-4). In addition, (E) displays the percentile achieved by ChatGPT (GPT-3.5 and GPT-4) for each year’s examination, based on the percentile limits published by the Institut für Medizinische und Pharmazeutische Prüfungssfragen [37-39].
Table 1. Summary statistics for ChatGPT’s (GPT-3.5 and GPT-4) accuracy during the written German medical licensing examination, 2021-2022.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Overall (N=834)</th>
<th>Accuracy of GPT-3.5</th>
<th>Accuracy of GPT-4</th>
<th>P value</th>
<th>Accuracy of GPT-3.5</th>
<th>Accuracy of GPT-4</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Students' correct response rate (%)</td>
<td></td>
<td>False (n=523)</td>
<td>True (n=511)</td>
<td></td>
<td>False (n=105)</td>
<td>True (n=729)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>77 (18)</td>
<td>71 (18)</td>
<td>80 (16)</td>
<td>70 (18)</td>
<td>78 (17)</td>
<td>&lt;.001a</td>
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<td></td>
<td></td>
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<tr>
<td>Accuracy of GPT-3.5, n (%)</td>
<td></td>
<td>511 (61)</td>
<td>N/A</td>
<td>N/A</td>
<td>38 (36)</td>
<td>473 (65)</td>
<td>&lt;.001c</td>
</tr>
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<tr>
<td>Accuracy of GPT-4, n (%)</td>
<td></td>
<td>729 (87)</td>
<td>256 (79)</td>
<td>473 (93)</td>
<td>N/A</td>
<td>N/A</td>
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<tr>
<td>Readability score of the question, mean (SD)</td>
<td></td>
<td>14.96 (1.89)</td>
<td>14.93 (1.87)</td>
<td>14.98 (1.90)</td>
<td></td>
<td>14.91 (2.26)</td>
<td>14.97 (1.84)</td>
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<td>Question type, n (%)</td>
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<tr>
<td>Connected (key feature)</td>
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<tr>
<td></td>
<td></td>
<td>532 (64)</td>
<td>204 (63)</td>
<td>328 (64)</td>
<td>79 (75)</td>
<td>453 (62)</td>
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</tr>
<tr>
<td>Single question</td>
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<tr>
<td></td>
<td></td>
<td>302 (36)</td>
<td>119 (37)</td>
<td>183 (36)</td>
<td>26 (25)</td>
<td>276 (38)</td>
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<td>Images referenced in questions</td>
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<tr>
<td></td>
<td></td>
<td>84 (10)</td>
<td>23 (7.1)</td>
<td>61 (12)</td>
<td>17 (16)</td>
<td>67 (9.2)</td>
<td>.03c</td>
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<td>Specialty, n (%)</td>
<td></td>
<td></td>
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<td>Gynecology</td>
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<td>61 (19)</td>
<td>85 (17)</td>
<td>20 (19)</td>
<td>126 (17)</td>
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aWilcoxon rank-sum test.
bN/A: not applicable.
cPearson chi-square test.

After controlling for all other variables, correct student responses (GPT-3.5: OR 0.01, 95% CI 0.00-0.01, P<.001; GPT-4: OR 0.00, 95% CI 0.00-0.00, P=.003) and questions with images (GPT-3.5: OR 0.19, 95% CI 0.08-0.30, P<.001; GPT-4: OR –0.09, 95% CI –0.16 to –0.01, P=.02) emerged as significant predictors of GPT-3.5’s and GPT-4’s accuracy, regardless of the version. Furthermore, our analysis revealed that only questions pertaining to psychiatry were significant predictors of correct GPT-3.5 responses (OR 0.19, 95% CI 0.02-0.36, P=.03). In contrast, questions related to internal medicine (OR 0.10, 95% CI 0.00-0.19, P=.04) and surgery (OR 0.12, 95% CI 0.00-0.25, P=.049) were the only medical subspecialties significantly predicting accurate responses of GPT-4. Conversely, questions concerning scientific practice (OR –0.14, 95% CI –0.29 to 0.00, P=.05) were less likely to be answered correctly by GPT-4 (Table 2 and Figure 3). The question SMOG readability score, however, did not significantly impact ChatGPT’s accuracy.
Table 2. Regression analysis to compare ChatGPT’s (GPT-3.5 and GPT-4) accuracy during the written German medical licensing examination (2021-2022; N=833).

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>GPT-3.5</th>
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<th>GPT-4</th>
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<td></td>
<td>P value 95% CI</td>
<td>Odds ratio β P value 95% CI</td>
<td>Odds ratio β</td>
<td>P value 95% CI</td>
<td>P value 95% CI</td>
<td>Odds ratio β</td>
<td>P value 95% CI</td>
<td>Odds ratio β</td>
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<td>Students’ correct response rate</td>
<td>1.03</td>
<td>1.02 to 1.04 &lt;.001</td>
<td>.01</td>
<td>0.00 to 0.01 &lt;.001</td>
<td>1.02</td>
<td>1.01 to 1.03 &lt;.001</td>
<td>.00</td>
<td>0.00 to 0.00 .003</td>
</tr>
<tr>
<td>Accuracy of GPT-4</td>
<td>3.25</td>
<td>2.13 to 5.02 &lt;.001</td>
<td>.26</td>
<td>0.16 to 0.36 &lt;.001</td>
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<td>N/A N/A N/A</td>
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<tr>
<td>Accuracy of GPT-3.5</td>
<td>N/A</td>
<td>N/A N/A N/A N/A N/A N/A N/A</td>
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<td></td>
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</tr>
<tr>
<td>October 2021 examination</td>
<td>0.94</td>
<td>0.70 to 1.27 .68</td>
<td>.00</td>
<td>−0.08 to 0.08 .94</td>
<td>0.90</td>
<td>0.59 to 1.40 .64</td>
<td>.02</td>
<td>−0.04 to 0.07 .55</td>
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<tr>
<td>April 2022 examination</td>
<td>1.15</td>
<td>0.86 to 1.54 .35</td>
<td>.03</td>
<td>−0.05 to 0.11 .47</td>
<td>1.85</td>
<td>1.17 to 3.03 .01</td>
<td>.06</td>
<td>0.01 to 0.11 .03</td>
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<td>October 2022 examination</td>
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<td>N/A</td>
<td>0.63</td>
<td>0.42 to 0.96 .03</td>
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<td>Question type</td>
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<td>−.03</td>
<td>−0.10 to 0.04 .39</td>
<td>1.86</td>
<td>1.18 to 3.01 .01</td>
<td>.06</td>
<td>0.02 to 0.11 .007</td>
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<tr>
<td>Images referenced in questions</td>
<td>1.77</td>
<td>1.09 to 2.98 .03</td>
<td>.19</td>
<td>0.08 to 0.30 &lt;.001</td>
<td>0.52</td>
<td>0.30 to 0.96 .03</td>
<td>−.09</td>
<td>−0.16 to −0.01 .02</td>
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<td>Other specialty</td>
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<td>0.71 to 1.30 .80</td>
<td>.00</td>
<td>−0.13 to 0.14 .94</td>
<td>0.57</td>
<td>0.37 to 0.86 .007</td>
<td>.02</td>
<td>−0.07 to 0.11 .73</td>
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<td>Gynecology and obstetrics</td>
<td>1.62</td>
<td>0.84 to 3.33 .17</td>
<td>.12</td>
<td>−0.06 to 0.31 .19</td>
<td>0.71</td>
<td>0.32 to 1.78 .42</td>
<td>.01</td>
<td>−0.12 to 0.14 .88</td>
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<td>Surgery</td>
<td>0.62</td>
<td>0.33 to 1.14 .12</td>
<td>−.12</td>
<td>−0.30 to 0.31 .18</td>
<td>2.03</td>
<td>0.72 to 8.49 .24</td>
<td>.12</td>
<td>0.00 to 0.25 .049</td>
</tr>
<tr>
<td>Internal medicine</td>
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<td>0.66 to 1.30 .63</td>
<td>−.02</td>
<td>−0.15 to 0.12 .81</td>
<td>1.7</td>
<td>0.99 to 3.14 .07</td>
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<td>0.00 to 0.19 .043</td>
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<tr>
<td>Infectious diseases</td>
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<td>0.82 to 2.28 .24</td>
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<td>−0.10 to 0.22 .48</td>
<td>1.7</td>
<td>0.78 to 4.48 .23</td>
<td>.09</td>
<td>−0.02 to 0.20 .11</td>
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<td>1.57 to 5.40 .005</td>
<td>.19</td>
<td>0.02 to 0.36 .03</td>
<td>1.44</td>
<td>0.62 to 4.23 .45</td>
<td>.03</td>
<td>−0.09 to 0.15 .61</td>
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<td>Neurology</td>
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<td>0.49 to 1.08 .12</td>
<td>−.04</td>
<td>−0.18 to 0.11 .61</td>
<td>1.23</td>
<td>0.68 to 2.45 .52</td>
<td>.08</td>
<td>−0.02 to 0.11 .11</td>
</tr>
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<td>N/A</td>
<td>0.64</td>
<td>0.34 to 1.34 .21</td>
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<td>Diagnostic competence</td>
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<td>0.70 to 1.23 .60</td>
<td>−.03</td>
<td>−0.17 to 0.11 .67</td>
<td>1.22</td>
<td>0.81 to 1.85 .33</td>
<td>−.05</td>
<td>−0.14 to 0.05 .34</td>
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<td>Therapeutic competence</td>
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<td>0.60 to 1.24 .41</td>
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<td>−0.19 to 0.12 .65</td>
<td>0.89</td>
<td>0.54 to 1.54 .66</td>
<td>−.06</td>
<td>−0.16 to 0.05 .28</td>
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<td>.08</td>
<td>−0.09 to 0.24 .36</td>
<td>1.00</td>
<td>0.55 to 1.94 &gt;.99</td>
<td>−.05</td>
<td>−0.16 to 0.36 .06</td>
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<td>Prevention competence</td>
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<td>.00</td>
<td>−0.20 to 0.20 &gt;.99</td>
<td>0.71</td>
<td>0.31 to 1.93 .45</td>
<td>−.11</td>
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<td>.01</td>
<td>−0.20 to 0.22 .95</td>
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<td>0.21 to 1.09 .06</td>
<td>−.14</td>
<td>−0.29 to 0.05 .00</td>
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<td>N/A</td>
<td>1.66</td>
<td>0.66 to 5.61 .34</td>
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<td>0.94 to 1.09 .70</td>
<td>.01</td>
<td>−0.01 to 0.03 .24</td>
<td>1.02</td>
<td>0.91 to 1.14 .76</td>
<td>.00</td>
<td>−0.01 to 0.01 .98</td>
</tr>
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</table>

aN/A: not applicable.
**Discussion**

**Principal Findings**

With the introduction of ChatGPT’s GPT-3.5 and GPT-4 iterations, the potential application for AI in research, patient care, and medical education is gaining recognition [2,8,40]. By improving the users’ experience and facilitating more efficient information retrieval, ChatGPT might even revolutionize the future of search engines and shift the focus of medical education from memorization to practical application [8,10,11].

Under this premise, the nearly passing scores of the freely available GPT-3.5 iteration, along with the exceptional scores of GPT-4, are highly relevant. Even with the varying scores of 51%-67% of GPT-3.5 across various input languages [13-15,41,42], both models consistently outperform most prominent general and domain-specific LLMs, such as
InstructGPT (53%), GPT-3 (25%), and BioMedLM (50%) [14,43,44]. Despite these improvements, GPT-3.5’s or GPT-4’s performance still fell short in comparison to that of medical students in a Japanese medical examination according to the study by Takagi et al [15]. In comparison to the German medical students, however, GPT-3.5 scored in the 8.6th percentile, while GPT-4 ranked in the 92.8th, 99.5th, and 92.6th percentiles in the October 2021, April 2022, and October 2022 examinations [39,45,46]. The observed variations in the AI’s accuracy across input languages may partially reflect the language composition of their data sets, as LLMs tend to favor languages that are more represented in their training data [16,17]. Since ChatGPT appears to perform optimally with English inputs, language emerges as a limiting factor for its accuracy, suggesting that globally consistent application is dependent upon users’ proficiency in English.

Moreover, the nearly 30% performance increase from GPT-3.5 to GPT-4, as indicated in this study and supported by a Japanese study, which suggests a similar language distribution within the GPT-3.5 and GPT-4 data sets [15]. GPT-4, unlike GPT-3.5, also did not answer questions containing images on repetition, showing an improvement in the previously incorrect content produced by GPT-4’s predecessor [17].

Thus, health care professionals could potentially benefit, especially from GPT-4’s conclusive and often nonobvious insights to multiple-choice questions, as these users have the ability to verify crucial details [13,14,41]. For instance, there is potential for using GPT-3.5 and GPT-4 in a medical education tutoring environment, as evidenced by its successful application in anatomy [47]. However, when using either GPT-3.5 or GPT-4 for medical applications, its differing accuracy across specialties must also be taken into account [48]. GPT-3.5 initially displayed a high degree of accuracy within the field of psychiatry, while GPT-4 demonstrated its strength in internal medicine and surgery. Considering the rising prevalence of psychiatric disorders and concomitant challenges in providing care, it seems likely that nonprofessionals would also turn to the chatbot for mental health issues at the time of GPT-3.5’s release [8,49,50]. Hence, it is conceivable that GPT-3.5’s training data set includes not only a substantial and reliable portion of psychiatric data, but also its developers might have first fine-tuned ChatGPT specifically in this domain in anticipation of its high demand [51-53]. Thus, the developers might have also fine-tuned GPT-4 specifically in internal medicine and surgery, possibly reacting to a high demand in this area from users of its predecessor. GPT-4’s impressive performance is not limited to the medical field, as it demonstrated comparable percentile scores in the Uniform Bar Exam, showcasing its potential as a versatile tool across diverse academic disciplines [17]. However, assessing the possible reasons for the performance differences between GPT-3.5 and GPT-4 is complicated by the confidential architecture of GPT-4 [54], posing challenges for research on future applications.

In turn, GPT-4’s excellent achievements shed light on the limitations of current testing paradigms in medical education that often favor rote memorization over a critical and context-aware approach. They also highlight the inadequacy of multiple-choice questions as a means of assessing medical knowledge, as they tend to encourage binary thinking as “true” and “false,” which often fails to capture the complex reality of the medical practice [11]. Although GPT-3.5 and GPT-4 allow the simple and fast retrieval of medical information from any internet-capable device that fits in one’s pocket [9,10], neither GPT-3.5 nor GPT-4 verifies the information they provide. Thus, ChatGPT’s output needs to be approached with a critical mindset, recognizing that misinformation may be more difficult to detect than in the output of other search engines that offer multiple sources in response to a query and take login credentials into account [8,55]. To navigate these changing informational landscapes, a basic understanding in data science seems necessary alongside traditional medical expertise [56]. It may even be beneficial for future iterations of AI tools to include references to the sources underlying each search in order to increase transparency and allow users to assess the reliability of the information they receive.

In a previous study by Nov et al [57], considering that 59% of participants trusted chatbots more than traditional search engines, it must be noted that GPT-3.5 and GPT-4 have only been tested on medical examination questions and not questions by nonprofessionals, limiting general recommendations for unsupervised patient education or the general population. It seems evident that GPT-4 has been benchmarked against medical licensing examinations, explaining not only GPT-4’s excellent scores but also exceeding achievements in internal medicine and surgery, which, for instance, have been overrepresented in the medical examinations assessed in this study [12,17].

Since GPT-3.5 failed the German medical licensing examination by a narrow margin, its use for answering medical questions is generally not advisable. Moreover, the remarkable performance of GPT-4 in the German Medical State Examination may not be universally applicable outside a medical examination setting, especially considering that GPT-4 was presumably benchmarked on academic and professional examinations [17].

As literature on ChatGPT is scarce, and it can be difficult to detect incorrect output from this AI tool, the content it generates must be carefully assessed. Nevertheless, medical professionals may still be able to benefit from GPT-3.5’s and GPT-4’s explanations and, in some cases, gain new nonobvious insights. With the release of GPT-4’s ability to handle pictures on the horizon, the potential for further applications of GPT-3.5 and GPT-4 to improve the medical workflow or medical education seems eminent, emphasizing the need for continued research into AI.

Limitations

This study’s findings on GPT-3.5’s and GPT-4’s medical proficiencies are limited to multiple-choice questions from the German medical licensing examination, which may not be representative of other types of examinations or contexts. However, it is worth noting that GPT-3.5 and GPT-4 have demonstrated similar performances in examinations in other countries and languages, which suggests some degree of generalizability.

https://mededu.jmir.org/2024/1/e50965

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In addition, the sample size of 937 questions and the exclusion of image-based questions may not capture the full range of difficulty levels or content areas. Although the collected parameters did not differ in terms of GPT-3.5’s and GPT-4’s accuracy in the excluded cases, the decision to exclude image-based questions may have introduced a sampling bias. By testing for differences, efforts were made to minimize this bias and maintain the integrity of the results.

As GPT-3.5’s and GPT-4’s performances were compared to those of German medical students using the MEDI-LEARN service, a selection bias might have been introduced. However, the high correlation between the MEDI-LEARN statistics and the IMPP statistics indicates at best a weak expression of this selection bias [58].

It should also be noted that a replication of this study might not yield the exact same results, as the literature suggests that GPT-3.5 is inconsistent in answering 15% of medical questions [59]. However, the trends observed in this study appear to be consistent with those reported in other published and preprint studies on GPT-3.5’s and GPT-4’s performance.

Conclusions

In conclusion, the results of this study indicate that only GPT-4 consistently passed all 3 medical examinations, ranking in the 92.8th to 99.5th percentile in comparison to medical students. These findings highlight the strengths and limitations of ChatGPT in the context of medical examinations and raise questions about the future of medical education.

Although GPT-3.5’s and GPT-4’s accuracy in medical examinations seems consistent across different countries and languages, its inconsistencies, potential biases, and number of incorrect answers restrain a recommendation for its use by the general population for medical purposes. However, its elaborate explanations and potential to yield nonobvious insights may benefit medical professionals in training.

While this study hints to a moderate accuracy of GPT-3.5 and a stellar performance of GPT-4 in answering medical examination questions, further research is necessary to gain deeper insights, explore future applications, and ensure safe use of ChatGPT for end users.

Acknowledgments

The authors thank Dorothee Meyer, Linea Luise Fuchs, Ari Soleman, GPT-3.5, and GPT-4 for proofreading this manuscript. In this study, we used ChatGPT for several purposes: to translate our manuscript into English, to refine its linguistic presentation, to evaluate and improve our methodological approach, and to scrutinize the R code underlying our statistical analysis, with a particular focus on identifying and resolving any error warnings generated. Subsequently, all outputs provided by ChatGPT were rigorously reviewed and critically appraised by the authors to ensure accuracy and reliability.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Responses of (A) GPT-3.5 and (B) GPT-4 to the queries on its ability to pass a medical exam, 2023.

[DOCX File, 592 KB - mededu_v10i1e50965_app1.docx]

Multimedia Appendix 2

Summary statistics for all questions regarding exam time and ChatGPT’s (GPT-3.5 and GPT-4) accuracy in the German medical licensing exam, 2021-2022.

[DOCX File, 21 KB - mededu_v10i1e50965_app2.docx]

Multimedia Appendix 3

Summary statistics for excluded questions regarding ChatGPT’s (GPT-3.5 and GPT-4) accuracy in the German medical licensing exam, 2021-2022.

[DOCX File, 20 KB - mededu_v10i1e50965_app3.docx]

Multimedia Appendix 4

Summary statistics for included questions regarding exam time in the German medical licensing exam, 2021-2022.

[DOCX File, 17 KB - mededu_v10i1e50965_app4.docx]

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Abbreviations

- **AI**: artificial intelligence
- **IMPP**: Institut für Medizinische und Pharmazeutische Prüfungsfragen
- **LLM**: large language model
- **SMOG**: Simple Measure of Gobbledygook

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Performance of ChatGPT on the Chinese Postgraduate Examination for Clinical Medicine: Survey Study

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Abstract

Background: ChatGPT, an artificial intelligence (AI) based on large-scale language models, has sparked interest in the field of health care. Nonetheless, the capabilities of AI in text comprehension and generation are constrained by the quality and volume of available training data for a specific language, and the performance of AI across different languages requires further investigation. While AI harbors substantial potential in medicine, it is imperative to tackle challenges such as the formulation of clinical care standards; facilitating cultural transitions in medical education and practice; and managing ethical issues including data privacy, consent, and bias.

Objective: The study aimed to evaluate ChatGPT’s performance in processing Chinese Postgraduate Examination for Clinical Medicine questions, assess its clinical reasoning ability, investigate potential limitations with the Chinese language, and explore its potential as a valuable tool for medical professionals in the Chinese context.

Methods: A data set of Chinese Postgraduate Examination for Clinical Medicine questions was used to assess the effectiveness of ChatGPT’s (version 3.5) medical knowledge in the Chinese language, which has a data set of 165 medical questions that were divided into three categories: (1) common questions (n=90) assessing basic medical knowledge, (2) case analysis questions (n=45) focusing on clinical decision-making through patient case evaluations, and (3) multichoice questions (n=30) requiring the selection of multiple correct answers. First of all, we assessed whether ChatGPT could meet the stringent cutoff score defined by the government agency, which requires a performance within the top 20% of candidates. Additionally, in our evaluation of ChatGPT’s performance on both original and encoded medical questions, 3 primary indicators were used: accuracy, concordance (which validates the answer), and the frequency of insights.

Results: Our evaluation revealed that ChatGPT scored 153.5 out of 300 for original questions in Chinese, which signifies the minimum score set to ensure that at least 20% more candidates pass than the enrollment quota. However, ChatGPT had low accuracy in answering open-ended medical questions, with only 31.5% total accuracy. The accuracy for common questions, multichoice questions, and case analysis questions was 42%, 37%, and 17%, respectively. ChatGPT achieved a 90% concordance across all questions. Among correct responses, the concordance was 100%, significantly exceeding that of incorrect responses (n=57, 50%; P<.001). ChatGPT provided innovative insights for 80% (n=132) of all questions, with an average of 2.95 insights per accurate response.
Conclusions: Although ChatGPT surpassed the passing threshold for the Chinese Postgraduate Examination for Clinical Medicine, its performance in answering open-ended medical questions was suboptimal. Nonetheless, ChatGPT exhibited high internal concordance and the ability to generate multiple insights in the Chinese language. Future research should investigate the language-based discrepancies in ChatGPT’s performance within the health care context.

KEYWORDS
ChatGPT; Chinese Postgraduate Examination for Clinical Medicine; medical student; performance; artificial intelligence; medical care; qualitative feedback; medical education; clinical decision-making

Introduction
Artificial intelligence (AI) was initially conceptualized in 1956 [1], but it has only gained significant momentum in recent years. AI aims to replicate human intelligence and thinking processes through the use of brain-like computer systems to solve complex problems. What is most inspiring is that AI systems can be trained on specific data sets to improve prediction accuracy and tackle intricate problems [2-4], which means that one of the possible applications of AI is the ability to help doctors to rapidly search through vast amounts of medical data, enhancing their creativity and enabling them to make error-free decisions [5,6].

ChatGPT (OpenAI) is an AI model that has spurred great attention due to the revolutionary innovations in its ability to perform a diverse array of natural language tasks. By using a class of large-scale language models, ChatGPT (version 3.5) can predict the likelihood of a sequence of words based on the context of the preceding words. With sufficient training on vast amounts of text data, ChatGPT can generate novel word sequences that closely resemble natural human language and have never been observed before by other AI [7].

A study was conducted on the effectiveness of the version of generative pretrained transformer’s large-scale language model (ChatGPT, version 3.5) in passing the United States Medical Licensing Examination (USMLE). The results showed that the AI model achieved an accuracy rate of over 50% in all the tests, and in some analyses, it even surpassed 60% accuracy. It is imperative to highlight and emphasize that the study was conducted mostly using English input, and the AI model was also trained in English.

However, despite the success of AI models like ChatGPT in the English language, their performance in understanding and generating medical text in the Chinese language remains largely unexplored because ChatGPT’s ability to understand and generate text in any given language is limited by the quality and quantity of training data available in that language. Chinese is the second-most widely spoken language in the world, with more than 1.3 billion speakers globally, while the quality and quantity of Chinese language data may not be compared with English due to some reasons, such as complexity of the written characters. Thus, the performance of ChatGPT in Chinese medical information warrants further investigation.

In this study, ChatGPT’s clinical reasoning ability was evaluated by administering questions from the Chinese Postgraduate Examination for Clinical Medicine. This standardized and regulated test assesses candidates’ comprehensive abilities. The questions are textually and conceptually dense, and the difficulty and complexity of the questions are highly standardized and regulated. Additionally, this examination has demonstrated remarkable stability in raw scores and psychometric properties over the past years. Moreover, the examination comprises 43% (n=71) basic science and medical humanities, with 14% (n=23) physiology, 10% (n=17) biochemistry, 13% (n=28) pathology, and 6% (n=10) medical humanities. Clinical medicine makes up the remaining 57% (n=94), with internal medicine and surgery accounting for 37% (n=61) and 20% (n=33), respectively. Due to the examination’s linguistic and conceptual complexity, we hypothesize that it will serve as an excellent challenge for ChatGPT. By evaluating ChatGPT’s performance on this examination, we aimed to gain insights into the AI model’s potential for understanding and generating medical text in Chinese and assess its applicability in Chinese medical education and clinical practice.

Methods

Ethical Considerations
This study does not involve direct interaction with human participants or the collection of personal identifiable information. As a result, it falls under the category of nonhuman subject research. Therefore, no human subject ethics review approvals were required for this study. Since this study does not involve human participants or the collection of personal identifiable information, obtaining informed consent from individuals is not applicable. As this study does not involve the collection or use of personal identifiable information, privacy and confidentiality concerns are not applicable. Since this study does not involve human participants, there is no compensation provided to individuals.

Artificial Intelligence
ChatGPT uses self-attention mechanisms and extensive training data to generate contextually relevant responses in a conversational setting. It excels in managing long-range dependencies and creating coherent replies. However, it is important to clarify that ChatGPT (version 3.5), a server-based language model, does not possess internet browsing or search functionalities. Consequently, its responses are constructed solely on abstract relationships between words or “tokens” within its neural network [7]. Furthermore, it should be noted that OpenAI released the latest version, ChatGPT (version 4), in March 2023, but the data in this study were from February 2023, when ChatGPT (version 3.5) was the most recent version.
Input Source

The Chinese Postgraduate Examination for Clinical Medicine questions from 2022 were not officially released. However, a comprehensive set of 165 questions totaling 500 points was found on the web (Table S1 in Multimedia Appendix 1) and treated as original questions. Point values differed among question types: each case analysis question (CAQ) and multichoice question (MCQ) was worth 2 points, while common questions (CQs) were either worth 1.5 or 2 points each. All inputs fed into the ChatGPT (version 3.5) model were valid samples, not part of the training data set. This was due to the database not being updated since September 2021, predating the release of these questions. For future research convenience, the 165 questions were categorized into three types:

1. CQs (n=90): These questions are to evaluate the knowledge of basic science in physiology, biochemistry, pathology, and medical humanities. Each question has 4 choices, and the respondent should select only the correct answers. For example: “The closure time of the aortic valve during the cardiac cycle is? (A) Atrial systolic end card, (B) Rapid ejection beginning, (C) Slow ejection beginning, (D) Isovolumic diastole beginning.”

2. CAQs (n=45). It is a method used in clinical medicine to examine and evaluate patient cases. It involves an in-depth review of a patient’s medical history, presenting symptoms, laboratory and imaging results, and diagnostic findings to arrive at a diagnosis and treatment plan. There are 4 choices, and the respondent should select only the correct answers. The difference between CAQs and CQs is that CAQs focus on clinical decision-making. For example: “A 38-year-old male, suffering chest pain and fever for 3 days, having a 5 years of diabetes history. Physical examination: t=37.6°C, right lower lung turbid knock, breathing sound is reduced. A chest X radiograph suggests a right pleural effusion. Pleural aspiration liquefaction test showed WBC 650×10⁶/L with fine lymph Cell 90% in pleural fluid, with glucose of 3.2 mmol/L, the diagnosis for this patient is? (A) Tuberculous pleurisy, (B) Malignant pleural effusion, (C) Empyema, (D) Pneumonia-like pleural effusion.”

3. MCQs (n=30): There are 4 choices, and the respondent should select at least 2 correct answers. There is no point for choosing more or less. For example: “The structures of auditory bone conduction include? (A) Skull, (B) Round window film, (C) Ossicular chain, (D) Cochlear bone wall.”

Scoring

Initially, the question format had to be adjusted to properly evaluate the performance of ChatGPT in the Chinese Postgraduate Examination for Clinical Medicine questions. Specifically, we included a “multichoice” or “single-choice” notation, as we found ChatGPT’s responses varied without these cues. MCQs were adjusted to state “Please choose one or more correct options,” while CQs and CAQs were altered to indicate “There is only one correct answer.” This adjustment was necessary for evaluating ChatGPT’s performance in the Chinese language.

We then compiled a data set of these examination questions along with their correct answers. To ensure validity, the answers were cross-verified with web-based resources and consultations with senior doctors. ChatGPT’s performance was then evaluated by comparing its responses to the standard answers in the data set. A high examination score would suggest that ChatGPT handled this task effectively. In our comprehensive analysis, we also delved into examining the correlation between different question types and accuracy using the Pearson correlation coefficient as a statistical measure to investigate this relationship.

Encoding

The structured examination questions were transformed into open-ended inquiries for better simulation of real-world clinical scenarios. Multiple-choice questions for the CAQ were removed, and ChatGPT was required to diagnose the patient’s disease and prove its reason.

Regarding the MCQs, we eliminated all the choices and did not prompt ChatGPT about the existence of multiple correct answers. The CQs were treated similarly to the MCQs. However, we encountered a distinct subset within these 3 categories that could not be processed like the other questions. This subset comprised questions that required 1 answer choice to be selected from the provided options. Therefore, these questions were converted into a special format (n=26).

For instance, an original question like, “Which can inhibit insulin secretion? (A) Increased free fatty acids in blood, (B) Increased gastric inhibitory peptide secretion, (C) Sympathetic nerve excitation, (D) Growth hormone secretion increases” was reformatted as “Can an increase in free fatty acids in the blood, an increase in gastric inhibitory peptide secretion, an increase in sympathetic nerve excitation, or an increase in growth hormone secretion inhibit insulin secretion?” This encoding strategy was applied across all 3 subgroups.

Additionally, to mitigate potential memory retention bias, we commenced a new chat session for each query. This process of reformatting questions, presenting them to ChatGPT, and initiating new sessions for each question constituted our methodology for evaluating ChatGPT’s performance using the data set. The clarity of this process should address the concerns raised in the comment about the lack of understanding of the way we used the data set for evaluation.

Adjudication

To assess ChatGPT’s performance thoroughly, 2 physicians independently scored AI outputs for accuracy, concordance, and insight using predefined criteria (Table S2 in Multimedia Appendix 1). These physicians were not aware of each other’s evaluations. To familiarize the physicians with the scoring system, a subset of 20 questions was used for training, during which the physicians were unblinded to each other’s assessments.

ChatGPT’s responses were classified into 3 categories under the accuracy parameter: accurate, inaccurate, and indeterminate. “Accurate” responses were those where ChatGPT provided the right answer, while “inaccurate” encompassed instances of no answer, an incorrect response, or multiple answers containing incorrect options. “Indeterminate” responses were those where
the AI output did not present a definitive answer, suggesting insufficient information to make a selection.

Concordance was determined by whether ChatGPT’s explanation affirmed its provided answer, with discordance occurring if the explanation contradicted the answer. We defined valuable insights as unique text segments within the AI’s explanations meeting specific criteria: they were nondefinitional, nonobvious, valid, and unique. These insights required additional knowledge or deductions beyond the input question, provided accurate clinical or numerical information, and potentially eliminated multiple answer choices with a single insight.

To mitigate potential within-item anchoring bias, the adjudicators first evaluated the accuracy for all items, followed by concordance. In case of discrepancies in domain assessments, a third physician adjudicator was consulted. This third-party intervention was required for 11 items (n=11, 7% of the data set). We used the Cohen \( \kappa \) statistic to evaluate the interrater agreement between the physicians for the questions (Table S3 in Multimedia Appendix 1). A schematic overview of the study protocol is presented in Figure 1 to provide a clearer understanding of our methodology.

### Results

**ChatGPT Performs Poor Toward the Original Questions**

After inputting the original questions into ChatGPT and collecting their answers, ChatGPT received a score of 153.5 out of 300, which means that it only obtained 51.2% of the total points on the test. This score is much lower than expected but slightly higher than the passing threshold (129/300) defined by official agencies.

Among 3 subgroups of questions, the evaluation revealed that of a total of 90 CQs, ChatGPT only provided 50 (56%, 95% CI 45%-66%) correct answers. Similarly, of 45 CAQs, ChatGPT provided 25 (56%, 95% CI 41%-70%) correct answers. Furthermore, of 30 MCQs, ChatGPT provided 10 (33%, 95% CI 16%-50%) completely accurate answers (Figure 2). These results suggest that ChatGPT’s ability to resolve medical problems in Chinese needs to be improved.

Additionally, we have noticed a Pearson correlation coefficient value of approximately 0.228. This finding suggests a relatively weak correlation between the different question types and the accuracy of the responses.
ChatGPT Performs Worse on Encoded Questions Compared to the Original Questions

We encoded questions from the Chinese Postgraduate Examination for Clinical Medicine and inputted them into ChatGPT, which simulates scenarios where a student answers a common medical question without any choices or a doctor tries to diagnose a patient based on multimodal clinical data (ie, symptoms, history, physical examination, and laboratory values). ChatGPT’s accuracy for all questions was 31.5%. Among the 3 subgroups, namely, CQs, MCQs, and CAQs, the accuracy was 42%, 37%, and 17%, respectively (Figure 2). Compared to the original questions, the accuracy of the encoding questions decreased by 19%, 17%, and 17% for CQs, MCQs, and CAQs, respectively, which demonstrates that the ability of ChatGPT to answer the open-ended questions in Chinese is a shortcoming. During the adjudication stage, there was substantial agreement among physicians on prompts in all 3 subgroups (κ ranged from 0.80 to 1.00).

ChatGPT Demonstrates High Internal Concordance

Concordance, which is a measure of the level of agreement or similarity between the option selected by AI and its subsequent explanation, was also taken into consideration. The results showed that ChatGPT achieved 90% concordance across all questions, and this high concordance was maintained across all 3 subgroups (Figure 3). Additionally, we analyzed the concordance difference between correct and incorrect answers and found that concordance among accurate responses was perfect and significantly greater than among inaccurate responses (n=52, 100% vs n=113, 50%; P<.001; Figure 3). These findings suggest that ChatGPT has a high level of answer-explanation concordance in Chinese, likely due to its strong internal consistency in its probabilistic language model.
ChatGPT Shows Multiple Insights Toward the Same Questions

Another evaluation index considered was the frequency of insights generated by the AI model that quantifies the quantity of insights produced. After evaluating the score, accuracy, and concordance of ChatGPT, its potential was investigated to enhance medical education by augmenting human learning. We analyzed the frequency of insights provided by ChatGPT. Remarkably, ChatGPT generated at least 1 significant insight in 80% (n=132) of all questions (Figure 4). Moreover, the analysis revealed that the accuracy response had the highest frequency of insights with an average of 2.95. The indeterminate response followed closely behind with an average of 2.7, while the inaccurate response had a lower frequency of insights with an average of 1.39 (Figure 4). The high frequency of insights in the accurate group suggests that it may be feasible for a target learner to acquire new or remedial knowledge from the ChatGPT AI output.

Discussion

Major Findings

To evaluate ChatGPT’s problem-solving capabilities and assess its potential for Chinese medical education integration, its performance on the Chinese Postgraduate Examination for Clinical Medicine was tested. We had two major findings: (1) the score of ChatGPT needs to be improved when facing questions asked in the Chinese language and (2) there is still potential for this AI to generate novel performance that can assist humans due to the high concordance and the frequency of insights. This is the first study to assess the performance of ChatGPT in medical care and clinical decisions in Chinese.
ChatGPT's Performance Needs Improvement for Medical Questions in Chinese

A recent study showed that ChatGPT (version 3.5) performed with an accuracy rate of over 50% across all examinations and even exceeded 60% accuracy in some analyses when facing the USMLE [7]. Our results indicate that ChatGPT exhibited moderate accuracy in answering open-ended medical questions in Chinese, with an accuracy of 31.5%. Given the differences between English and Chinese inputs, it suggests that ChatGPT requires further improvement in answering medical questions in the Chinese language.

We sought to understand why there is a significant discrepancy between the performance of ChatGPT on Chinese and English language examinations. To investigate this, we asked the ChatGPT for the reasons, it explains that the training data used to train AI in different languages may be different, and the algorithms used to process and analyze text may vary from language to language (data not shown). Therefore, even for the same question, the output generated may vary slightly based on the language and the available language-based data.

Upon analyzing the results of this research, we found that the accuracy of ChatGPT was lowest for MCQs, followed by CQs and CAQs. The lower accuracy on MCQs may be due to the model being undertrained on the input as well as the MCQ samples being significantly less than those of single-choice questions. On the other hand, the CAQs may have extensive training compared to MCQs and are similar in type to the USMLE question.

Furthermore, we noticed that high accuracy outputs were associated with high concordance and a high frequency of insight, whereas poorer accuracy was linked to lower concordance and a lack of insight. Thus, it was hypothesized that inaccurate responses were primarily driven by missing information, which could result in reduced insight and indecision in the AI, rather than an overcommitment to an incorrect answer [7]. The results indicate that enhancing the database and providing additional training with Chinese questions could substantially improve the performance of the model.

Challenges of AI in Future Applications

Despite the promising potential of AI in medicine, it also poses some challenges. Standards for using AI in health care still need to be developed [8,9], including clinical care, quality, safety, malpractice, and communication guidelines. Furthermore, the implementation of AI in health care requires a shift in medical culture, which poses a challenge for both medical education and practice. Additionally, ethical considerations must be taken into account, such as data privacy, informed consent, and bias prevention, to ensure that AI is used ethically and for the benefit of patients. Surprisingly, a recently launched AI system for autonomous detection of diabetic retinopathy carries medical malpractice and liability insurance [10].

Prospective of AI

AI is a rapidly growing technology. At the time of writing, ChatGPT (version 4) has been released with significant improvements. Numerous practical and observational studies have demonstrated the versatile role of AI in almost all medical disciplines and specialties, particularly in improving risk assessment [11,12], data reduction, clinical decision support [13,14], operational efficiency, and patient communication [15,16]. We anticipate that advanced language models such as ChatGPT are reaching a level of maturity that will soon have a significant impact on clinical medicine, enhancing the delivery of personalized, compassionate, and scalable health care.

A comparison of ChatGPT's performance with other AI models, particularly in the context of Chinese language performance, could yield more comprehensive insights and underscore the unique challenges of using AI in diverse linguistic landscapes. However, this was primarily due to the fact that AI models that focus on other aspects, while enhancing medical education and achieving promising results in medical question answering, are mostly developed and evaluated using English language data sets. This limitation restricts their applicability for performance comparisons in the context of the Chinese language.

Limitations

One limitation of this research is the small sample size. We only accessed 165 samples to qualify its accuracy and 30 CAQs to qualify its concordance and frequency of insight due to the limitations of the data, which focused solely on the diagnosis of the patient. Furthermore, the clinical situation is more complicated than the test, and larger and deeper analyses were needed. Finally, bias and error were inevitable in human adjudication, although there was a good interrater agreement between the physicians for the adjudication.

Moreover, comparing ChatGPT’s performance with other AI models, especially in the context of Chinese language, can provide valuable insights and highlight the distinctive challenges associated with leveraging AI in diverse linguistic environments. One notable factor contributing to this need for comparison is the prevalence of AI models such as Bidirectional Encoder Representations from Transformers, CLUE-Med, and MedQA that have made significant contributions to medical education and demonstrated promising outcomes in medical question answering. However, these models have predominantly been developed and assessed using English language data sets. This particular limitation hampers their suitability for conducting performance assessments within the Chinese language domain.

Conclusions

In conclusion, although the ChatGPTs got a score over the passing score in the Chinese Postgraduate Examination for Clinical Medicine, the performance was limited when presented with open-ended questions. On the other hand, ChatGPT demonstrated a high level of internal concordance, which suggests that the explanations provided by ChatGPT support and affirm the given answers. Moreover, ChatGPT generated multiple insights toward the same questions, demonstrating its potential for generating a variety of useful information. Further prospective studies are needed to explore whether there is a language-based difference in the performance of medical education settings and clinical decision-making, such as Chinese and minority languages.
Acknowledgments
The authors acknowledge ChatGPT for polishing their paper.

Data Availability
All data generated or analyzed during this study are included in this published paper (and Multimedia Appendix 1).

Authors’ Contributions
Xiao Liu was responsible for the entire project and revised the draft. CF, AA, and YW performed the data extraction, statistical analysis, and interpretation of the data. WZ, Z Chen, YZ, and JW drafted the first version of the paper. All authors participated in the interpretation of the results and prepared the final version of the paper.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Original questions, adjudication criteria for accuracy and concordance, and κ statistic for interrater agreement between adjudicating physicians.

References


Abbreviations

- **AI**: artificial intelligence
- **CAQ**: case analysis question
- **CQ**: common question
- **MCQ**: multiple-choice question
- **USMLE**: United States Medical Licensing Examination
Original Paper

Cocreating an Automated mHealth Apps Systematic Review Process With Generative AI: Design Science Research Approach

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Abstract

Background: The use of mobile devices for delivering health-related services (mobile health [mHealth]) has rapidly increased, leading to a demand for summarizing the state of the art and practice through systematic reviews. However, the systematic review process is a resource-intensive and time-consuming process. Generative artificial intelligence (AI) has emerged as a potential solution to automate tedious tasks.

Objective: This study aimed to explore the feasibility of using generative AI tools to automate time-consuming and resource-intensive tasks in a systematic review process and assess the scope and limitations of using such tools.

Methods: We used the design science research methodology. The solution proposed is to use cocreation with a generative AI, such as ChatGPT, to produce software code that automates the process of conducting systematic reviews.

Results: A triggering prompt was generated, and assistance from the generative AI was used to guide the steps toward developing, executing, and debugging a Python script. Errors in code were solved through conversational exchange with ChatGPT, and a tentative script was created. The code pulled the mHealth solutions from the Google Play Store and searched their descriptions for keywords that hinted toward evidence base. The results were exported to a CSV file, which was compared to the initial outputs of other similar systematic review processes.

Conclusions: This study demonstrates the potential of using generative AI to automate the time-consuming process of conducting systematic reviews of mHealth apps. This approach could be particularly useful for researchers with limited coding skills. However, the study has limitations related to the design science research methodology, subjectivity bias, and the quality of the search results used to train the language model.

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KEYWORDS

generative artificial intelligence; mHealth; ChatGPT; evidence-base; apps; qualitative study; design science research; eHealth; mobile device; AI; language model; mHealth intervention; generative AI; AI tool; software code; systematic review; language model

Introduction

The delivery of health-related services through the use of mobile devices (mHealth) [1] has been growing at a tremendous pace. A decade ago, in the first “era of mHealth,” the literature surrounding mHealth called for the generation of evidence demonstrating the impact of mHealth solutions on health system processes and patient outcomes [2]. In 2013, Labrique et al [2]
conducted a preliminary search on the US federal clinical trials database (ClinicalTrials.gov) and had to combine the keywords “mHealth,” “mobile,” and “cell AND phone” to obtain 1678 studies and their results. Today, that same number can be obtained using “mHealth” alone as a keyword. As the need for mHealth evidence has grown, so too has the necessity for summarizing both the state of the art and the practice.

Systematic reviews seek to collect and combine relevant evidence within the specific scope of a research question while also striving to minimize bias [3,4]. In PubMed alone, the number of systematic reviews published on digital health–related topics has increased a hundredfold in the last 10 years. In fact, the pace at which the mHealth field is developing for certain conditions like breast cancer is such that systematic reviews can be found every 2 or 3 years [5-9]. The systematic review process, however, is a time- and resource-intensive process, reportedly requiring a median of 5 researchers and approximately 40 weeks of work to reach submission [10-12].

The emergence of generative AI has been seen as a breakthrough in the field of automation. With the ability to generate content such as text, images, and even music, AI has been reported as a potential solution to tedious time-consuming and labor-intensive tasks [13]. For instance, generative AI can be used to automatically generate product descriptions, news articles, or even code [14]. By eliminating the need for human intervention, generative AI can free up valuable time and resources for more complex tasks, thereby improving efficiency and accuracy. ChatGPT, a natural language processing model with a capacity of 175 billion parameters, has been trained on extensive amounts of data and is designed to produce human-like responses to user inputs. Since its release in November 2022, ChatGPT has received significant attention from media and academia alike, provoking ethical discussions on scientific authorship [15,16], attempting to pass medical license and specialist examinations [17-19], and even designing medical education curricula [20].

The objective of this study was to explore the feasibility of using generative AI tools to automate time-consuming and resource-intensive tasks in a systematic review process and assess the scope and limitations of using such tools.

**Methods**

**Study Design**

This study uses a design science research (DSR) methodology. DSR is a problem-solving paradigm that seeks to enhance human knowledge via the creation of innovative artifacts [21]. DSR commonly involves the identification of a problem or opportunity, followed by the development, implementation, and evaluation of a solution. In DSR, as well as in action research, the process happens within an organization that provides context and that would be changed as a result of the use of the artifact [21]. An overview of the process adapted from Hevner [22] can be seen in Figure 1.

**Problem Definition**

The problem to which DSR was applied was the time-consuming and resource-intensive process of conducting systematic reviews of mHealth applications.

**Organizational Context**

The organizational context consisted of the More Stamina team of researchers, software developers, and health care professionals, working collaboratively within the host research institutions (ie, the University of Oulu and Trinity College Dublin).

The More Stamina project aims to create an evidence-driven gamified mHealth solution for people with multiple sclerosis (MS), where each step of the development follows a scientific process, as follows: MS needs as well as barriers and facilitators were explored through qualitative studies [23]; the state of the practice for MS apps was systematically reviewed [24,25]; user-centered design was used to create “MS personas” [23]; and...
coercation sessions took place to produce solution concepts [26]; the design, prototyping, and initial usability testing were described [27]; early health technology assessment was used to guide software development [28]; patient representatives were involved throughout the project [29]; and user testing and feasibility studies were ongoing in a multicenter study [30].

A script using the software application for audience targeting called 42matters [31] was used in the past to extract information from different app stores. The script is no longer functional, and person-hours from the software development team were not able to be dedicated to this task.

Background Studies

The research plans and outlines from previous studies, where systematic review methodologies were used to identify, select, collect, and analyze features and content of mHealth apps [6,24,25], served as models for our study. In those studies, a search strategy was defined, using relevant main keywords for each condition. App stores were searched, taking steps to ensure that no previous search history or cookies influenced results. Screening took place based on mHealth applications’ titles, descriptions, and metadata.

Solution

The solution was to apply a coercion process with a generative AI (ie, ChatGPT 3.5, as of June 2023) to produce software code that automated the process for conducting systematic reviews.

Coercation Goal

The goal of the coercion process was to use ChatGPT as a design and development partner for the automation process. The generative AI was to be interacted with as if it were a valid interloper who was more technologically skilled than the user and was guiding them through the process over text messages.

Development and Implementation

Development and implementation of the automated process happened through iterative and continuous conversations with the generative AI by one of the authors (GG). GG is a primary care physician with over a decade of experience leading digital health software design and development. Table 1 provides an overview of his digital skills background using the European Qualifications Framework and with a self-assessment score from 1 to 10 to describe his competency level. Regardless of the skill level, the development cycle was to be conducted as if no coding skill was present on the part of the user.

Table 1. Digital skills background.

<table>
<thead>
<tr>
<th>Competency</th>
<th>Level</th>
<th>Experience</th>
<th>Self-assessment score (of 10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scrum master</td>
<td>Certified Scrum Master</td>
<td>Agile methodologies and team management</td>
<td>7</td>
</tr>
<tr>
<td>Product owner</td>
<td>Certified Scrum Product Owner</td>
<td>Product road mapping and stakeholder management</td>
<td>8</td>
</tr>
<tr>
<td>Game design</td>
<td>Intermediate</td>
<td>Game mechanics, storytelling, and level design</td>
<td>7</td>
</tr>
<tr>
<td>Web design</td>
<td>Advanced</td>
<td>User experience and user interface design and responsive design</td>
<td>8</td>
</tr>
<tr>
<td>JavaScript</td>
<td>Beginner</td>
<td>Front-end development</td>
<td>5</td>
</tr>
<tr>
<td>HTML5</td>
<td>Intermediate</td>
<td>Front-end development</td>
<td>7</td>
</tr>
<tr>
<td>PHP: Hypertext Preprocessor</td>
<td>Beginner</td>
<td>Front-end and back-end development</td>
<td>4</td>
</tr>
</tbody>
</table>

Evaluation

The results were evaluated for their effectiveness and efficiency in replicating the initial steps of the background studies. The measurements were considered with respect to the amount of time required to generate a spreadsheet containing the necessary information for human reviewers to start the systematic review process. The output was compared to the output generated by the previous script, which required further processing of the data.

Ethical Considerations

No ethics board review is needed as the work does not use patient data or involve human participants.

Results

The following section reports the overall design, development, and implementation process as well as the evaluation results and highlights of the experience. Prompts provided by GG and generative AI are tagged accordingly.

ChatGPT requires prompts to trigger interaction. For this purpose, a lay language description of the desired outcome was engineered by GG (triggering prompt), as follows:

I need a script that crawls the Google Play Store for apps that target people with multiple sclerosis. The script should generate a spreadsheet file that contains name, links, description and other metadata, as well as have a specific column to highlight if the description mentions any medical or clinical evidence. The script should then search Pubmed database looking for each app listed on the spreadsheet, and create a separate spreadsheet relating the apps with any scientific publication that mentions them in Pubmed. [GG]

The generative AI’s response was to provide a sample script in Python that was suggested as a starting point, as shown in Figure 2.

https://mededu.jmir.org/2024/11/e48949

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(page number not for citation purposes)
Following the premise of the cocreation goal, ChatGPT was asked (by GG) “I am new to Python, how do I run a Python script?” to which the response was the following:

To run a Python script, you need to follow these steps:
1. Install Python on your computer, if it's not already installed. You can download Python from the official website: https://www.python.org/downloads/.
2. Open a text editor (e.g. Notepad, Sublime Text, Atom) and create a new file.
3. Write your Python code in the file.
4. Save the file with a .py extension (e.g. “my_script.py”).
5. Open a command prompt or terminal and navigate to the directory where your Python script is saved.
6. Type “python” followed by the name of your script and press enter. For example, if your script is named “my_script.py”, you would type “python my_script.py” and press enter.
7. Your Python script will now run, and you should see any output or results in the command prompt or terminal.

Note: If you’re using an Integrated Development Environment (IDE) like PyCharm or Visual Studio Code, you can run your script directly from the IDE by clicking on the “Run” button or pressing a keyboard shortcut. [ChatGPT]

ChatGPT provided step-by-step guidance for the installation and setup of Visual Studio Code, along with the required libraries and dependencies. After the development environment was ready, the suggested Python script was copied and pasted to check its functionality. The code produced several errors, which were fed back to ChatGPT by GG, as follows:

I am getting “ModuleNotFoundError: No module named 'requests'”
Now it says “ModuleNotFoundError: No module named 'bs4'”

ChatGPT stated that the “requests” library was imported but not used, so it should be removed. Subsequent error messages were troubleshooting with the AI. At times, the script would stop responding due to a time-out error or issues with the output. To make the debugging process easier to follow and understand, ChatGPT was prompted by GG to do the following:

add error messages that explain what went wrong.
add indicators for each step that it is working.
could you add a progress bar indicator to each step?

I would like the responses to be colored.

Upon review, it was clear that some error caused the output files to be overwritten. The author requested the following: “how would you add a condition to check whether a file with the same name already exists and if it does ask whether to overwrite it?” The AI added the pertinent libraries to the script and produced an input prompt for the user (Figure 3).

**Figure 3.** Added libraries and code for checking existing files.

```python
import os

# Check if file already exists
filename = "multiple_sclerosis_apps.csv"
if os.path.isfile(filename):
    choice = input("The file {filename} already exists. Do you want to overwrite it? ("y" or "n")")
    if choice != "y":
        # Exit the script if the user does not want to overwrite the file
        print(colored("Operation cancelled by user.", "red"))
        exit()

# Create a DataFrame and save it to a CSV file
app_df = pd.DataFrame(app_data, columns=["Name", "Link", "Description", "Med"])
print(colored("- Removing duplicates...", "yellow"))
app_df.drop_duplicates(subset="Name", inplace=True) # Remove duplicates based on name
app_df.to_csv(filename, index=False)
print(colored(F"\n{len(app_df)} apps were saved to '{filename}'.", "blue"))
```

The triggering prompt expected the script not only to be searching app stores for matches with “multiple sclerosis” but also to cross-reference them with scientific publications found in PubMed. As described in the Background Studies section of this paper, this process was done by looking for keywords present in the app description. As it were, the script was designed to only search for “multiple sclerosis” and crashed when it reached the PubMed phase. ChatGPT diagnosed a time-out error due to the number of publications and provided a potential solution to improve the indicator bars:

> The progress bar for PubMed search may not be moving because the total value for it is set to 3600, which is the number of seconds in an hour. This is the unit being used for the progress bar, not the total number of items to be searched. To fix this, you should update the total value for the progress bar to be the total number of apps being searched, which is the length of the app_df dataframe multiplied by the maximum number of PubMed IDs to be retrieved for each app (100 in this case). You can update the progress bar as follows... [ChatGPT]

After these issues were sorted and the script could properly fetch PubMed results, more keywords were entered into the script by prompting ChatGPT with the following:

> how would you make it so that the items in the medical_keywords list are taken from a csv file called “keywords.csv”? [GG]

A screenshot of the final Python script running can be seen in Figure 4.
Evaluation
As explained in the Background Studies section of this paper, app data extraction from the Google Play Store resulted in a spreadsheet file that contained the mHealth app’s name, store link, app description, developer’s name, developers’ URL, price, number of downloads, and app rating. During the screening phase of the studies, the research team read the apps’ descriptions and flagged those that contained keywords or sentences suggestive of the evidence base for in-depth review.

The ChatGPT-generated code resulted in a CSV file that contained the app’s name, store link, app description, and a column titled “Medical Evidence.” There were no columns containing metadata, and the Medical Evidence column only contained “Yes” or “No,” accordingly. Closer inspection revealed that the script was searching for a full match on the apps’ titles in PubMed results. The resulting document was useful as an intermediate outcome but was deemed unsuitable as a final output. The overall cocreation process had a total duration of 4 hours and 39 minutes, providing a working script version available on GitHub [32].

Using the results from the ChatGPT-generated script to fully automate the process would likely require further work refining the script, either by using the steps of the background studies to base the script or by providing clearer starting prompts for the generative AI. However, leveraging this approach as a means to advance work when the software developing team was otherwise engaged was useful.

Highlights
Some highlights of this study are as follows:

- The overall cocreation process exercise had a total duration of 4 hours and 39 minutes.
- There were several misunderstandings during the interactions, not unlike the challenges one might encounter when messaging a more experienced coder.
- Structured thinking ahead of time reduced the number of misunderstandings.
- No knowledge of Python scripting was required by the author.
- The resulting output was useful to continue a systematic review but not sufficient to replace the final outputs.

Discussion
Principal Results
This study is the first to describe the cocreation process with a generative AI in developing an automated script for conducting a systematic review of mHealth apps. The study provides insights into the potential of using this kind of AI tools for researchers with little to no coding skills, and it identifies an innovative way of approaching a research problem and facilitating interdisciplinary collaborations. This study also makes a methodological contribution, expanding knowledge as it uses DSR, an approach that is not commonly used in health care and health informatics [33].

Comparison With Prior Work
The resource-intensive process and the burden that systematic reviews represent have been highlighted in the literature before. The use of multiple databases, such as MEDLINE, Embase, Cochrane Library, and Web of Science as well as clinical trial registries like ClinicalTrials.gov are common practices to increase results [34]. However, this tactic requires a lengthy deduplication process, involving long manual procedures, potentially introducing quality-affecting errors and biases [35-37]. In fact, automation attempts using AI models have been made in the past, with a focus on the deduplication problem, as seen in studies by Borissov et al [38] and Bramer et al [39].

Performing a systematic review is a common step in doctoral researchers’ studies [40,41], as a means of introducing the candidate to the topic. The use of generative AI to cocreate scripts like the one presented in this study could help automate the time-consuming process, allowing researchers to focus on other aspects of the research process.

The ethical implications of using generative AI models, such as ChatGPT, to generate scientific authorship have sparked discussions [15,16]. AI’s potential for assisting in academic research needs to be considered and weighed against the potential for its misuse. Although generative AI can assist in the development of a systematic review script, it is important to note that the final review still requires human oversight and input to not only assess the accuracy and relevance of the results but also ensure that the ethical principles have been followed.
Beyond research, there are wider implications for the use of generative AI in both medical education and the upskilling of the health care workforce. The need for more digital skills training for health care professionals is widely recognized [42], and other authors have further explored medical degree programs’ curricula to examine how AI is included [43,44]. A recent publication explored the specific competencies needed for the effective and ethical use of AI in health care [45]. Understanding basic knowledge of AI and its applications as well as how to integrate AI into the general workflow of different tasks ranked among the top 6 key competency domains.

The role of generative AI in evolving health care education is pivotal, especially as universities adapt to its challenges. Generative AI has the potential to streamline processes like systematic reviews and clinical information retrieval, thereby allowing health care professionals to focus more on patient-centered, empathetic care and the co-design of effective treatment outcomes.

Limitations

The results of this study must be considered within its limitations. The DSR methodology was developed for this specific problem, which limits applicability in other contexts. In addition, subjectivity is a common bias present in DSR, which can make it difficult to establish the reliability and validity of the results. The main goal of DSR is to generate prescriptive knowledge, which provides guidelines on how to effectively design and implement solutions in the organizational context. However, as DSR focuses more on developing practical solutions rather than generating new theoretical insights, it was aligned with the goal of this study. DSR differs from traditional research paradigms by focusing more on creating and evaluating new solutions rather than on understanding existing phenomena. Further, while generative AI can assist in the development of a systematic review script, the result will be greatly affected by the training data used for the language model. Additionally, there may be limitations in the quality of the search results obtained from the previous studies, which only become apparent through automated processes.

Conclusions

This study outlined the cocreation process of an automated script for systematic reviews of mHealth apps, using generative AI. The study shed light on the potential of such AI tools for researchers with limited coding abilities and highlighted a novel approach for addressing research problems and promoting interdisciplinary collaborations.

Acknowledgments

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The authors are grateful for ChatGPT, whose collaboration was essential for the completion and inception of this study.

Conflicts of Interest

None declared.

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Abbreviations

AI: artificial intelligence
DSR: design science research
mHealth: mobile health
MS: multiple sclerosis

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Learning to Make Rare and Complex Diagnoses With Generative AI Assistance: Qualitative Study of Popular Large Language Models

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Abstract

Background: Patients with rare and complex diseases often experience delayed diagnoses and misdiagnoses because comprehensive knowledge about these diseases is limited to only a few medical experts. In this context, large language models (LLMs) have emerged as powerful knowledge aggregation tools with applications in clinical decision support and education domains.

Objective: This study aims to explore the potential of 3 popular LLMs, namely Bard (Google LLC), ChatGPT-3.5 (OpenAI), and GPT-4 (OpenAI), in medical education to enhance the diagnosis of rare and complex diseases while investigating the impact of prompt engineering on their performance.

Methods: We conducted experiments on publicly available complex and rare cases to achieve these objectives. We implemented various prompt strategies to evaluate the performance of these models using both open-ended and multiple-choice prompts. In addition, we used a majority voting strategy to leverage diverse reasoning paths within language models, aiming to enhance their reliability. Furthermore, we compared their performance with the performance of human respondents and MedAlpaca, a generative LLM specifically designed for medical tasks.

Results: Notably, all LLMs outperformed the average human consensus and MedAlpaca, with a minimum margin of 5% and 13%, respectively, across all 30 cases from the diagnostic case challenge collection. On the frequently misdiagnosed cases category, Bard tied with MedAlpaca but surpassed the human average consensus by 14%, whereas GPT-4 and ChatGPT-3.5 outperformed MedAlpaca and the human respondents on the moderately often misdiagnosed cases category with minimum accuracy scores of 28% and 11%, respectively. The majority voting strategy, particularly with GPT-4, demonstrated the highest overall score across all cases from the diagnostic complex case collection, surpassing that of other LLMs. On the Medical Information Mart for Intensive Care-III data sets, Bard and GPT-4 achieved the highest diagnostic accuracy scores, with multiple-choice prompts scoring 93%, whereas ChatGPT-3.5 and MedAlpaca scored 73% and 47%, respectively. Furthermore, our results demonstrate that there is no one-size-fits-all prompting approach for improving the performance of LLMs and that a single strategy does not universally apply to all LLMs.

Conclusions: Our findings shed light on the diagnostic capabilities of LLMs and the challenges associated with identifying an optimal prompting strategy that aligns with each language model’s characteristics and specific task requirements. The significance of prompt engineering is highlighted, providing valuable insights for researchers and practitioners who use these language models for medical training. Furthermore, this study represents a crucial step toward understanding how LLMs can enhance diagnostic reasoning in rare and complex medical cases, paving the way for developing effective educational tools and accurate diagnostic aids to improve patient care and outcomes.
Introduction

Background

Natural language processing has witnessed remarkable advances with the introduction of generative large language models (LLMs). In November 2022, OpenAI released ChatGPT-3.5 (OpenAI), a large natural language processing chatbot trained on a large corpus collected from the internet to generate human-like text in response to user queries. ChatGPT-3.5 has seen massive popularity, and users have praised its creativity and language comprehension for several tasks, such as text summarization and writing computer programs [1]. In March 2023, OpenAI responded to the success of ChatGPT-3.5 by introducing an enhanced iteration called GPT-4, specifically designed to address intricate queries and nuanced directives more effectively. Shortly thereafter, Google released their comparable model, Bard (Google LLC), which joined the league of impressive LLMs. What sets Bard apart is its real-time access to and use of internet information, enriching its response generation with up-to-date information [2]. In contrast, GPT-4 possesses multimodal capabilities, including image inputs, albeit not publicly available during the study [3].

These LLMs were not originally designed for medical applications. However, several studies [4,5] have shown their extraordinary capabilities in excelling in various medical examinations, such as the Self-Assessment in Neurological Surgery examination and the USMLE (United States Medical Licensing Examination). Their results demonstrated the ability of these models to handle clinical information and complex counterfactuals. Furthermore, numerous investigations [6-8] have revealed the remarkable advantages of harnessing the power of LLMs in diverse medical scenarios. Notably, Lee et al [8] demonstrated using LLMs as a reliable conversational agent to collect patient information to assist in medical notetaking, whereas Patel and Lam [9] delved into using LLMs as a valuable tool for generating comprehensive patient discharge summaries. The ability of LLMs to process and generate medical text has unlocked new opportunities to enhance diagnostic reasoning, particularly in tackling rare and complex medical cases.

Rare diseases are characterized by their low prevalence in the general population, whereas complex diseases are conditions with overlapping factors and multiple comorbidities that are often difficult to diagnose [10,11]. Sometimes, a condition can be rare and complex if it is infrequent and challenging to diagnose accurately [11]. Rare and complex diagnoses present significant challenges across various medical levels and often require extensive medical knowledge or expertise for accurate diagnosis and management [10,11]. This may be because, during their education, physicians are trained to prioritize ruling out common diagnoses before considering rare ones during patient evaluation [12]. In addition, most medical education programs rarely cover some complex conditions, and guidance for practicing clinicians is often outdated and inappropriate [13,14].

As a result, most physicians perceive their knowledge of rare diseases as insufficient or very poor, and only a few feel adequately prepared to care for patients with these conditions [12,15]. This knowledge gap increases the risk of misdiagnosis among individuals with rare and complex conditions. Furthermore, the scarcity of available data and the relatively small number of affected individuals create a complicated diagnostic landscape, even for experienced and specialized clinicians [10]. Consequently, patients often endure a prolonged and arduous diagnostic process. Therefore, there is a pressing need for comprehensive educational tools and accurate diagnostic aids to fill the knowledge gap and address these challenges effectively.

This study aims to explore the potential of 3 LLMs, namely Bard, GPT-4, and ChatGPT-3.5, as continuing medical education (CME) systems to enhance the diagnoses of rare and complex conditions. Although these models have demonstrated impressive success in standardized medical examinations [4,5], it is important to acknowledge that most examinations reflect general clinical situations, which may not fully capture the intricacies encountered in real-world diagnostic scenarios. Furthermore, these standardized tests often feature questions that can be answered through memorization [16]. In contrast, real-world complex diagnostic scenarios that physicians face involve dynamic, multifaceted patient cases with numerous variables and uncertainties. Although previous studies by Liu et al [17] and Cascella et al [18] have highlighted the ability of LLMs to support health care professionals in real-world scenarios, their effectiveness in diagnosing rare and complex conditions remains an area of exploration. Despite the promising use of LLMs in medical applications, studies have reported that their responses to user queries are often nondeterministic (ie, depending on the query format) and exhibit significant variance [17,19]. This attribute may pose challenges in clinical decision support scenarios because the dependability of a system is uncertain when its behavior cannot be accurately predicted. However, no investigation has been conducted to show how different input formats (prompts) affect LLM responses in the medical context.

Prompt engineering is a technique for carefully designing queries (inputs) to improve the performance of generative language models [20,21]. We can guide LLMs to generate more accurate and reliable responses by carefully crafting effective prompts. Our study investigated effective prompting strategies to improve the accuracy and reliability of LLMs in diagnosing rare and complex conditions within an educational context. We evaluated the performance of LLMs by comparing their responses to those of human respondents and the responses of
MedAlpaca [22], an open-source generative LLM designed for medical tasks. Given the documented advantages of using LLMs as a complementary tool rather than a substitute for clinicians [17,18], our study incorporated LLMs with the understanding that clinicians may use them beyond real-time diagnostic scenarios. Although our premise is based on a clinician having established an initial diagnostic hypothesis and seeking further assistance to refine the precise diagnosis, we acknowledge the broader utility of LLMs. They can be valuable in real-time decision support and retrospective use during leisure or documentation, allowing physicians to experiment with and enhance their understanding of rare and complex diseases. This approach recognizes the inherent uncertainty in diagnosis and harnesses the capabilities of LLMs to assist clinicians in various aspects of their diagnostic processes. In the context of CME, our study highlights the possibility of integrating LLMs as a valuable addition. By providing further assistance in refining complex and rare diagnoses, these LLMs could support evidence-based decision-making among health care professionals for improved patient outcomes.

**Objectives**

Our study has 2 main objectives: first, to examine the potential of LLMs as a CME tool for diagnosing rare and complex conditions, and second, to highlight the impact of prompt formatting on the performance of LLMs. Understanding these aspects could significantly contribute to advancing diagnostic practices and effectively using LLMs to improve patient care.

**Methods**

**Data Sets**

We used 2 data sets to examine the capacity of LLMs to diagnose rare and complex conditions as follows:

1. Diagnostic case challenge collection (DC3) [11] comprises 30 complex diagnostic cases curated by medical experts in the *New England Journal of Medicine* web-based case challenges. The original cases contained text and image descriptions of patients’ medical history, diagnostic imaging, and laboratory results; however, we used only textual information to form prompts (queries). The web-based polls recorded an average of 5850 (SD 2522.84) respondents per case, many of whom were health care professionals. The participants were required to identify the correct diagnosis from a list of differential diagnoses. Case difficulty was categorized based on the percentage of correct responses received from the respondents on the web-based survey. The case categories were: “rarely misdiagnosed cases” (with $\geq 21/30$, 70% correct responses), “moderately misdiagnosed cases” (with $>9/30$, 30% and $<21/30$, 70% correct responses), and “frequently misdiagnosed cases” (with $59/30$, 30% correct responses). Furthermore, the final diagnoses determined by the treating physicians of the cases were provided alongside the poll results, enabling the comparison of the performance of human respondents with that of the targeted LLMs.

2. Medical Information Mart for Intensive Care-III (MIMIC-III) [23] comprises deidentified electronic health record data from approximately 50,000 Boston Beth Israel Deaconess Medical Center intensive care unit patients. We focused on discharge summaries containing the accumulated patient information from admission to discharge. Similar to previous work on clinical outcome prediction by van Aken et al [24] and Abdullahi et al [25], we filtered document sections unrelated to admissions, such as discharge information or hospital course and retained sections related to admissions, such as chief complaint, history of illness or present illness, medical history, admission medications, allergies, physical examination, family history, and social history. Each discharge summary had a discharge diagnosis section that indicated the patient’s final diagnosis for that admission. We reviewed the discharge summaries to identify rare diseases and referred to the Orphanet website [26]. In this study, we randomly selected 15 unique, rare conditions as our target. These cases were selected as pilot studies for a focused and in-depth analysis.

**Models**

In this study, we conducted experiments using LLMs designed for conversational context. Specifically, we used the July 6, 2023, version of Bard; the July 4, 2023, versions of GPT-4 and ChatGPT-3.5; and the publicly available version of MedAlpaca 7b [22]. We entered prompts individually through the chat interface to evaluate Bard, GPT-4, and ChatGPT-3.5, treating each prompt as a distinct conversation. MedAlpaca differs from Bard, ChatGPT-3.5, and GPT-4 in that it requires users to submit queries or prompts through a Python (Python Software Foundation) script. Consequently, we used a single Python script for each prompt strategy to submit queries for each data set. It is worth noting that Bard has certain limitations compared with ChatGPT-3.5 and GPT-4. Bard has a restricted capacity to handle lengthy queries. Moreover, Bard is more sensitive to noisy input and specific characters. For example, the MIMIC-III data set contained deidentified patients’ notes filled with special characters such as ["**Hospital 18654**"] and laboratory results written in shorthand, for example, *Hgb*-9.6; *Hct*-29.7; *MCV*-77; *MCH*-24.9. Consequently, to work effectively with Bard, we preprocessed the text by removing special characters and retaining only alphanumeric characters.

**Prompting Strategies**

Direct (standard prompting) and iterative prompting (chain of thought prompting) [27] are the 2 major prompting methods. Iterative prompting is a promising method for improving LLM performance on specialized tasks; however, it requires a predefined set of manually annotated reasoning steps, which can be time consuming and difficult to create, especially for specialized domains. Most users opt for a direct prompt method to save time and obtain an immediate response. Therefore, to analyze the effect of prompt formats on LLM performance, we assessed each model’s performance for every case using the 3 distinct direct prompt strategies outlined in Table 1. These strategies varied from open-ended to multiple-choice formats.
Table 1. Prompt strategies.

<table>
<thead>
<tr>
<th>Approach</th>
<th>Prompt strategy description</th>
<th>Prompt sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Approach 1 (open-ended</td>
<td>In this approach, prompts were formatted in an open-ended fashion. Formatting a prompt using</td>
<td>&quot;What is the diagnosis? The case is: A 32-year-old man was evaluated in the</td>
</tr>
<tr>
<td>prompt)</td>
<td>this method allows the model to formulate a hypothesis for the case and explain why and what</td>
<td>emergency department of this hospital for the abrupt onset of postprandial</td>
</tr>
<tr>
<td></td>
<td>it thinks is the diagnosis. Here, we scored a model based on its ability to provide the</td>
<td>chest pain...&quot;</td>
</tr>
<tr>
<td></td>
<td>correct diagnosis without additional assistance.</td>
<td></td>
</tr>
<tr>
<td>Approach 2 (multiple-choice prompt)</td>
<td>We formatted prompts as multiple-choice questions, and the LLMs were expected to select a single diagnosis from a list of options. The models were assigned a positive score in this task if they selected the correct diagnosis from the options.</td>
<td>&quot;Choose the most likely diagnosis from the following: Option I: Cholecystitis, Option II: Acute coronary syndrome, Option III: Pericarditis, Option IV: Budd-Chiari syndrome. The case is: A 32-year-old man was evaluated in the emergency department of this hospital for the abrupt onset of postprandial chest pain...&quot;</td>
</tr>
<tr>
<td>Approach 3 (ranking prompt)</td>
<td>The prompts were presented as a case and a list of diagnoses to be ranked by the LLMs. Models were assigned a positive score if the correct diagnosis was ranked first in this format.</td>
<td>&quot;Rank the following diagnoses according to the most likely. Option I: Cholecystitis, Option II: Acute coronary syndrome, Option III: Pericarditis, Option IV: Budd-Chiari syndrome. The case is: A 32-year-old man was evaluated in the emergency department of this hospital for the abrupt onset of postprandial chest pain...&quot;</td>
</tr>
</tbody>
</table>

aLLM: large language model.

Building upon prior research by Wang et al [28] and Li et al [29], we hypothesized that using a diverse range of prompts can reveal distinct reasoning paths while maintaining consistency in the correct responses regardless of the variations. When using multiple-choice prompts for the DC3 cases, we presented the same options available in the original web-based polls to the models, but on the MIMIC-III data set, we generated random wrong answers that were closely related to the correct diagnosis. We evaluated each LLM by assigning a positive or negative score (binary score) based on their responses. A positive score was assigned only if the models correctly selected the diagnosis for either data set. Conversely, we omitted the options for open-ended prompts, expecting the models to generate the correct diagnosis independently. Positive scores were awarded only if the models accurately provided the correct diagnosis.

**Prompt Ensemble: Majority Voting**

To safely use imperfect language models, users must determine when to trust their predictions, particularly in critical situations, such as clinical decision support. Therefore, we used a majority voting (prompt ensembling) strategy to enhance the reliability of LLMs’ responses. The majority voting approach involves aggregating multiple responses and selecting the most common answer. By applying this approach to responses generated by different LLMs, we can observe the level of agreement and infer the consistency in their outputs for a given prompt. Specifically, we hypothesized that using a majority voting approach from the ensemble of prompt responses would boost the reliability of language models, minimizing potential errors, variations, and biases associated with individual prompting approaches. To achieve this, in independent chats, we prompted the LLM with 3 distinct prompt formats per case, as presented in Table 1. Subsequently, we collected the responses of each model and applied majority voting to aggregate its predictions, as presented in Figure 1. In majority voting, each prompt produced a response from the language model, and the majority response was chosen as the final response. In a scenario where all prompt strategies resulted in different responses, we assumed that the model was unsure of that question and scored the final response as a failure case. We limited the number of prompts in the ensemble to 3 because studies by Wang et al [28] and Li et al [29] have shown that we obtain diminishing returns as we increase the overall number of prompts in an ensemble.

**Figure 1.** Our proposed method contains the following steps: (1) prompt a language model using a distinct set of prompts, (2) obtain diverse responses, and (3) choose the most consistent response as the final answer (majority voting).

**Ethical Considerations**

No ethics approval was pursued for this research, given that the data was publicly accessible and deidentified. This aligns with the guidelines outlined in the National Institutes of Health investigator manual for human subjects research [30].
Results

Performance Across Prompt Strategies

Figure 2 reveals the performance of LLMs across different prompts on the DC3 data set. Overall, approach 2 (multiple-choice prompt) yielded the highest score for all 30 cases, with GPT-4 and Bard achieving an accuracy score of 47% (14/30) and ChatGPT-3.5 obtaining a score of 43% (13/30). However, when considering case difficulty, the results varied. On the frequently misdiagnosed cases category, GPT-4 and ChatGPT-3.5 performed better with open-ended prompts (approach 1), scoring 30% (3/10) and 20% (2/10), respectively. In contrast, Bard demonstrated superior performance with multiple-choice prompts for selection and ranking (approaches 2 and 3), achieving a score of 30% (3/10). ChatGPT-3.5 and Bard performed equally well on the rarely misdiagnosed cases category using approaches 2 and 3, achieving a perfect score of 100% (2/2). Furthermore, GPT-4 attained a score of 100% (2/2) but only with approach 2. For the moderately misdiagnosed cases category, all LLMs achieved their best performance with approach 2, scoring 67% (12/18), 56% (10/18), and 50% (9/18) for GPT-4, ChatGPT-3.5, and Bard, respectively. Table S1 in the Multimedia Appendix 1 presents the inconsistencies in the correct responses across the approaches for different cases. For example, Bard could only diagnose milk alkali syndrome using approach 1 but failed to use other prompt approaches. ChatGPT-3.5 correctly diagnosed primary adrenal insufficiency (Addison disease) with only approach 2, whereas GPT-4 was able to diagnose acute hepatitis E virus infection with only approach 1. These results indicate that no universal prompt approach is optimal for all LLMs when dealing with complex cases.

Results on the MIMIC-III data set in Figure 3 showed that the LLMs also performed best using approach 2 (multiple-choice prompt), with Bard and GPT-4 obtaining scores of 93% (14/15) each and ChatGPT-3.5 obtaining 73% (11/15). Using approach 3 (ranking prompt) resulted in a slight drop in performance for GPT-4 and Bard, with a 6% decrease, whereas the performance of ChatGPT-3.5 dropped by 26%. Approach 1 (open-ended prompt) proved challenging for the LLMs, with scores of 47% (7/15), 60% (9/15), and 27% (4/15) for Bard, GPT-4, and ChatGPT-3.5, respectively. Table S2 in the Multimedia Appendix 1 illustrates that approach 1 was only beneficial to GPT-4 in diagnosing amyloidosis, whereas it was consistently never the sole correct approach for Bard and ChatGPT-3.5. These results aligned with the findings from the DC3 data set and emphasized the varying performances of different models and prompt approaches across tasks.

Figure 2. Results of the diagnostic case challenge collection data set comparing prompt strategies. OpenAI GPT-4 outperformed all other models, achieving the highest score in all 30 cases using the majority voting approach. Furthermore, all large language models except MedAlpaca outperformed the human consensus (denoted by a black dashed line) across all cases, regardless of the difficulty, using at least 1 prompt approach. GPT-4: generative pretrained transformer-4.
Performance With Majority Voting

Previous experiments have demonstrated that there is no perfect prompting strategy because LLM users may not know beforehand which prompt will produce a correct response. We used the majority voting approach to estimate consistency, maximize the benefits of different prompt strategies, and enhance the reliability of the LLMs’ responses. Figure 2 illustrates the results for all DC3 cases. Majority voting improved the overall performance of GPT-4 from 47% to 50%, whereas the performance of ChatGPT-3.5 remained at 43% because majority voting did not decrease its performance compared with that of approach 2. In contrast, the performance of Bard decreased from 47% to 43% compared with that of approach 2. Summarizing the overall performance based on query difficulty, majority voting resulted in a perfect score of 100% for the rarely misdiagnosed cases category across all the LLMs. For the frequently misdiagnosed cases category in DC3, Bard achieved the highest score with majority voting and multiple-choice prompts, whereas GPT-4 performed best for the moderately misdiagnosed cases category with majority voting and approach 2. In addition, GPT-4 outperformed all other LLMs across all DC3 cases using the majority voting approach, regardless of the case difficulty. This score surpassed the performance of the individual prompt approaches in all cases.

Comparison With Human Respondents

In the DC3 cases, although the human respondents had the advantage of accessing supporting patient information such as image scans and magnetic resonance imaging, the LLMs consistently outperformed the average human consensus. As shown in Figure 2, using the majority voting approach, all LLMs achieved a higher performance than the human consensus (denoted by a black dashed line), with a minimum margin of 5% across all 30 cases. Specifically, when considering query difficulty, the LLMs demonstrated even greater superiority. In the rarely misdiagnosed cases category, all LLMs surpassed the average human consensus by a substantial margin of 26%. For the moderately misdiagnosed cases category, GPT-4 and ChatGPT-3.5 maintained their advantage over human respondents, achieving a minimum margin of 11% with the majority voting approach. In contrast, only Bard outperformed the human average consensus on the frequently misdiagnosed cases category, with a margin of 14%.

We conducted a Spearman rank correlation test to analyze the pattern in the responses between each LLM and the human respondents. This involved correlating the average percentage of correct responses for each LLM across the prompt strategies with that of correct human responses. The results of the Spearman correlation test revealed that Bard had a relatively weak correlation coefficient of 0.30, whereas GPT-4 and ChatGPT-3.5 exhibited moderate positive correlations of 0.51 and 0.50, respectively. This suggested that the diagnostic performance patterns of GPT-4 and ChatGPT-3.5 aligned moderately with those of the human respondents. The observed correlation in answering patterns between human respondents and LLMs may stem from the inherent data bias present in the training data sets. The LLMs learn from vast amounts of data, and if the training data are biased toward certain diagnostic or decision-making patterns commonly expressed by human physicians, the model is likely to replicate those patterns. Although the correlation suggested that the LLMs have the
potential to be valuable tools in medical education, it is important to note their correlation with human physicians and that the performance of LLMs does not necessarily mean that they are as good as human physicians in diagnosing and treating diseases.

We could not directly compare the performance of human respondents on the MIMIC-III data sets because of the unavailability of data. Overall, the results indicated that the LLMs consistently outperformed the average human consensus in diagnosing medical cases, showcasing their potential as a tool to complement and enhance care quality and education for complex diagnostic cases.

**Comparison With MedAlpaca**

On the DC3 data sets, Bard, GPT-4, and ChatGPT-3.5 outperformed MedAlpaca across all cases using the majority voting approach by a minimum margin of 13%. MedAlpaca also displayed the worst performance in the open-ended prompts, irrespective of query difficulty. However, when multiple-choice options were provided, MedAlpaca outperformed the other LLMs in the frequently misdiagnosed cases category. Similar to the DC3 data set, MedAlpaca consistently demonstrated its best performance using the ranking prompt on the MIMIC-III data sets. However, its overall performance was significantly poorer than the other LLMs, with each LLM outperforming the model by at least 26% using the majority voting approach. In contrast to the general-purpose LLMs (eg, Bard, GPT-4, and ChatGPT-3.5), investigating the MedAlpaca model was finetuned using diverse medical tasks and assessed using multiple-choice medical examinations. This tailored training approach likely contributed to its notable performance, particularly excelling in DC3 cases (frequently misdiagnosed instances) and demonstrating optimal results in multiple-choice queries.

**Qualitative Analysis**

In our experiments, we manually observed the responses of each LLM to all our prompts and noted that each LLM consistently justified its diagnosis choice except for MedAlpaca. Specifically, each LLM offered a logical explanation for its chosen response regardless of the prompting strategy. For further investigation, we analyzed each LLM’s responses in 3 scenarios: (1) when presented with multiple-choice options containing the true diagnosis and they responded accurately, (2) when their response was incorrect, and (3) when given only incorrect multiple-choice options to pick from. In the first scenario, as presented in Multimedia Appendix 1, all 3 LLMs emphasized that the patient’s history of respiratory illness and the absence of any systemic symptoms, exposure risks, chest radiograph, computed tomography scan findings, and the suspected compromised potential for salmonellosis were important to note their correlation with human physicians and that the performance of LLMs does not necessarily mean that they are as good as human physicians in diagnosing and treating diseases.

Another notable finding occurred in the responses of GPT-4 and ChatGPT-3.5. Regardless of the correctness of their chosen diagnoses, these models consistently recommended further tests to confirm their responses. This behavior suggested a general tendency toward advocating additional examinations to validate their diagnoses, potentially reflecting a cautious approach. In contrast, Bard adopted a different approach. Instead of recommending further tests, Bard highlighted that the provided query information supported the diagnosis without suggesting additional confirmatory measures. In the scenario where only incorrect options were given, Bard, ChatGPT-3.5, and MedAlpaca made choices and justified their responses. In contrast, GPT-4 explicitly mentioned that none of the provided options matched the case presentation. Furthermore, GPT-4 suggested a more probable diagnosis and recommended additional testing to explore its feasibility.

**Discussion**

**Principal Findings**

Previous studies have presented the impressive success of LLMs in standardized medical examinations. We conducted experiments to assess the potential of LLMs as a CME system for rare and complex diagnoses, and our findings demonstrated that LLMs have the potential to be a valuable tool for rare disease education and differential diagnosis. Although LLMs demonstrated superior performance compared with the average human consensus in diagnosing complex diseases, it is essential to note that this does not imply their superiority over physicians. Numerous unknown factors, including the level of respondents’ expertise, may influence the outcome of web-based polls. Furthermore, we examined the knowledge capacity of LLMs through open-ended and multiple-choice prompts and found that LLMs, including MedAlpaca, performed better with multiple-choice prompts. This improvement can be attributed to the options provided, which narrowed the search space for potential diagnoses from thousands to a few likely possibilities. Consequently, we surmise that LLMs are not yet ready to be used as stand-alone tools, which aligns with the findings of previous studies. Our observations revealed the consistent outperformance of general-purpose LLMs over MedAlpaca in various experiments. Their superior ability to provide valuable justifications for making diagnoses was particularly noteworthy, a strength not matched by MedAlpaca. This difference may stem from MedAlpaca’s exclusive finetuning and assessment for multiple-choice medical examinations, which slightly differ in format from the clinical cases in our experiments.

A notable finding in the response of LLMs to queries was their consistent provision of coherent and reasoned explanations, regardless of the query format. In contrast, when diagnosing miliary tuberculosis, all 3 LLMs emphasized that the patient’s systemic symptoms, exposure risks, chest radiograph, computed tomography scan findings, and the suspected compromised
immune state collectively support the diagnosis of *miliary tuberculosis*. Furthermore, Bard and GPT-4 ruled out other diagnoses presented in the multiple-choice prompt by highlighting their less typical presentations and lack of certain associated symptoms or risk factors. In addition, the conversational nature of LLMs allows users to ask follow-up questions for further context. These attributes hold great potential for educating users and offering them insights. However, we observed that LLMs provided logical explanations, even when their diagnoses were incorrect. ChatGPT-3.5 and GPT-4 may suggest additional testing to validate their selected diagnosis or use cautious terms like “potential diagnosis.” However, it remains unclear whether these recommendations stem from the models’ internal confidence or whether there are features intentionally designed by the developers for cautious use. The absence of explicit information regarding the level of uncertainty of LLMs for a specific case is concerning as it could potentially mislead clinicians. The ability to quantify uncertainty is crucial in medical decision-making, in which accurate diagnoses and treatment recommendations are paramount. Clinicians heavily rely on confidence levels and probability assessments to make informed judgments [29]. Without an indication of uncertainty, there is a risk that clinicians may trust the logical explanations provided by the LLMs even when they are incorrect, leading to misdiagnoses or inappropriate treatment plans.

Considering the delicate role of clinical decision support, it is essential to address validity and reliability as crucial aspects of uncertainty. Moreover, a reliable system is of paramount importance for medical education. However, the stochastic nature of LLMs introduces doubts among clinicians regarding their reliability. Although a specific metric to quantitatively assess the reliability of the LLMs used in this study is currently lacking, we acknowledge the significance of consistency in achieving reliability. To address this, we used different prompting strategies and implemented a majority voting approach to select the most consistent response from each LLM. After examining the individual prompt strategies, we anticipated consistent responses across strategies for a specific case. However, our findings revealed that the responses of LLMs were sensitive to concrete prompt formats, particularly in complex diagnoses. For instance, ChatGPT-3.5 and GPT-4 performed better with the open-ended prompt (approach 1) in the frequently misdiagnosed cases category of DC3 cases but struggled with similar cases using multiple-choice and ranking prompts (approaches 2 and 3). In contrast, Bard performed better with multiple-choice prompts. These results highlighted that there is no one-size-fits-all prompting approach nor does a single strategy apply universally to all LLMs. Although the majority voting strategy did not yield optimal results for all models across data sets, it served as a means to consolidate responses from multiple prompts and provided a starting point for incorporating reliability.

Several studies [10-12,14,15] have emphasized the significance of enhancing the education of clinicians at all levels to provide better support for rare and complex diagnoses. In this pursuit, the studies by Lee et al [8] and Decherchi et al [31] have highlighted the potential advantages of artificial intelligence (AI) systems, whereas the studies by Abdullahi et al [25] and Sutton et al [32] have reported a lack of acceptance of AI tools among clinicians. For instance, younger medical students and residents appeared more receptive to integrating technology [33]. One notable reason for this lack of acceptance is that conventional AI systems typically require training before clinicians can effectively use them, which can be burdensome and time consuming [32]. In contrast, conversational LLMs, such as ChatGPT-3.5, Bard, and GPT-4, offer a distinct advantage with their simple interface and dialogue-based nature. These conversational LLMs eliminate the need for extensive training, increasing their potential for high acceptance across all levels of medical practice. Although the exciting ease of use, conversational nature, impressive display of knowledge, and logical explanations of LLMs have the potential for user education and insights, their current limitations in reliability and expressing uncertainty must be addressed to ensure their effective and responsible use in critical domains, such as health care.

**Limitations**

First, the limitations of the knowledge of ChatGPT-3.5 and GPT-4 to the latest trends and updates in health care (or medical) data till 2021 pose the risk of potentially incomplete information and hamper the effectiveness of the models as a CME tool, especially when addressing emerging diseases. In contrast, although continuous updates to Bard are advantageous for keeping the model up-to-date, this attribute may impact the reproducibility of our study. Second, it is notable that our experiments had a limited scope owing to a small sample size consisting of only 30 diseases from the DC3 data set and 15 cases from the MIMIC-III data set. In addition, although we took precautions to preprocess the MIMIC-III notes to prevent leakage of the final diagnosis, the discharge summaries may still contain nuanced information that could make the diagnosis obvious. Furthermore, the closed nature of the LLMs used in this study restricted our technique for measuring reliability to a majority voting approach, which consolidated responses from diverse prompts. Although majority voting can help to mitigate the variability of LLM output, it is notable that LLMs may still generate different responses for the same prompt. This variability should be considered when interpreting the results of this study. However, when these LLMs are released with an enhanced iteration that allows for finetuning and calibration, future work should incorporate more effective mechanisms to estimate and communicate uncertainty. An example of such an approach could involve assigning a confidence score to the probability score of their responses. This methodology could allow clinicians to make informed decisions regarding whether to accept or reject responses that fall within a desired threshold.

**Conclusions**

In this study, we conducted experiments to assess the potential of LLMs, including ChatGPT-3.5, GPT-4, and Bard, as a CME system for rare and complex diagnoses. First, we evaluated their diagnostic capability specifically for rare and complex cases. Subsequently, we explored the impact of prompt formatting on their performance. Our results revealed that these LLMs possessed potential diagnostic capacities for rare and complex
medical cases, surpassing the average crowd consensus on the DC3 cases. For selected rare cases from the MIMIC-III data set, Bard and GPT-4 achieved a diagnostic accuracy of 93%, whereas ChatGPT-3.5 achieved an accuracy of 73%. Our findings highlighted that users might discover an approach that yields favorable results for various queries by exploring different prompt formats. In contrast, using majority voting of responses from multiple prompt strategies offers the benefit of a robust and reliable model, instilling confidence in the generated responses. However, determining the best prompt strategy versus relying on the majority voting approach involves a tradeoff between exploration and exploitation. Although prompt engineering research is continuing, we hope that future studies will yield better solutions to enhance the reliability and consistency of the responses of LLMs. Overall, our study’s results and conclusions provide a benchmark for the performance of LLMs and shed light on their strengths and limitations in generating responses, expressing uncertainty, and providing diagnostic recommendations. The insights gained from this study can serve as a foundation for further exploration and research on using LLMs as medical education tools to enhance their performance and capabilities as conversational language models.

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Data Availability

The URLs for the diagnostic case challenge collection data set can be obtained via A Diagnostic Case Challenge Collection [34]. The Medical Information Mart for Intensive Care data sets can be accessed via the database, Medical Information Mart for Intensive Care-III Clinical Database v1.4 [35], after obtaining permission from Physionet.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Comprehensive tables detailing the performance of each model across data sets, with included examples of prompts and responses for each model.

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Using ChatGPT-Like Solutions to Bridge the Communication Gap Between Patients With Rheumatoid Arthritis and Health Care Professionals

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Abstract

The communication gap between patients and health care professionals has led to increased disputes and resource waste in the medical domain. The development of artificial intelligence and other technologies brings new possibilities to solve this problem. This viewpoint paper proposes a new relationship between patients and health care professionals—"shared decision-making"—allowing both sides to obtain a deeper understanding of the disease and reach a consensus during diagnosis and treatment. Then, this paper discusses the important impact of ChatGPT-like solutions in treating rheumatoid arthritis using methotrexate from clinical and patient perspectives. For clinical professionals, ChatGPT-like solutions could provide support in disease diagnosis, treatment, and clinical trials, but attention should be paid to privacy, confidentiality, and regulatory norms. For patients, ChatGPT-like solutions allow easy access to massive amounts of information; however, the information should be carefully managed to ensure safe and effective care. To ensure the effective application of ChatGPT-like solutions in improving the relationship between patients and health care professionals, it is essential to establish a comprehensive database and provide legal, ethical, and other support. Above all, ChatGPT-like solutions could benefit patients and health care professionals if they ensure evidence-based solutions and data protection and collaborate with regulatory authorities and regulatory evolution.

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KEYWORDS
rheumatoid arthritis; ChatGPT; artificial intelligence; communication gap; privacy; data management

Introduction

In recent years, the communication gap has led to intense relationships between patients and health care professionals. The use of ChatGPT-like solutions in health care has enormous potential to improve the patient-provider relationship, such as patient clinic letter writing [1], medical note-taking and consultation [2], and rheumatoid arthritis treatment. Although ChatGPT (OpenAI) [3] is not the only solution available, the technology has generated a lot of traction due to its advanced features, such as the ability to enhance rule-based chatbots. However, it is important to note that ChatGPT-like solutions should not be viewed as a stand-alone solution but as an integrated interface in a larger ecosystem that allows access to
multiple data sources. In terms of the patient-provider relationship, the use of ChatGPT can enable more fluid and effective communication between the 2 parties, which can improve the quality of care. In particular, the use of ChatGPT-like solutions in the context of methotrexate treatment for rheumatoid arthritis could have a significant impact. This viewpoint paper proposes a new relationship between patients and providers—“shared decision-making”; explains the potential of ChatGPT-like solutions in improving the patient–health care professional relationship from the clinical and patient perspectives; and suggests the importance of establishing a comprehensive database to promote the implementation of “shared decision-making” between patients and health care professionals.

**Toward Shared Decision-Making**

In conventional medical settings, the relationship between patients and health care professionals was not equal, mainly because of the huge information gap between them, since patients lacked medical knowledge and decision-making capacity. In recent years, the rapid development of ChatGPT possesses enormous potential to bridge the information gap and improve the relationship between patients and health care professionals. For instance, ChatGPT could help provide the risk-benefit analysis of different treatment options, assisting health care professionals and patients to understand the advantages and disadvantages of each option and then make informed decisions together. It could also assist patients in understanding the complex medical jargon and technical details and provide information about the disease, treatment options, potential risks, and expected outcomes, allowing patients to participate in making informed decisions with health care professionals together. ChatGPT-like solutions allow bilateral communications between patients and health care professionals toward shared decision-making.

**Clinical Perspective**

From the clinical standpoint, early diagnosis of rheumatoid arthritis is crucial [4] for health care professionals and should be based on clinical examinations and biological results such as serological tests [5]. However, the differential diagnosis of complex diseases such as rheumatoid arthritis–associated interstitial lung disease [6] remains a major concern [7], as it is responsible for a significant increase in mortality [8]. ChatGPT-like solutions could bring complementary support to diagnose the disease and predict its evolution. Thus, to the query “What could be the reason for cough and dyspnea in a patient with rheumatoid arthritis?” ChatGPT suggests interstitial lung disease in the first place. By integrating external data on risk factors (age, sex, and smoking), biological results (pulmonary function testing, autoantibodies, and biopsy), and imaging (high-resolution computed tomography and ultrasound) [6], ChatGPT-like solutions can assist in suggesting additional tests and confirming the diagnosis.

The initiation of treatment for rheumatoid arthritis should be in accordance with the latest official recommendations, such as those from the European League Against Rheumatism [9] and the American College of Rheumatology (ACR) [4]. An advanced tool such as ChatGPT provides clinicians with exhaustive information on the latest guidelines for the management of rheumatoid arthritis. For instance, if a clinician asks “What are the current guidelines for treating rheumatoid arthritis according to the ACR?” ChatGPT can retrieve the key points of rheumatoid arthritis management in accordance with the official ACR guidelines [4]. However, in the specific case of a request regarding recommendations for treating rheumatoid arthritis–associated interstitial lung disease, ChatGPT erroneously refers to nonexistent ACR guidance [10]. Currently, the tool has limitations, such as data exclusion after 2021 and response size limits.

The determination of a patient’s drug dose by the clinician is based on a comprehensive evaluation of the results of the biological tests and clinical examination. However, dose adjustment may not always be performed according to a standardized procedure and evidence-based solution, although this is crucial to ensure the effectiveness and tolerability of the treatment for the patient. Methotrexate is the most common treatment for rheumatoid arthritis, and an initial dose of 7.5-15 mg once a week is recommended, followed by a gradual increase in dose. However, poor patient adherence and nonpersistence to methotrexate therapy have been reported [11] mainly due to low dose tolerance. Optimization of methotrexate dose is therefore essential for treating rheumatoid arthritis [12]. The use of methotrexate monotherapy has shown similar efficacy to the combined use of methotrexate monotherapy with biologic disease–modifying antirheumatic drugs [13]. Process automation and integration of complementary data, based on solutions such as ChatGPT, could improve outcome prediction, contribute to drug dose optimization, and thus reduce costs to the health care system.

Access to information on ongoing clinical trials and their results would enable clinicians to propose treatments for people with rare conditions in rheumatoid arthritis. Compiling data on clinical trials and patient characteristics would allow clinicians to propose alternatives, for example, for patients who have failed current therapies. Identifying subpopulations would facilitate patient recruitment and bring more effective and safer drugs to market. However, one challenge is to deidentify data to comply with the US Health Insurance Portability and Accountability Act (HIPAA) [14]. As such, it is important for clinicians to prioritize patient privacy and confidentiality when accessing and using such data. In addition, it is necessary for further interdisciplinary research to improve the accuracy and persuasiveness of artificial intelligence (AI) chatbots to influence patients’ behaviors [15]. Moreover, the application of AI and machine learning in health care should still be regulated by establishing norms to reduce bias and reflect the real problems [16].

**Patient Perspective**

From the patient’s perspective, it allows easy access to a large volume of information with a certain degree of scientific evidence, which improves the patient’s knowledge of rheumatoid arthritis and their health literacy. ChatGPT-like
solutions thus contribute to dealing with the proliferation of unreliable sources of emerging information and widespread disinformation [17]. It is also a tool that could not only enable empowerment by acting interactively throughout the care pathway but also promote patient adherence to treatment. However, some concerns persist regarding the lack of supervision of this type of solution and the liability involved [18]. For example, in the case of methotrexate side effects, to the query “I have gastrointestinal problems and fatigue, is this related to my methotrexate intake?” ChatGPT suggests that the doctor can adjust the dosage. It does not provide suggestions to state that concomitant folate or folic acid changes would reduce toxicity. It also raises questions about the risk of patients adjusting their own dosage. ChatGPT-like solutions can strengthen expert patients’ collaboration, allowing the cocreation of care pathways; however, it can also be a source of conflict by pitting the tool’s and the caregiver’s advice against each other. Therefore, it is crucial to better supervise this tool from the beginning of its development, in order to clearly distinguish between its general public and medical use and to define the responsibilities of each. The use of ChatGPT-like solutions can improve communication and access to information for patients with rheumatoid arthritis but must be carefully managed to ensure safe and effective care.

A ChatGPT-like solution allows the patient to have continuous access to information in an interactive way that promotes understanding outside the clinical setting. This solution can play an important role in therapeutic education by providing information on the self-management of rheumatoid arthritis, on a drug such as methotrexate, or on the administration methods (oral and subcutaneous). Therefore, the query of “What precautions should be taken when taking methotrexate?” could instantly provide basic and exhaustive information (taking it with food, avoiding alcohol, staying hydrated, using contraceptives, etc) and could contribute to therapeutic education [19]. In addition, a ChatGPT-like solution could be used to communicate medical information on potential benefits and assist in administration [20], for example, when modifying the route of administration of methotrexate. This would have an impact on facilitating the acceptability of subcutaneous methotrexate, allowing better bioavailability and clinical efficacy. It would also reduce the time required to initiate treatment and avoid the use of biologics, thus having a significant impact on health care costs [21].

Further integration and analysis of patient requests would also accelerate the transition to more personalized medicine. ChatGPT-like solutions could identify patient profiles and adapt communication strategies to overcome resistance and nudge behavior. These solutions will have to be adapted to each country in terms of public health systems and beliefs.

Establishment of a Comprehensive Database

The database is one of the critical elements of digital infrastructure for digital technology applications [22], especially AI-based solutions that require huge amounts of data to achieve more accurate results. However, using AI-based technology can be limited by the nontransparent learning process, difficulties in explanation and validation, and the influence of improper data [23]. Hence, the establishment of a comprehensive database, which is sourced from real-world data and updated on time and precisely, could contribute to overcoming limitations caused by insufficient data and support evidence-based clinical applications.

In recent decades, the Taiwan government launched the National Health Insurance (NHI) system that collected health-related data of health care providers, citizens, and legal residents. Since its establishment, the NHI database has been continuously improved by using the latest technologies to accommodate the increasing needs. During the COVID-19 pandemic, the NHI database successfully supported the Taiwan government in tracking patients, distributing face masks, and containing the infections [24,25].

On the other hand, using mobile health tools also contributes to the establishment of a comprehensive database. In recent years, tools such as the Apple Watch have been widely used to collect data about health conditions and identify possible illnesses of people. Mobile health tools allow the collection active data and passive data, which could better inform the health condition of the people [26].

Above all, the establishment of a comprehensive database is fundamental to applying AI-based solutions in the digital governance of health care. Moreover, applying AI-based solutions and other digital technologies should also be accompanied with comprehensive planning and flexible strategies to achieve effective digital governance in health care [22].

Conclusions

In conclusion, ChatGPT-like solutions have the potential to improve the patient-provider relationship through “shared decision-making.” ChatGPT solutions should optimize the patient’s care pathway while improving the patient’s experience of using methotrexate in rheumatoid arthritis. However, there is a need to ensure evidence-based solutions and quantify these benefits. In the future, we may question the compatibility of the business model of mass-market solutions with health care system purposes, particularly concerning data protection. Using federated learning might be a way for developers to overcome this limitation. The implementation in a specific health care context should increase in the coming years with the development of solutions in specific domains such as Bio-Generative Pre-Trained Transformer. A deployment in clinical settings will require collaboration with regulatory authorities and potentially an evolution of the software as a medical device regulatory framework [27].

The need to include individuals in the design of these solutions is also crucial to consider from an efficiency point of view to avoid certain biases and from an ethical point of view. This solution also facilitates access to health care information for the entire world population in pursuit of the sustainable development goals set by the United Nations.
References


Abbreviations

ACR: American College of Rheumatology
AI: artificial intelligence
HIPAA: Health Insurance Portability and Accountability Act
NHI: National Health Insurance

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Exploring the Feasibility of Using ChatGPT to Create Just-in-Time Adaptive Physical Activity mHealth Intervention Content: Case Study

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Abstract

Background: Achieving physical activity (PA) guidelines’ recommendation of 150 minutes of moderate-to-vigorous PA per week has been shown to reduce the risk of many chronic conditions. Despite the overwhelming evidence in this field, PA levels remain low globally. By creating engaging mobile health (mHealth) interventions through strategies such as just-in-time adaptive interventions (JITAIs) that are tailored to an individual’s dynamic state, there is potential to increase PA levels. However, generating personalized content can take a long time due to various versions of content required for the personalization algorithms. ChatGPT presents an incredible opportunity to rapidly produce tailored content; however, there is a lack of studies exploring its feasibility.

Objective: This study aimed to (1) explore the feasibility of using ChatGPT to create content for a PA JITAI mobile app and (2) describe lessons learned and future recommendations for using ChatGPT in the development of mHealth JITAI content.

Methods: During phase 1, we used Pathverse, a no-code app builder, and ChatGPT to develop a JITAI app to help parents support their child’s PA levels. The intervention was developed based on the Multi-Process Action Control (M-PAC) framework, and the necessary behavior change techniques targeting the M-PAC constructs were implemented in the app design to help parents support their child’s PA. The acceptability of using ChatGPT for this purpose was discussed to determine its feasibility. In phase 2, we summarized the lessons we learned during the JITAI content development process using ChatGPT and generated recommendations to inform future similar use cases.

Results: In phase 1, by using specific prompts, we efficiently generated content for 13 lessons relating to increasing parental support for their child’s PA following the M-PAC framework. It was determined that using ChatGPT for this case study to develop PA content for a JITAI was acceptable. In phase 2, we summarized our recommendations into the following six steps when using ChatGPT to create content for mHealth behavior interventions: (1) determine target behavior, (2) ground the intervention in behavior change theories, (3) design the intervention structure, (4) input intervention structure and behavior change constructs into ChatGPT, (5) revise the ChatGPT response, and (6) customize the response to be used in the intervention.

Conclusions: ChatGPT offers a remarkable opportunity for rapid content creation in the context of an mHealth JITAI. Although our case study demonstrated that ChatGPT was acceptable, it is essential to approach its use, along with other language models, with caution. Before delivering content to population groups, expert review is crucial to ensure accuracy and relevancy. Future research and application of these guidelines are imperative as we deepen our understanding of ChatGPT and its interactions with human input.

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KEYWORDS
ChatGPT; digital health; mobile health; mHealth; physical activity; application; mobile app; mobile apps; content creation; behavior change; app design

Introduction

Physical inactivity is a key modifiable risk factor for many chronic conditions, including cardiovascular disease, type 2 diabetes, and cancers, throughout the lifespan [1]. Despite this evidence, adults and adolescents alike are not consistently meeting the recommended guidelines to prevent developing these chronic conditions [2]. Previous studies have shown that 150 minutes of moderate-to-vigorous physical activity (MVPA) can reduce the risk of all-cause mortality by at least 30%, along with reducing the risk for chronic conditions such as cardiovascular disease (30%), colon cancer (20%), and breast cancer (14%) [3]. Although many chronic diseases affect adults, healthy lifestyle habits need to be developed early from childhood. Children aged 8 to 12 years are more flexible than adults in their ability to change behaviors because they are just beginning to develop self-regulation skills, habits, and identities for healthy living [4,5]. Thus, many countries such as Canada [6], the United States [7], and the United Kingdom [8] have set guidelines recommending 60 minutes of MVPA per day for children 17 years and younger [2]. However, despite these recommendations, physical inactivity is prevalent among children, with less than one-quarter of children meeting the guidelines in countries such as Canada [9] and the United States [9]. Consequently, promoting regular PA to prevent chronic diseases and maintain lifelong health has been a key priority for governments worldwide.

Recent studies suggest that family-based PA programs can be an effective strategy to improve PA levels in children [10,11]. These programs focus on providing guidance for parents to support their child’s PA (eg, encouragement, providing opportunity, and logistic support) [12]. With advancements in mobile health (mHealth) technologies and improved access to smartphones, emerging evidence indicates that PA interventions delivered through mHealth technology can be effective while improving scalability and personalization. However, the effectiveness and engagement of interventions vary depending on the intervention design and the degree of tailoring [13,14]. Studies have demonstrated that tailored mHealth interventions are more effective in improving behavior and health outcomes compared with nontailored interventions [15]. A recent advancement in tailored mHealth interventions is the development of just-in-time adaptive interventions (JITAIs), which use mHealth technology to assess the dynamically changing needs of individuals and deliver tailored support in real time [14,16]. Thus far, JITAIs have shown great promise in promoting PA among adults [17], university students [18], and chronic disease populations [19]. Further, innovative mHealth “no-code” development platforms, such as Pathverse, have made the development and implementation of JITAIs much easier and cost-effective [20,21]. However, the development of content for JITAIs can be extremely labor-intensive due to the need to create various versions of health-related content for different tailored algorithms. Although the documentation of content creation timelines for PA JITAIs is in its infancy, a typical timeline for PA content creation from the formative phase to pilot testing reportedly ranges from 12 [22] to 15 months [23,24].

Specific to JITAIs, the typical process of creating evidence-based and engaging content for these mHealth interventions typically involves the following steps [21,25]: (1) defining the behavior change theories and behavior change techniques (BCTs) required for the intervention [26]; (2) gathering evidence from various sources, such as previous literature, public health sources, gray literature, and blogs, and then adapting it to suit the needs of the intervention and deliver it through the chosen medium; and (3) writing content that is engaging and matches the literacy level of the target population for the app. These steps can often be time-consuming, with the need for researchers to follow these steps iteratively and repetitively for the duration of the design of the intervention. Further, despite the consideration of these steps, several challenges still arise in the development of JITAi content. Existing studies have identified limitations, such as the need for more extensive content within interventions, struggles in creating novel and meaningful messages, and challenges in tailoring messages to diverse user preferences [27,28]. These studies have also recognized the resource constraints in developing content to meet these needs and the complex, multidimensional nature of creating tailored and engaging content for their sample. Therefore, an artificial intelligence (AI) tool such as ChatGPT (OpenAI) [29] can be extremely useful in making the process of generating JITAi content for mHealth interventions faster and more cost-effective. ChatGPT offers a solution to the need for more content within interventions by leveraging its vast training data and the ability to generate a diverse set of messages efficiently. Further, its generative capabilities and the ability for users to continually prompt new rules address the challenge of creating novel content, reducing the risk of messages being perceived as overly simplistic.

ChatGPT was first launched by OpenAI in November 2022 and is an open AI language model that generates human-like responses to text-based prompts [30]. It can understand and generate responses in various languages, as well as debug code, write stories in different genres and lengths, summarize information from complex texts, offer explanations on various topics, and even reject answering inappropriate prompts [31]. Unlike other generative large language models (LLMs), ChatGPT stands out as the inaugural member of a series of highly scaled LLMs that attain state-of-the-art performance with minimal need for fine-tuning [32]. Further, ChatGPT is highly sophisticated in that it is able to provide continuous dialog by remembering what the user has said earlier in the conversation thread [33].

Although ChatGPT hosts an impressive suite of features and capabilities, there are also several ethical and privacy concerns
to keep in mind while using this service. First, it is important to note that ChatGPT “learns” its information from human input. This is subject to error and is limited based on what others have input into its system. Further, when generating health information content, in particular, this LLM has been extensively trained with data up to 2021, thus limiting some of the relevance and accuracy of current practices [34]. Second, ChatGPT stores its data in the United States, which, depending on the type of information being input into the United States, may be subjected to privacy concerns based on US freedom and privacy laws. To build on this consideration of data storage, it is crucial not to input any personal health information or other sensitive data into ChatGPT, as this LLM continues to learn from text prompts.

Since its inception, ChatGPT has been widely cited in various bodies of behavioral science literature as a virtual assistant, chatbot, and language translation tool [35]. To generate output from the program, a concept called prompt engineering is one method that explains how ChatGPT generates output [36]. In LLMs, a prompt is defined as an instruction to the model that customizes, enhances, or refines the output [37]. However, there is currently a lack of studies examining the feasibility of using ChatGPT to help develop intervention content for JITAI aimed to promote PA when given a behavior change theory and a behavior target outcome.

Thus, the primary objective of this paper was to present an autoethnographic case study that explored the feasibility, including the acceptability and ease of use, of using ChatGPT to create content for a family-based PA JITAI mobile app. The secondary objective was to describe lessons learned and future recommendations for using ChatGPT in developing mHealth intervention content.

Methods

Study Design

This case study consisted of 2 phases, which took place from March 1, 2023, to April 30, 2023. In phase 1 (0-2 months), we used ChatGPT-3 to develop a 10-week family-based PA JITAI. In phase 2 (3-4 months), we described lessons learned based on our experience of using ChatGPT in phase 1 and provided future recommendations for using ChatGPT in the development of mHealth interventions.

Ethical Considerations

This paper outlines the procedural aspects of using ChatGPT for content generation for a subsequent study. Given that it operates independently without involvement of human participants or sensitive data, formal ethics approval from our institution was deemed unnecessary.

Phase 1

We explored the feasibility of using ChatGPT to create content for the PA JITAI mobile app. To determine the feasibility of using ChatGPT to rapidly create JITAI content, we used an autoethnographic case study approach [38]. This method enabled the researchers (AW and SL) to reflect on their experience of using ChatGPT. While using ChatGPT, the researchers created field notes and had a meeting to discuss their independent experiences with using ChatGPT-3. Specifically, we reflected on the acceptability and ease of use as key areas of focus for feasibility [39]. Results of the meeting were themed into acceptability and ease of use of using ChatGPT. Assessing acceptability metrics involved reflecting on the satisfaction of the response generated by ChatGPT. The ease-of-use assessment involved reflecting on ChatGPT usability [39]. In this phase, we used 2 tools, Pathverse and ChatGPT. Pathverse is a no-code app builder platform that supports mHealth research [20,40]. It consists of a web portal for researchers to create engaging mobile app interventions with “drag and drop” features instead of coding. The content is then instantly displayed on the Pathverse mobile app. We used ChatGPT-3 to generate the content needed to be added to Pathverse. To gather feasibility data, we generated intervention content to support parents to help their child (8-12 years of age) to be physically active.

The content generated for this app was developed based on the Multi-Process Action Control (M-PAC) framework [41,42]. The M-PAC framework addresses the intention-behavior gap through the understanding that ongoing reflective processes (ie, affective attitude and perceived opportunity) and regulation processes (ie, behavioral and cognitive tactics to maintain intention focus) are necessary for the intention to become an action [41]. Specific to a JITAI, the M-PAC framework was selected as the framework for this intervention to dynamically and contextually address users’ failed intentions to be physically active. Thus, the just-in-time intervention options can be tailored to the specific circumstances of the individual, aligning with either the reflective, regulatory, or reflexive process [41,42]. The M-PAC framework was additionally chosen as we have seen success with this framework and its associated BCTs (ie, action planning, repetition, and habit formation) in previous family-based PA programs [43]. To address these circumstances, our research team created decision tree algorithms to tailor the family lessons and challenges recommended throughout the weeks. The algorithms were designed using the M-PAC framework and take into consideration (1) child MVPA minutes, (2) parent support behavior, and (3) parent self-efficacy and motivation for supporting their child’s PA (Figure 1). Based on the decision tree, weekly tailored lessons needed to be created to target each M-PAC construct. Topics included parental support, affective attitudes toward supporting their children’s PA, capability, opportunity, self-monitoring of PA, and restructuring the environment for PA. These topics stemmed from previous research for family-based PA interventions using the M-PAC framework [43]. With these considerations, a variety of prompts were created based on these topics.
Figure 1. Names of modules in the decision tree algorithm for personalized lessons.

There are various components to consider when generating a prompt for ChatGPT. Specific to academic uses of ChatGPT, the elements to be included in a prompt include an instruction (ie, an overview of the output you would like to receive), context (ie, other background information to help tailor the output), input data (ie, additional specifications for the output that may include its strengths or limitations), and output indicator (ie, how you would like the output to be presented, including word count and paragraph format) [44]. When creating a prompt for this case study, we included the target behavior and the M-PAC framework, with each output to be delivered in bullet point form. Once the content was created, we then used the Pathverse mHealth no-code app design tool to develop the JITAI app [20,38-40].

Phase 2

We summarized lessons learned and future recommendations for using ChatGPT in the development of mHealth interventions. Our team identified common themes and patterns emerging from the process of creating the JITAI content using ChatGPT. We then compared our data with previous literature to develop recommendations for future use. This involved a literature search to identify relevant studies and lessons learned from using ChatGPT in mHealth interventions. The primary aim of the literature search was to gather a wide range of insights into the acceptability, including the application of ChatGPT and its effectiveness in this context and challenges associated with integrating ChatGPT into mHealth interventions to refine our recommendations.

Results

Phase 1: Exploring the Feasibility of Using ChatGPT to Create JITAI Content

The results of phase 1 are first reported on how the researchers (AW and SL) used ChatGPT to generate content, followed by an analysis of the feasibility of the use of ChatGPT in this context. Overall, we created 13 lessons with the help of ChatGPT in phase 1. Figure 2 displays an example of how this content was displayed in the mobile app. We provided specific prompts about the length of the content generated, the target constructs of the M-PAC framework, the tone of the lesson, and the literacy levels needed. We used multiple question prompts to optimize text output. Table 1 provides examples of prompts used for different lessons. We started with broad prompts (eg, explain the various constructs in the M-PAC framework) and then used specific prompts based on the output (eg, provide specific fun examples to help parents improve opportunities to support child PA; Table 1). After the prompts were input into ChatGPT, the output was copied into a separate document for review by the researchers (AW and SL). If more or alternate content was needed, prompts such as “provide additional information about [this topic]” were used. To ensure that the output given by ChatGPT was relevant and accurate, we referred to previous literature and previous content examples following the M-PAC framework [21,45,46]. Once the content was deemed acceptable and accurate by the researchers, it was uploaded to the Pathverse platform. This step additionally involved creating graphics to include along with the text responses and formatting the content into different app “pages” with fewer than 400 characters per page of the mobile app.
We evaluated the acceptability of ChatGPT for creating mHealth content by reflecting on content accuracy, relevance, and tone. Both researchers found that ChatGPT demonstrated an acceptable level of accuracy and relevance and provided relevant responses to the prompts. However, on some occasions, ChatGPT provided false academic references. This is a serious issue that needs to be addressed to prevent misinformation. Thus, both authors reflected the need to place a filtering mechanism to ensure that the content generated was appropriate. Furthermore, some of the answers lacked specificity (eg, provide examples of PA programs in my area). This may be due to the fact that ChatGPT-3 was trained using data up to September 2021. Finally, we found the tone of ChatGPT responses to be acceptable for research purposes. The overall tone matched the prompt given (eg, write in a fun and positive voice). Overall, ChatGPT did not generate any inappropriate content. There is an evident need to provide clear prompts in order for ChatGPT to provide optimal responses. Additionally, multiple questions are often needed to optimize ChatGPT responses. The researchers additionally agreed that providing a role to ChatGPT, for example, telling the LLM that it is a health researcher delivering a family-based PA intervention, may have further refined the tone and quality of the response given.

When reflecting on the feasibility of implementing ChatGPT for this case study, we (AW and SL) found ChatGPT to be easy to use. Both researchers (AW and SL), with varying levels of technical expertise, found the user interface to be intuitive. The ease of use also allowed us to test various prompts to help optimize the ChatGPT responses. Overall, we found that minimal training or prior experience is needed to use this tool, and it has the potential to make it widely accessible for researchers.

Figure 2. Screenshots of physical activity content generated by ChatGPT in the mobile app Pathverse.
Table 1. Prompts and responses from a conversation with ChatGPT in generating content for a 10-week family-based physical activity mobile app.

<table>
<thead>
<tr>
<th>Prompt entered</th>
<th>ChatGPT response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Write a fun to read article about the role of parental capabilities to support child physical activity based on the M-PAC(^a) framework</td>
<td>• Are you struggling to find ways to support your child’s physical activity? Do you want to improve your parental capabilities to make physical activity a fun and regular part of your child’s life? Look no further than the M-PAC framework, which provides a roadmap for parents to support their child’s physical activity. The M-PAC framework stands for Multi-Process Action Control, and it emphasizes the importance of three key components for parents to successfully support their child’s physical activity: instrumental support, regulatory support, and motivational support. Instrumental support refers to the tangible resources and skills that parents provide to support their child’s physical activity. This could include things like providing transportation to and from activities, purchasing sports equipment, or enrolling your child in a physical activity program. Regulatory support focuses on creating an environment that supports physical activity. This could include setting rules and boundaries around screen time, creating a routine for physical activity, or providing healthy food options to fuel physical activity. Motivational support is all about fostering a positive attitude towards physical activity. This could include providing praise and encouragement, setting goals, and finding ways to make physical activity fun and enjoyable.</td>
</tr>
<tr>
<td>Provide specific fun examples to help parents improve their capabilities for supporting child physical activity in bullet points</td>
<td>• Certainly! Here are some specific fun examples to help parents improve their capabilities for supporting child physical activity: 1. Instrumental Support: • Have a weekly family game night that involves physical activity such as charades, Pictionary or dance party. • Organize a scavenger hunt with physical activity challenges for your child and their friends. • Plan a family hike or outdoor adventure at a nearby park or nature reserve. 2. Regulatory Support: • Start a vegetable garden together and teach your child the importance of physical activity and nutrition for a healthy lifestyle. • Use a fitness tracker or pedometer with your child to encourage them to walk more and set goals for daily steps. • Plan a family bike ride or roller skating adventure on a weekend afternoon. 3. Motivational Support: • Make a fun reward system for reaching physical activity goals, such as a family outing to a local amusement park or water park. • Watch sports games or videos of active events with your child and talk about the benefits of physical activity for overall health. • Encourage your child to invite friends over for a game of soccer, basketball or other team sport to promote socialization and physical activity. By incorporating these fun examples into your family’s routine, you can improve your capabilities for supporting your child’s physical activity and make healthy habits a fun and rewarding part of your family’s lifestyle.</td>
</tr>
</tbody>
</table>

\(^a\)M-PAC: Multi-Process Action Control.

Phase 2: Recommendations for the Future Use of ChatGPT

Overview
On the basis of our experience in developing the above content and based on previous research \([21,25,47]\), we have compiled the following recommendations for using ChatGPT for similar purposes. First, a 6-step recommendation was proposed to help make the process of using ChatGPT more efficient for future research. These steps included defining the target behavior for the intervention, applying behavior change theory, creating the intervention structure, inputting this information into ChatGPT, refining the output, and customizing the content to be delivered to the target population. Second, we discussed ethical considerations for the use of ChatGPT in academic research. Lastly, we discussed transparency with using ChatGPT in academic research.

Step 1: Determine Target Behavior
The first step of these guidelines involves determining a target behavior or behaviors for the target population of your intervention. This could be based on previous research for certain demographic groups or based on a gap in the current literature. The selected target behavior defines the purpose of the intervention and the outcomes on which the intervention will be assessed \([25]\). This is considered an essential first step as it will guide the remaining steps of these recommendations.

Step 2: Ground in Behavior Change Theory
The second step recognizes the need to deliver digital health content grounded in behavior change theory. Based on previous literature and considering the target behavior selected in step 1, it is advised to select a health behavior theory to guide the intervention. Thus, constructs of the behavior change theory must be considered when searching for and developing digital health intervention content. Further, other elements of the intervention, such as BCTs, to strengthen the behavior change theory \([26]\) should be considered during this step.
**Step 3: Design Intervention Structure**

Step 3 involves designing the intervention structure. In this step, the length of the intervention and the length and amount of content to be delivered should be considered first. After this information has been determined, it is recommended to consider the medium of delivery of the digital health intervention content. Previous research has shown varying success for both web-based interventions and mobile-based interventions [48,49]. Additionally, there are important considerations for best practices with delivering content through these different mediums, which are explored later in this development process.

It is important to note that this step may involve an additional agenda. Examining previous literature, using participatory action research or co-design principles, or other methods may be necessary to ensure that you are gathering content that will be both engaging to the participants and promoting adherence to the target behavior.

**Step 4: Input Intervention Structure and Behavior Change Constructs Into ChatGPT**

The next step is to input the information gathered from steps 1 to 3 and create varying prompts into ChatGPT. If this is your first time logging into ChatGPT through OpenAI, you will need to create a free account. Once your account has been created, you may type your prompt into the text box at the bottom of the screen. Determining an optimal prompt to input includes considering the target behavior, the proposed structure of the intervention, the behavior change theory and its constructs, and BCTs. Further, it is important to consider the rules in which ChatGPT delivers its output, for instance, whether you would prefer the response to be in paragraph form or bullet points. This step is iterative as you receive responses and continue to modify your prompt until you receive the desired output. Additionally, it has been previously recommended to consider assigning a role and tone for ChatGPT to embody in its response or to provide a similar example, when available [50].

**Step 5: Revise the Output of ChatGPT**

This step involves revising the response received from ChatGPT. There is a possibility that the language model has created errors or has provided incorrect references with their output. We compared the results with previous literature and revise and adapted as necessary to ensure that the most accurate information is being provided. Including information from the previous literature in the next prompt may continue to provide more refined ChatGPT responses.

**Step 6: Customize the Content to be Delivered**

The final step of this framework is to customize the content to meet the needs of your intervention. This involves considering the layout and design of how you will deliver the content on your selected medium from step 3, as well as any images or graphics used to supplement the given content. This step may involve working with an additional team to develop a web-based or mobile-based platform to support the health behavior change intervention. Further, user experience and design should be considered to improve usability and satisfaction of the content [51-54]. Table 2 summarizes the steps of these guidelines and considerations to meet the needs of each step.

By following these guidelines and using ChatGPT to assist in the rapid creation of digital health content, many ethical considerations arise. The first consideration, as highlighted above, is ensuring that the responses from ChatGPT are accurate and validated to be used as health information in a research study. This can be done by referencing previous literature or creating a panel of experts in the field to review the output created by ChatGPT. Further, it is vital to ensure that users engaging with AI-generated content through ChatGPT or other LLMs are adequately informed about its limitations, decision-making capabilities, and the crucial nature of their involvement. Transparent communication and obtaining informed consent are pivotal to respect user autonomy and comprehension. Although ChatGPT demonstrates remarkable efficiency in generating responses to prompts, evaluating its applicability within the intervention’s context remains crucial to ensure substantial value to using ChatGPT.

As ChatGPT inevitably continues to support academic research across disciplines, it is also important to consider how ChatGPT is being cited by those who use it. There has been a variety of techniques used so far, with some authors including ChatGPT as an author [55] and others acknowledging the use of ChatGPT [34] to assist with their manuscript.
Table 2. Proposed recommendations for developing digital health content using ChatGPT and a summary of considerations for using this tool.

<table>
<thead>
<tr>
<th>Step</th>
<th>Task</th>
<th>Consideration</th>
</tr>
</thead>
</table>
| 1    | Determine target behavior                 | • Previous research  
       |                              | • Needs of the target population                                             |
| 2    | Ground in behavior change theory          | • Stage of readiness of participants  
       |                              | • Needs of the population group                                               |
| 3    | Design the intervention structure         | • Web or mobile based  
       |                              | • Length of the intervention                                                  |
|      |                                           | • Amount of content to be delivered in each bout (i.e., how many words, characters, or pages of content to be delivered)  
|      |                                           | • Use co-design or other frameworks to ensure that the intervention aligns with the needs of the target population |
| 4    | Input intervention structure and behavior change constructs into ChatGPT | • Structure prompt to input into ChatGPT (considering instruction, context, input data, and output indicator)  
       |                              | • Iteratively adapt prompts based on desired output                             |
|      |                                           | • Order in which relevant information relating to each construct is delivered, if not predefined by the literature |
| 5    | Revise the output of ChatGPT              | • Refer outputs to previous literature to ensure accuracy                      |
|      |                                           | • Confirm whether references used by ChatGPT are accurate                       |
| 6    | Customize the content to be delivered     | • Layout and design of content                                                 |
|      |                                           | • Images or graphics to supplement text output                                 |
|      |                                           | • User experience and design of the intervention platform                      |

Discussion

Principal Findings

The primary objective of this study was to explore the feasibility of using ChatGPT to develop content for a mobile-based JITAI to promote parental support for their children’s PA. The secondary objective was to propose recommendations for using ChatGPT for future work in this area. To our knowledge, the process of using ChatGPT to develop health intervention content has not yet been documented, so we considered the key components required to develop effective behavior change interventions. We found that using ChatGPT was overall acceptable for this case study. However, a human check by researchers in the field is imperative to ensure the relevance and accuracy of the output provided. The use of ChatGPT and similar LLMs is rapidly evolving, and as such, these proposed recommendations are highly dynamic to the developing nature of these technologies.

This study has several implications for researchers using ChatGPT when developing mHealth app content. First, ChatGPT can help researchers improve the efficiency of creating digital health content for various tailored lessons. Previously, it was determined that ChatGPT can expedite the research process by allowing researchers to focus on steps of the research design process that require more human input, for example, focusing on the experimental design [56,57]. The improvement and versatility of text generation, knowledge translation, and literature review have been documented in various studies that have used ChatGPT in health care education [58]. As seen in this study, ChatGPT can help create various versions of content (varying in writing styles and tones) using a series of different prompts. Further, coupled with the efficiency of developing intervention content, this study has highlighted the ability to efficiently create a variety of tailored content specific to PA messaging. The need for more variety and content options has been previously stated as a limitation in previous studies that did not use ChatGPT for the creation of content [28]. Overall, this study highlights one use case that benefited from the use of ChatGPT to rapidly create digital health content. As ChatGPT is in its infancy, we expect it to evolve quickly [58].

Second, this study highlights the current limitations of using ChatGPT for creating mHealth behavior interventions. Although ChatGPT has great potential to improve the efficiency with which digital health content creation can occur, it is not possible to replicate responses by ChatGPT while using the same prompt [58,59]. This unpredictability poses a significant challenge for health researchers and developers who may require stable and reliable outputs [58]. Because of the probabilistic nature of ChatGPT and similar LLMs, the responses generated from ChatGPT are generated based on a probability distribution, meaning the same response will not be generated [60]. Further, a significant concern is the generation of references by ChatGPT that do not exist or are inaccurate. This lack of interpretability hampers the transparency of mHealth content development, making it difficult for researchers to have a clear understanding of the AI’s decision-making process. Other limitations have been recognized by previous work around ChatGPT. These include limited accuracy, bias and limitations of data, lack of context, and the potential of limited engagement with the content [34]. To mitigate these challenges, we highly recommend a rigorous human fact-checking process, as indicated in our recommendations for mHealth intervention content development.
using ChatGPT, and fine-tuning specific prompts to ensure that the information given by ChatGPT is relevant.

Finally, the integration of ChatGPT with existing mHealth app development tools, such as Pathverse, holds the potential to significantly enhance the efficiency and effectiveness of developing and evaluating JITAI apps. By incorporating ChatGPT’s language generation capabilities into Pathverse, developers can expedite the creation of content-rich JITAI apps. Additionally, reinforcement learning algorithms can play a crucial role in JITAI apps by dynamically adapting the intervention based on real-time data and user feedback [61]. Developers can leverage ChatGPT’s language generation capabilities using its application programming interface to assist with content creation [61]. With the integration of ChatGPT, these algorithms can benefit from the AI-generated content to offer more tailored and contextually relevant interventions. By combining the strengths of reinforcement learning and ChatGPT, JITAI apps can become more adaptive and responsive to individual user’s needs, thereby increasing their effectiveness in promoting behavior change and improving health outcomes.

There are several limitations to this study. First, we used ChatGPT to create content for only 1 JITAI, potentially restricting the generalizability of the study findings. Second, because of ChatGPT’s tendency to provide different responses for the same prompt, it was challenging to accurately characterize the content’s reproducibility and consistency. Lastly, as ChatGPT is rapidly evolving, the use case described in this study may have limited applicability a few years from now. We also want to add that although ChatGPT-3 is currently free to use, it is likely that as it improves, it is likely to come with an associated cost.

Conclusions
By using ChatGPT, we were able to expedite the process of creating 13 lessons that were guided by the M-PAC framework, thus highlighting the incredible opportunity ChatGPT presents to rapidly create content for various mHealth JITAI apps. Although we found that ChatGPT was acceptable for this case study, we still encourage the cautious use of ChatGPT and other LLMs in similar contexts. The use of ChatGPT expedited the process of content development to 2 months, the bulk of which was spent on reviewing the content by experts in the field before delivering to population groups. This process was imperative to ensure that accurate and relevant content was being created to be delivered. The results from this study found implications in 3 areas. The first is efficiency in generating a variety of content based on different prompts. Second, this study highlighted the potential limitations of ChatGPT, including the inability to replicate responses from the same prompts and the need for human input to ensure that the output from ChatGPT is accurate. Finally, this case study has highlighted the efficiency of using no-code app builders, such as Pathverse, to disseminate information generated by ChatGPT. It is without a doubt that as ChatGPT and other LLMs continue to improve in sophistication and accuracy, they will continue to integrate into intervention design and other various contexts for researchers. Further research and applications of ChatGPT and the guidelines proposed in this study are imminent in this field as we continue to understand ChatGPT.

Acknowledgments
The authors acknowledge that ChatGPT was used to generate results for this study. For a summary of the ChatGPT conversations, see Multimedia Appendix 1.

Conflicts of Interest
None declared.

Multimedia Appendix 1
ChatGPT Transcript.
[PDF File (Adobe PDF File), 172 KB - mededu_v10i1e51426_app1.pdf ]

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60. Why ChatGPT and other LLMs generate different answers to same questions. Ayfie. 2023. URL: https://blog.ayfie.com/why-chatgpt-and-other-llms-generate-different-answers-to-same-questions [accessed 2023-12-14]


Abbreviations

- AI: artificial intelligence
- BCT: behavior change technique
- JITAI: just-in-time adaptive intervention
- LLM: large language model
- mHealth: mobile health
- M-PAC: Multi-Process Action Control
- MVPA: moderate-to-vigorous physical activity
- PA: physical activity

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Incorporating ChatGPT in Medical Informatics Education: Mixed Methods Study on Student Perceptions and Experiential Integration Proposals

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Abstract

Background: The integration of artificial intelligence (AI) technologies, such as ChatGPT, in the educational landscape has the potential to enhance the learning experience of medical informatics students and prepare them for using AI in professional settings. The incorporation of AI in classes aims to develop critical thinking by encouraging students to interact with ChatGPT and critically analyze the responses generated by the chatbot. This approach also helps students develop important skills in the field of biomedical and health informatics to enhance their interaction with AI tools.

Objective: The aim of the study is to explore the perceptions of students regarding the use of ChatGPT as a learning tool in their educational context and provide professors with examples of prompts for incorporating ChatGPT into their teaching and learning activities, thereby enhancing the educational experience for students in medical informatics courses.

Methods: This study used a mixed methods approach to gain insights from students regarding the use of ChatGPT in education. To accomplish this, a structured questionnaire was applied to evaluate students’ familiarity with ChatGPT, gauge their perceptions of its use, and understand their attitudes toward its use in academic and learning tasks. Learning outcomes of 2 courses were analyzed to propose ChatGPT’s incorporation in master’s programs in medicine and medical informatics.

Results: The majority of students expressed satisfaction with the use of ChatGPT in education, finding it beneficial for various purposes, including generating academic content, brainstorming ideas, and rewriting text. While some participants raised concerns about potential biases and the need for informed use, the overall perception was positive. Additionally, the study proposed integrating ChatGPT into 2 specific courses in the master’s programs in medicine and medical informatics. The incorporation of ChatGPT was envisioned to enhance student learning experiences and assist in project planning, programming code generation, examination preparation, workflow exploration, and technical interview preparation, thus advancing medical informatics education. In medical teaching, it will be used as an assistant for simplifying the explanation of concepts and solving complex problems, as well as for generating clinical narratives and patient simulators.

Conclusions: The study’s valuable insights into medical faculty students’ perspectives and integration proposals for ChatGPT serve as an informative guide for professors aiming to enhance medical informatics education. The research delves into the potential of ChatGPT, emphasizes the necessity of collaboration in academic environments, identifies subject areas with discernible benefits, and underscores its transformative role in fostering innovative and engaging learning experiences. The envisaged proposals hold promise in empowering future health care professionals to work in the rapidly evolving era of digital health care.

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KEYWORDS
education; medical informatics; artificial intelligence; AI; generative language model; ChatGPT

Introduction

Generative pre-trained transformers have evolved into potent language models with diverse education applications, including personalized and problem-based learning that emphasizes critical thinking [1]. They offer a chat interface for natural interactions, which can be valuable in engaging students in educational discussions. Additionally, these models can be adjusted to align with specific educational objectives and generate text embeddings, enabling tasks such as classification, recommendations, and similarity analysis. Furthermore, their accessibility through application programming interfaces (APIs) opens the door to integrate them into various educational applications beyond chat interfaces.

The integration of these artificial intelligence (AI) technologies, including ChatGPT, into the educational environment has the potential to improve the student learning experience [1-6]. By incorporating ChatGPT into the teaching and learning process in higher education, students can be supported throughout their educational journey and develop the necessary skills to effectively use AI in professional settings [4,7,8].

Integrating ChatGPT into the field of medical informatics education could not only enrich the learning experience but also empower students to apply AI skills, preparing them to tackle the complex challenges they will encounter in their future careers in health care [9]. For instance, professionals in medical informatics can use AI in developing decision support systems for diagnosing medical images and predicting patient outcomes based on data analysis. These applications demonstrate how a strong foundation in AI, facilitated by ChatGPT, can enhance the capabilities of future medical informatics professionals in delivering quality health care services.

Medical informatics, commonly referred to as biomedical or health informatics, is an umbrella term [10,11] that encompasses the use of information and communication technologies in health care. It is a fundamental field of study that caters to a diverse range of disciplines [12]. The field concentrates on using biomedical data, information, and knowledge for scientific inquiry, problem-solving, and decision-making endeavors that aim to advance care quality and delivery [13]. There is a growing interest in biomedical and health informatics (BMHI) education [14] due to the increasing demand for professionals who can address BMHI issues through the development, implementation, and evaluation of innovative technological solutions [15].

The educational requirements for BMHI vary depending on the level of education and career progression, with different pedagogical approaches needed to provide theoretical knowledge, practical skills, and a mature attitude [16]. Although medical informatics knowledge is globally applicable and requires international standards, education in this field is typically localized, with competencies being tailored to the specific environment in which they will be used [17]. Variations in educational and health care systems result in differences in BMHI education across countries. Nevertheless, despite this variability, fundamental similarities can be identified and used as a framework for recommendations [16,18].

The International Medical Informatics Association (IMIA), through its educational recommendations, has outlined essential knowledge domains for teaching in the field of BMHI, including the domain of computer science, data, and information [19]. Within this domain, there is a particular emphasis on imparting students with a deep understanding of the fundamental principles underlying emerging technologies, such as AI [19]. Notably, the most recent IMIA recommendation signifies the first explicit inclusion of AI as a topic within a BMHI knowledge domain. These IMIA recommendations offer a valuable framework for the development of educational programs, enabling the integration of essential competencies in medical informatics into the curricula of undergraduate medicine programs and master programs in the field, for instance. However, there is currently a dearth of specific recommendations regarding the inclusion of AI skills in the curriculum [9].

Since its launch, ChatGPT has ignited discussions surrounding its application in education. Rather than outright banning its use in universities, this presents an opportune moment to reassess teaching methodologies and examination practices in higher education, with the goal of preparing students for the digital world [2,3,5,7,20,21]. ChatGPT represents the initial step of a broader trend, and we must adapt to collaborate with it instead of opposing its presence [22]. In the education domain, ChatGPT will be able to offer interactive and personalized learning experiences, accessible on various devices. It can speed up routine tasks like assessments, allowing professors more time for personalized teaching. Furthermore, it can generate diverse educational content, ensure round-the-clock availability, assist in language learning, and promote innovative teaching methods.

It is crucial for faculty, professors, and students to be cognizant of both the potential and limitations of ChatGPT while also addressing ethical concerns [1,4,7,23,24] and ensuring accessibility in its implementation within academic settings. Encouraging the integration of ChatGPT in education requires the formulation of policies that promote best practices, nurturing students’ critical thinking and equipping them with the necessary skills to effectively use AI tools [4,7,25]. To foster the development of critical thinking, engaging students in activities that prompt them to verify the accuracy, veracity, and potential biases of the text generated by ChatGPT is essential [2,26,27].

Building upon the aforementioned discussions and considerations, this study aims to contribute meaningfully to the broader objective of integrating AI education within the field of medical informatics. Recognizing the significant relevance of ChatGPT as an AI tool to the medical informatics courses offered in the master’s programs in medicine and medical informatics at the Faculty of Medicine of the University of Porto (FMUP) in Portugal, this research seeks to address a proposal for integration of ChatGPT in the educational process.
The first objective is to compile the opinions of students enrolled in all levels of the medical faculty’s programs with the aim of obtaining a general perception of their perspectives and experiences regarding the use of ChatGPT as an educational tool. Furthermore, this study endeavors to provide practical proposals for professors, offering examples of prompts for incorporating ChatGPT into their teaching activities, in order to enhance the educational benefits for students in medical informatics courses.

**Methods**

**Ethical Considerations**

A structured questionnaire was designed and submitted to the ethics committee of Faculty of Medicine of the University of Porto (105/CEFMUP/2023) to ensure ethical considerations in conducting this research and obtain approval for data collection. Students who participated in the questionnaire were explicitly informed that their participation in the research was entirely voluntary and were assured of confidentiality and anonymity regarding their responses.

**Participants and Questionnaire**

This study used a mixed methods approach involving students enrolled at all levels of the medical faculty’s programs. The survey aimed to provide initial insight into medical informatics students’ perspectives regarding the use of ChatGPT in teaching. The exploratory survey served as a preliminary assessment to outline proposals for incorporating the tool classes.

The questionnaire consisted of a total of 25 questions, comprising both closed-ended and open-ended formats, which were electronically distributed to 105 students enrolled in programs at the FMUP that offer medical informatics courses. The closed-ended questions aimed to assess the participants’ familiarity with ChatGPT, their perception of the technology’s use in educational contexts, and their attitudes toward using the application in academic and learning tasks. Participants were asked to indicate their level of agreement on a Likert scale, ranging from “strongly agree” to “strongly disagree,” enabling nuanced responses.

In parallel, the open-ended questions encouraged participants to provide comprehensive and detailed feedback, sharing specific instances of their interactions and experiences with ChatGPT.

**Data Analysis**

The data collected from the questionnaire were analyzed using descriptive statistical techniques to summarize the quantitative responses. Thematic analysis was used to identify recurring themes and patterns in the qualitative responses, providing deeper insights into the students’ perceptions and suggestions.

**Literature Review and Description of Course Learning Outcomes**

The methodology of this study also involved conducting a comprehensive literature review to explore the current publications pertaining to the implementation of AI in higher education settings. Specifically, the focus was on examining the integration of ChatGPT within the context of teaching medical informatics and assessing its alignment with international recommendations for effective pedagogy in this domain.

To assess the potential benefits of incorporating ChatGPT into educational practices, the study describes the learning outcomes of 2 proposed courses, carefully designed based on the competencies and skills expected of medical informatics students. The authors of this research, along with other esteemed members of the faculty, collaboratively deliberated on the proposals for using ChatGPT, aiming to optimize its functionalities both in master’s programs in medicine and medical informatics.

In addition, it is expected to exemplify specific prompts to be used by students and professors to maximize the tool’s potential to facilitate learning experiences. These prompts are carefully designed to engage students in critical thinking, problem-solving, and knowledge exploration while also aiding professors in delivering exemplary instruction.

**Results**

**Questionnaire**

In July 2023, the questionnaire was distributed to the students through their institutional email addresses. Out of the recipients, a noteworthy 25 university students actively participated by responding to the survey, resulting in a response rate of approximately 24%. The majority of respondents identified as male, accounting for 56% (n=14) of the total sample, with an average age of 35.2 (SD 8.6) years. Table 1 provides a concise summary of the key demographic characteristics of the participating students.
Table 1. Characteristics of the participants (N=25).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sex, n (%)</strong></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>11 (44)</td>
</tr>
<tr>
<td>Male</td>
<td>14 (56)</td>
</tr>
<tr>
<td><strong>Age (years)</strong></td>
<td></td>
</tr>
<tr>
<td>20-25, n (%)</td>
<td>2 (8)</td>
</tr>
<tr>
<td>26-30, n (%)</td>
<td>6 (24)</td>
</tr>
<tr>
<td>31-35, n (%)</td>
<td>8 (32)</td>
</tr>
<tr>
<td>&gt;35, n (%)</td>
<td>9 (36)</td>
</tr>
<tr>
<td><strong>Mean (SD)</strong></td>
<td>35.2 (8.6)</td>
</tr>
</tbody>
</table>

Regarding the use of ChatGPT (Table 2), 52% (n=13) of the students indicated that they had their initial encounter with the chatbot during the second semester of 2022. Among them, a considerable proportion (n=4, 16%) reported using it on a daily basis, while the majority (several times during the week) found it to be a frequent resource. Impressively, 92% (n=23) of the students conveyed their satisfaction with the responses generated by ChatGPT, with 48% (n=12) expressing a high level of reliance on its answers and offering strong endorsements of its implementation among their peers. Nevertheless, a subset of participants (n=5, 20%) disclosed that they rarely place trust in the responses provided by the system. Furthermore, 96% (n=24) of the participants asserted that the tool comprehends the contextual intricacies of questions well. However, they noted that occasionally, to obtain the desired response, it becomes necessary to reformulate the query.
Table 2. Answers to questionnaire questions about the use of ChatGPT by medical faculty students (N=25).

<table>
<thead>
<tr>
<th>Question and answers</th>
<th>Respondents, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Do you usually talk to your colleagues about ChatGPT?</strong></td>
<td></td>
</tr>
<tr>
<td>Ever</td>
<td>11 (44)</td>
</tr>
<tr>
<td>Occasionally</td>
<td>13 (52)</td>
</tr>
<tr>
<td>Often</td>
<td>1 (4)</td>
</tr>
<tr>
<td><strong>When did you first use ChatGPT?</strong></td>
<td></td>
</tr>
<tr>
<td>Between March and April 2023</td>
<td>4 (16)</td>
</tr>
<tr>
<td>Between January and February 2023</td>
<td>7 (28)</td>
</tr>
<tr>
<td>Between July and December 2022</td>
<td>13 (52)</td>
</tr>
<tr>
<td>Between January and June 2022</td>
<td>0 (0)</td>
</tr>
<tr>
<td>In 2021</td>
<td>1 (4)</td>
</tr>
<tr>
<td><strong>Do you use ChatGPT regularly?</strong></td>
<td></td>
</tr>
<tr>
<td>Yes every day</td>
<td>4 (16)</td>
</tr>
<tr>
<td>Yes, several times a week</td>
<td>13 (52)</td>
</tr>
<tr>
<td>I use it from time to time</td>
<td>8 (32)</td>
</tr>
<tr>
<td><strong>How satisfied are you with ChatGPT's responses?</strong></td>
<td></td>
</tr>
<tr>
<td>Very satisfied</td>
<td>5 (20)</td>
</tr>
<tr>
<td>Satisfied</td>
<td>18 (72)</td>
</tr>
<tr>
<td>I have a neutral position on this</td>
<td>2 (8)</td>
</tr>
<tr>
<td><strong>Do you trust the information provided by ChatGPT?</strong></td>
<td></td>
</tr>
<tr>
<td>Most of the time</td>
<td>12 (48)</td>
</tr>
<tr>
<td>Sometimes</td>
<td>8 (32)</td>
</tr>
<tr>
<td>Rarely</td>
<td>5 (20)</td>
</tr>
<tr>
<td><strong>Does ChatGPT understand the context of your questions well?</strong></td>
<td></td>
</tr>
<tr>
<td>Very good</td>
<td>7 (28)</td>
</tr>
<tr>
<td>Good</td>
<td>17 (68)</td>
</tr>
<tr>
<td>No opinion</td>
<td>1 (4)</td>
</tr>
<tr>
<td><strong>When using ChatGPT, do you have to rephrase questions to get the answers you want?</strong></td>
<td></td>
</tr>
<tr>
<td>Rarely</td>
<td>7 (28)</td>
</tr>
<tr>
<td>Sometimes</td>
<td>17 (68)</td>
</tr>
<tr>
<td>Often</td>
<td>1 (4)</td>
</tr>
<tr>
<td><strong>Would you recommend ChatGPT to your colleagues?</strong></td>
<td></td>
</tr>
<tr>
<td>Definitely</td>
<td>18 (72)</td>
</tr>
<tr>
<td>Probably</td>
<td>5 (20)</td>
</tr>
<tr>
<td>I am not sure</td>
<td>1 (4)</td>
</tr>
<tr>
<td>Probably not</td>
<td>1 (4)</td>
</tr>
</tbody>
</table>

Concerning attitudes toward the use of ChatGPT for learning and academic purposes (Table 3), a majority of students demonstrated openness to adopting this form of chatbot and express intentions to incorporate it regularly into their educational endeavors. Nevertheless, it is noteworthy that 8% (n=2) of the participants held a dissenting perspective and are resolutely against its use in academic activities.
Table 3. Attitudes toward using ChatGPT for learning and academic tasks.

<table>
<thead>
<tr>
<th>Statement and Likert scale</th>
<th>Respondents, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>I think using a tool like ChatGPT would be a good idea to support learning</strong></td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>13 (52)</td>
</tr>
<tr>
<td>Agree</td>
<td>8 (32)</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>4 (16)</td>
</tr>
<tr>
<td><strong>I will start using ChatGPT to support learning and completing academic tasks</strong></td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>8 (32)</td>
</tr>
<tr>
<td>Agree</td>
<td>9 (36)</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>7 (28)</td>
</tr>
<tr>
<td>Disagree</td>
<td>1 (4)</td>
</tr>
<tr>
<td><strong>I will ask my colleagues about ChatGPT and how they use it</strong></td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>7 (28)</td>
</tr>
<tr>
<td>Agree</td>
<td>8 (32)</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>10 (40)</td>
</tr>
<tr>
<td><strong>I intend to create the habit of using ChatGPT to support learning and carry out my academic work</strong></td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>6 (24)</td>
</tr>
<tr>
<td>Agree</td>
<td>12 (48)</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>5 (20)</td>
</tr>
<tr>
<td>Disagree</td>
<td>2 (8)</td>
</tr>
<tr>
<td><strong>I will use ChatGPT or other similar chatbots whenever the opportunity arises</strong></td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>9 (36)</td>
</tr>
<tr>
<td>Agree</td>
<td>11 (44)</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>3 (12)</td>
</tr>
<tr>
<td>Disagree</td>
<td>2 (8)</td>
</tr>
<tr>
<td><strong>I have a bad feeling about ChatGPT and artificial intelligence in general</strong></td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>2 (8)</td>
</tr>
<tr>
<td>Agree</td>
<td>1 (4)</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>8 (32)</td>
</tr>
<tr>
<td>Disagree</td>
<td>10 (40)</td>
</tr>
<tr>
<td>Strongly disagree</td>
<td>4 (16)</td>
</tr>
<tr>
<td><strong>In my opinion, the use of ChatGPT or similar chatbots for academic tasks should not be allowed</strong></td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>1 (4)</td>
</tr>
<tr>
<td>Agree</td>
<td>1 (4)</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>5 (20)</td>
</tr>
<tr>
<td>Disagree</td>
<td>6 (24)</td>
</tr>
<tr>
<td>Strongly disagree</td>
<td>12 (48)</td>
</tr>
</tbody>
</table>

Regarding the perceptions of ChatGPT as an academic support tool (Table 4), a significant proportion (n=18, 72%) of students concur with the notion that the ChatGPT tool has the potential to enhance and facilitate learning experiences. Furthermore, an overwhelming majority strongly agree that its implementation streamlines the execution of tasks, promoting efficiency within the academic context.
Table 4. Perceptions of ChatGPT as an academic support tool.

<table>
<thead>
<tr>
<th>Statement and Likert scale</th>
<th>Respondents, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Using ChatGPT improves learning</strong></td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>12 (48)</td>
</tr>
<tr>
<td>Agree</td>
<td>6 (24)</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>6 (24)</td>
</tr>
<tr>
<td>Disagree</td>
<td>1 (4)</td>
</tr>
<tr>
<td><strong>Using the ChatGPT can make learning tasks easier to complete</strong></td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>12 (48)</td>
</tr>
<tr>
<td>Agree</td>
<td>10 (40)</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>3 (12)</td>
</tr>
<tr>
<td><strong>I find ChatGPT a very useful tool to support learning</strong></td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>15 (60)</td>
</tr>
<tr>
<td>Agree</td>
<td>7 (28)</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>3 (12)</td>
</tr>
<tr>
<td><strong>Using ChatGPT can increase my productivity as a student</strong></td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>16 (64)</td>
</tr>
<tr>
<td>Agree</td>
<td>6 (24)</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>3 (12)</td>
</tr>
<tr>
<td><strong>Using ChatGPT allows me to complete tasks faster</strong></td>
<td></td>
</tr>
<tr>
<td>Strongly agree</td>
<td>19 (76)</td>
</tr>
<tr>
<td>Agree</td>
<td>4 (16)</td>
</tr>
<tr>
<td>Neither agree nor disagree</td>
<td>2 (8)</td>
</tr>
</tbody>
</table>

In terms of the use of ChatGPT or other AI bots in the future, the majority of responses indicate that participants find it extremely useful, especially for medical writers who are not proficient in English, as it aids in restructuring and correcting texts. Some believe that the adoption of these tools will be inevitable and increasingly common, both in academic and professional contexts, resulting in enhanced process efficiency. However, there are also ethical concerns and apprehensions regarding the potential impact on the employability of programming professionals. Moreover, participants emphasize the importance of informed use, understand the limitations, and use these tools intelligently and as complementary to specific objectives. Some express caution, recognizing that although the tools have advantages, they do not create anything new but rather help organize thoughts and facilitate a better understanding of concepts.

The responses reveal diverse opinions on the benefits and drawbacks of using AI bots like ChatGPT in education. Some students highlight the capacity to customize responses to specific questions without worrying about boring the instructor and speeding up repetitive tasks, envisioning its potential to revolutionize the educational landscape. However, there are concerns about the long-term effects and the need for caution. The AI’s biases and limitations are seen as potentially harmful to knowledge, and there are worries about the credibility of sources used and proper attribution of credits and bibliographic referencing.

While some view it as a valuable tutor or assistant that is always available, others caution against its potential to promote laziness, particularly in written work, which may discourage the development of quality writing skills. Nevertheless, the quick response time for academic tasks is regarded as an advantage by some, with no apparent disadvantages seen. The major concern is the risk of a bias in thinking, whereby AI-generated ideas or responses could influence one’s own thought process, potentially inhibiting critical thinking. Despite this, many believe that ChatGPT can be a useful aid in executing certain tasks, as it does not create content but rather assists in the development and enhancement of ideas. The list of suggestions from medical informatics students on how to use ChatGPT or other AI bots in education can be seen in Figure 1.
Integration of ChatGPT

Overview

The analysis of student responses to the questionnaire has revealed a positive receptiveness and interest in the use of ChatGPT as an educational tool. Building on these findings, the next phase of our investigation focused on the proposed integration of ChatGPT into classroom settings. This section explores the proposal to incorporate ChatGPT into 2 specific courses, outlining how prompts developed by professors can be applied to enhance medical informatics students’ learning experiences. Additionally, we will address the events held at the faculty to discuss and guide the implementation of ChatGPT in the context of education, emphasizing the collaboration among professors to foster educational innovation.

Master’s Program in Medicine

The master’s program in medicine at FMUP comprises an integrated cycle of studies totaling 360 credits, in accordance with the European Credit Transfer and Accumulation System (ECTS).

The course chosen for this study’s proposal of implementing ChatGPT in the master’s program in medicine is “DECIDES III: Decision, Data and Digital Health” (4 ECTS), which has been taught in the fourth year. By the end of this course unit, medical students are expected (1) to have knowledge and be able to discuss key topics related to health information systems and the integration of scientific evidence in health decision-making; (2) to proficiently and safely use health information systems; (3) to critically evaluate health scientific literature, particularly regarding health information systems, health technology assessment, and health decision analysis; and (4) to plan and interpret studies on health economic evaluation and decision analysis.

The course offered in the master’s program in medicine proposes the use of ChatGPT in 3 ways (Textbox 1).

Figure 1. List of suggestions from medical informatics course students on how to use ChatGPT in education generated with the assistance of artificial intelligence (AI).

1. Generate new relevant questions or exercises to enhance creativity and exploration in learning.
2. Simplify the explanation of complex concepts, answer questions, and clarify doubts.
3. Implement gaming elements to create engaging and interactive learning experiences.
4. Support writing for research dissemination and academic publications.
5. Revise content and simulate examination scenarios.
6. Debugging in programming and text rephrasing.
7. Summarize information, create descriptive tables, and explain differences between concepts.
8. Use AI bots for academic writing and brainstorming ideas for assignments and projects.
9. Supplementary resource for brain processing, enabling students to focus on higher-order thinking and creative adaptation of knowledge to the current subject matter.
Assistant for simplified explanation of concepts

ChatGPT will serve as an assistant to explain complex concepts in a simplified manner. Medical students will be encouraged to use ChatGPT outside of the classroom to enhance their understanding of various topics, including blockchain, cloud services, data quality, machine learning, electronic health records (EHRs), and mobile health. They will be prompted to request explanations in simple language. Example of prompt: Explain the following concepts to me in a simple manner, providing examples from the healthcare field, as if I were a 16-year-old: machine learning.

Assistant for addressing complex problems

ChatGPT will also be used as an assistant to address intricate problems. It will provide support to students in tackling challenging scenarios and offer insights and solutions related to medical informatics and health care. Example of prompt: What risks and benefits has the General Data Protection Regulation brought to clinical research? For each of the risks, propose a technological solution to mitigate it. Present your findings in a table format.

Generation of clinical narratives and patient simulators

This feature will enable students to simulate realistic patient cases and explore various clinical scenarios, thereby enhancing their ability to effectively and securely use health information systems with proficiency. A prompt was created, requesting that ChatGPT read the manual of a health information system used in public hospitals in Portugal and then generate a clinical case that would allow the professor to practice with the students the use of all specific functionalities of the system.

In addition to assisting students, ChatGPT will also serve as a valuable tool for professors. By using the version of ChatGPT which incorporates plugins, professors can leverage its capabilities to enhance their teaching methodologies. In Multimedia Appendix 1, an illustrative scenario of using ChatGPT is detailed, culminating in the creation of a comprehensive lesson plan for obstetrics. This includes practical exercise demonstrations, a data generator for classroom use, a compilation of clinical cases for educational purposes, and a decision tree highlighting the importance of data quality in the medical field. This setup enhances understanding of ChatGPT’s practical application in medical education, offering innovative tools for improving teaching and learning.

Master’s Program in Medical Informatics

The master’s program in medical informatics (MIM) comprises 120 ECTS. Established 17 years ago at FMUP, MIM recently earned accreditation from the European Federation for Medical Informatics in 2022, affirming its high quality and recognition within the field.

The MIM’s course unit proposed in this study to incorporate ChatGPT during classes in “health information systems and electronic health records” (6 ECTS), which is taught in the second semester of the master’s program.

The main objective of this course is to equip students with the necessary knowledge and skills to effectively select, design, and manage health information systems and EHRs. The course focuses on developing an understanding of health information systems, including their development and implementation processes, functions, historical evolution, the significance of shared concepts among these systems, barriers in data collection, data integration and process integration, change management, current trends in health information system development, and the main challenges and considerations related to meaningful use. By the end of the course, students are expected to have achieved specific learning outcomes and competencies in these areas.

In the MIM, the use of ChatGPT offers students a versatile tool that enhances their learning experience and skill development. By incorporating ChatGPT, students can explore new educational possibilities and engage with the technology in meaningful ways. There are 5 specific applications of ChatGPT in the course. (Textbox 2).
It is imperative to foster institutional collaboration to empower perceptions regarding its use in education is essential. Moreover, As ChatGPT is a recent tool, gaining insights into students' practical application in the realm of medical informatics.

These exercises are designed to not only improve technical skills but also to cultivate a mindset of problem-solving and practical application in the realm of medical informatics.

**Fostering Collaborative Efforts**

As ChatGPT is a recent tool, gaining insights into students’ perceptions regarding its use in education is essential. Moreover, it is imperative to foster institutional collaboration to empower professors in effectively integrating AI tools into the teaching process. Throughout the course of several months, a series of pioneering initiatives unfolded at FMUP, spearheading the integration of ChatGPT into medical informatics education. The journey commenced in January 2023, with the introduction of ChatGPT theme in the MIM classes, providing students with a discussion about the tool’s potential application in the health care sector. As the momentum grew, a presentation was held in March 2023, engaging faculty members and researchers in exploring the practical use of ChatGPT in education.

Building on this foundation, the month of May 2023 witnessed the event “ChatGPT: Challenges for Education and Research,” orchestrated in collaboration with FMUP’s ethics committee. Subsequently, in a grander gathering titled “ChatGPT: Learning Models for Higher Education,” diverse faculty members united from disciplines ranging from engineering and arts to psychology and sciences. Together with the participation of the ethics committee chairman and the university’s vice-rector, professors from several faculties presented proposals for the incorporation of ChatGPT in classes, paving the way for the implementation of ChatGPT in the upcoming academic year.

By July 2023, the momentum reached new heights during the FMUP Summer School, with a captivating workshop focused on...
Discussion

Principal Findings

Building on the proposal to integrate AI into medical programs to prepare students for their future use of such tools in professional contexts [5,8,28,29], the implementation of ChatGPT has emerged as a potentially transformative force in medical education [30,31], offering support to students in their learning journey [30,32]. The questionnaire administered to medical faculty students provided valuable insights into their perspectives and experiences with ChatGPT, shedding light on their attitudes, preferences, and intentions regarding the incorporation of AI chatbots in educational environments. The participants, with a mean age of approximately 35 (SD 8.6) years, predominantly comprised master’s and doctoral students, indicating a higher participation rate from these groups compared to undergraduate medical students. Engaging in frequent discussions with peers about ChatGPT, most participants were introduced to the tool during its initial launch in 2022. Remarkably, a majority of students used ChatGPT regularly for diverse purposes, including report writing, idea brainstorming, and text rewriting.

In general, students expressed satisfaction with ChatGPT’s responses, finding them to be reliable and contextually comprehensible. They recognized the educational potential of ChatGPT, highlighting its ability to facilitate the creation of relevant exercises, enhance writing skills, and foster exploration of new concepts. Drawing from these valuable insights, proposals for ChatGPT’s integration into the 2 master’s programs were developed. Additionally, existing references that offer a plethora of ideas for ChatGPT’s incorporation into medical education were also considered, ranging from personalized learning opportunities [33,34] to problem-based learning and clinical problem-solving approaches [35]. Moreover, ChatGPT can be harnessed for teaching assistance, generating case scenarios, and creating educational content such as summaries, questionnaires, and flashcards [34].

The participants also acknowledged the need for caution in its application and emphasized the importance of understanding its limitations. It is essential to be mindful that AI systems may engage in “hallucination,” a phenomenon where they fabricate facts and produce confident-sounding statements and seemingly legitimate citations that are, in reality, false, and not necessarily supported by their training data [2,36,37]. To mitigate such issues, future implementations of ChatGPT should consider raising student awareness of the possibility of AI-generated content and encouraging critical analysis of generated responses. Although students expressed openness to adopting ChatGPT, their critical analysis of potential impacts on education should be taken into consideration by professors when implementing ChatGPT in the classroom.

Privacy concerns surrounding student interactions with ChatGPT have been acknowledged in prior literature [4,7,24]. It is imperative that AI be used as an educational aid without the extraction of sensitive data, adhering to relevant data privacy regulations. Information acquired during a learner’s interactions with the AI system to acquire knowledge must be shielded from any inappropriate use [38]. Despite the recent availability of this tool, specific guidelines regarding anonymity techniques for ChatGPT’s full integration into our master’s programs and curricula have yet to be established within our academic context. Nevertheless, professors can proactively protect privacy by refraining from collecting personally identifiable information, opting for generic pseudonyms over real names, working with aggregated data, securing data transmission through encryption, implementing data retention policies with defined timeframes, restricting access to authorized personnel, and educating students on best practices for safeguarding their privacy. These measures collectively ensure adherence to privacy regulations and the preservation of the confidentiality of student interactions with ChatGPT.

Building upon the students’ recognition of both the potential and limitations of ChatGPT, it becomes evident that fostering a balanced approach to AI integration in education is paramount. It requires a concerted effort to leverage AI’s strengths while addressing its vulnerabilities. This is where the strategic organization of faculty events plays a pivotal role in shaping the future landscape of AI-driven education.

In terms of fostering collaboration in the academic environment, the strategic organization of faculty events scheduled between March and June 2023 presented a unique opportunity to facilitate the start of ChatGPT integration in the upcoming academic year. Facilitating open discussions on the integration of AI in education, including the use of tools like ChatGPT, is a pivotal undertaking within the academic realm [3]. It represents a critical step toward embracing best practices, exploring ethical considerations, and harnessing the potential of AI to enhance the educational experience [4]. Such efforts require the active collaboration and engagement of all stakeholders involved in educational settings, including professors, researchers, and experts in the field [4]. By fostering a collective dialogue, universities can pave the way for the effective and responsible incorporation of AI technologies into teaching and learning environments, ultimately benefiting students and shaping the future of education.

In the field of medical informatics, the development of skill-based curricula becomes indispensable to meet the complexities of health care delivery and market demands [39]. Sapci and Sapci [9] have put forth a framework for specialized AI training in medical and health informatics education, and our study’s proposals regarding the use of ChatGPT align with some of the competencies outlined in their research. For medical students, AI competencies include the application of predictive AI techniques to enhance health care efficiency and the critical evaluation of AI tools. In the case of medical informatics students, the competencies encompass the adept application of suitable machine learning algorithms to analyze intricate medical data, the seamless integration of data analytics into innovative clinical informatics systems and applications, and the...

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formulation of data-related queries to visualize large data sets. For students pursuing computer science, the focus lies on developing programming languages tailored to address complex medical challenges [9].

Through the integration of ChatGPT into the master’s program in medicine, both students and professors will have the opportunity to harness its diverse functionalities, which play a pivotal role in promoting, for example, an understanding of complex concepts, effective problem-solving, and creating realistic medical scenarios. Consequently, the following applications of ChatGPT have been proposed for implementation: (1) acting as an assistant for simplified explanation of concepts, (2) assisting in addressing complex problems, (3) generating clinical narratives and patient simulators, and (4) enhancing teaching techniques for professors. These proposed applications hold the potential to augment the educational experience and knowledge acquisition within the field of medical informatics by medical students.

Regarding the MIM, the integration of ChatGPT is intended to offer students learning experiences that promote active engagement. Students are expected to cultivate essential skills, enhance problem-solving abilities, and equip themselves for upcoming challenges in this domain. Therefore, we have identified five specific ChatGPT applications proposed for the course: (1) project planning assistant, (2) programming code generation, (3) examination preparation, (4) workflow and information exploration, and (5) technical interview preparation. These proposed applications carry the potential to enrich the educational journey by empowering students to excel in the dynamic and evolving field of medical informatics.

Limitations
The low number of questionnaire’s responses is a limitation of the study. However, it is important to highlight that the survey aimed to provide an initial insight into the perspectives of medical informatics students at the FMUP regarding the use of ChatGPT in teaching. The primary purpose of the survey was exploratory in nature, serving as a preliminary assessment to inform future initiatives rather than a comprehensive study with a large sample. The other limitation lies in the absence of practical implementation of the proposed ChatGPT incorporation in the current academic year. As a result, the actual impact on the teaching and learning process remains uncertain, and the benefits of AI use in medical informatics education require further empirical verification. However, the study provides valuable groundwork for future exploration and collaboration in exploring AI’s potential in education. While the ideas presented hold promise, empirical evaluation in the upcoming academic term will be imperative to ascertain their effectiveness and measure their impact on students’ learning experiences. Further research and assessment will be necessary to determine the concrete effects and refine the integration strategies. Until then, the study stands as a stepping stone for stimulating ongoing dialogue and inspiring future research endeavors in the dynamic field of AI-driven education in the teaching of medical informatics.

Conclusions
The results of the questionnaire suggest that students perceive ChatGPT as a valuable tool for enhancing learning experiences and academic tasks, although they also emphasize the importance of informed and responsible use. The study’s findings contribute valuable insights for professors in exploring the integration of AI chatbots like ChatGPT in educational settings, with a particular focus on its suitability for medical informatics courses at master’s levels.

Additionally, the study provided a description of the learning outcomes of the 2 courses proposed for the incorporation of ChatGPT in the classroom. The collaborative efforts undertaken during 2023, including workshops and meetings with faculty members, served as pivotal moments that contributed to optimizing the use of ChatGPT as a powerful educational tool within the institution. Furthermore, specific subject areas and topics were identified as prime candidates for benefits through ChatGPT integration. The alignment of ChatGPT with these areas demonstrates its potential to increase the quality of education in the field of medical informatics.

In conclusion, the findings of this study highlight ChatGPT’s promising role in enhancing medical informatics education by equipping students and faculty with a transformative AI-driven approach. The insights gained from this research effort provide valuable prompt examples for harnessing the power of AI to create innovative educational experiences in the ever-evolving landscape of medical informatics. As we move into the era of AI-driven education, these findings hold significant implications for future pedagogical approaches, fostering an enriched learning environment that empowers the next generation of health care professionals to operate in the digital age.

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Authors’ Contributions
SMA completed the literature review, data collection, interpretation of results, and writing of the paper. RC-C supervised the project and developed the proposals for using ChatGPT for both courses. All authors contributed to the final version of the paper.

Conflicts of Interest
None declared.
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Abbreviations

- **AI**: artificial intelligence
- **API**: application programming interface
- **BMHI**: biomedical and health informatics
- **ECTS**: European Credit Transfer and Accumulation System
- **EHR**: electronic health record
- **FMUP**: Faculty of Medicine of the University of Porto
- **IMIA**: International Medical Informatics Association
- **MIM**: master’s program in medical informatics
Assessing AI Awareness and Identifying Essential Competencies: Insights From Key Stakeholders in Integrating AI Into Medical Education

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Abstract

Background: The increasing importance of artificial intelligence (AI) in health care has generated a growing need for health care professionals to possess a comprehensive understanding of AI technologies, requiring an adaptation in medical education.

Objective: This paper explores stakeholder perceptions and expectations regarding AI in medicine and examines their potential impact on the medical curriculum. This study project aims to assess the AI experiences and awareness of different stakeholders and identify essential AI-related topics in medical education to define necessary competencies for students.

Methods: The empirical data were collected as part of the TüKITZMed project between August 2022 and March 2023, using a semistructured qualitative interview. These interviews were administered to a diverse group of stakeholders to explore their experiences and perspectives of AI in medicine. A qualitative content analysis of the collected data was conducted using MAXQDA software.

Results: Semistructured interviews were conducted with 38 participants (6 lecturers, 9 clinicians, 10 students, 6 AI experts, and 7 institutional stakeholders). The qualitative content analysis revealed 6 primary categories with a total of 24 subcategories to answer the research questions. The evaluation of the stakeholders' statements revealed several commonalities and differences regarding their understanding of AI. Crucial identified AI themes based on the main categories were as follows: possible curriculum contents, skills, and competencies; programming skills; curriculum scope; and curriculum structure.

Conclusions: The analysis emphasizes integrating AI into medical curricula to ensure students’ proficiency in clinical applications. Standardized AI comprehension is crucial for defining and teaching relevant content. Considering diverse perspectives in implementation is essential to comprehensively define AI in the medical context, addressing gaps and facilitating effective solutions for future AI use in medical studies. The results provide insights into potential curriculum content and structure, including aspects of AI in medicine.

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KEYWORDS
AI in medicine; artificial intelligence; medical education; medical students; qualitative approach; qualitative analysis; needs assessment

Introduction

Background and Significance of AI in Medicine

In 1966, the architect Cedric Price [1] posed the provocative question, “Technology is the answer, but what was the question?” to encourage his lecture audience to explore, question, and reconsider the impact of technological progress. More than 50 years later, this question remains as relevant as ever. One might similarly ask today, “The answer is AI, but what was the question?” The health care sector is currently undergoing a significant transformation process characterized by the increased integration of digital technologies [2-4]. German clinics have been incorporating computer-driven clinical
decision systems, such as the electronic patient record and other digital health tools, that can analyze data, identify patterns, and make decisions based on that data [3]. These intelligent systems can improve health care efficiency, accuracy, and quality while potentially reducing the burden on medical personnel [5,6]. Artificial intelligence (AI) technologies are already being implemented in various aspects of medical practice. For instance, they are used in imaging diagnostics where AI algorithms help analyze medical images [7]. Dictation systems with speech recognition powered by AI are also used, and AI chatbots are deployed to assist doctors and patients by providing appointments and information [8-10]. A range of sensor-based wearables, such as fitness trackers, smartwatches, and health apps, is already used in people’s daily lives. These devices use AI-supported algorithms to gather and analyze health data, including heart rate, sleep patterns, activity levels, and calorie consumption. Based on this information, personalized recommendations can be made to help individuals improve their well-being [11]. Although the use of medical AI systems remains in its early stages, ongoing research and development efforts are being undertaken worldwide. As technology rapidly advances, AI will increasingly play a crucial role in the future of health care [12,13]. This also requires restructuring medical curricula to adapt to dynamic technological advances to prepare students for the changing structures of medical practice [14,15]. Traditionally, medical education has focused on providing students with comprehensive knowledge of medical practices, diagnostic procedures, and treatment methods. Additionally, the effective use of AI in the medical field requires not only developing the necessary technological advances in AI applications but also ensuring that future physicians possess the required skills and expertise to effectively apply these technologies [16-18]. Therefore, it is crucial to consider integrating AI into the medical curriculum and determine how this technology can be effectively incorporated to benefit students and patients [19-21]. However, studies indicate that the integration of AI into the medical curriculum to enhance understanding of AI algorithms and optimize their use remains in its early stages, particularly in Germany [22-24]. Some institutions have developed specific courses and training programs to enhance medical students’ knowledge and skills in AI [25-27].

Research Objectives and Research Questions

Given the complex and rapidly evolving nature of AI, no standardized definition or structured learning objectives currently exist regarding the specific AI topics medical students should be familiar with. Several studies emphasize the importance of understanding the fundamentals of AI and data science, mathematical concepts, and related ethical and social issues [26,28]. Medical students should also develop skills in interpreting AI models and be familiar with machine learning, deep learning, and data analytics to apply AI in clinical practice [29].

As part of a project, “TüKITZMed – Tübingen KI – Trainingszentrum für die Medizin” (Tübingen AI Training Center for Medicine), funded by the German Federal Ministry of Education and Research (16DHBIK086), a comprehensive needs assessment was conducted involving various stakeholders to understand the requirements and skills for integrating AI into the medical curriculum following step one of Kern’s 6-step approach [30]. The project “TüKITZMed” aims to develop and establish a cross-faculty interprofessional curriculum focused on “AI in medicine” providing students with a comprehensive understanding of the topic across different levels and disciplines. This curriculum serves as a pioneering example of integrating AI into academic programs, offering students opportunities for both theoretical learning and practical application, thereby facilitating the transfer of knowledge into real-world contexts. This study aimed to investigate essential AI knowledge for medical education curricula, identify necessary competencies through stakeholder input, and address potential gaps in learning opportunities. Involving different stakeholders offers diverse perspectives based on their roles and experiences. This approach helps identify relevant AI competencies and appropriate teaching formats, addressing unmet needs and challenges associated with implementing AI-focused learning opportunities in medical education [31].

Therefore, this paper aims to address the following research questions regarding assessing AI awareness and identifying essential competencies:

- How familiar are the different stakeholders with AI in general?
- Which specific aspects and topics related to AI are viewed as important?
- What competencies are crucial for medical health students?

Methods

For a comprehensive understanding of AI and to address various aspects relevant to the surveyed stakeholders’ perspectives on an AI curriculum, an exploratory research approach using semistructured interviews was chosen. The incorporation of narrative-generating guideline-supported questions aimed to establish a structured framework for investigating research interests while also allowing flexibility to uncover new and insightful content [32].

Study Design and Setting

This qualitative study approach followed the Standards for Reporting Qualitative Research [33]. It was performed at the Medical Faculty and the Faculty of Science of the University of Tübingen as part of the TüKITZMed project.

Sample Selection and Recruitment

Semistructured interviews with 38 stakeholders involved in the implementation process of AI in medical curricula were conducted to gather diverse perspectives and insights. Relevant stakeholders were characterized as individuals impacted by the integration of AI in health care, those with professional experience with AI technology, and those who had previously encountered AI applications in the medical sector. The stakeholder groups comprised the following: 6 lecturers, 9 clinicians, 10 students, 6 AI experts, and 7 institutional stakeholders. The interview guide followed the guiding research questions for the needs assessment [34]. An illustrative interview guide is provided in Multimedia Appendix 1.
The selection of stakeholder groups was based on their crucial role in the field of medical education and their diverse perspectives. For participant recruitment, we used an open approach, reaching out to stakeholders primarily via email after identifying relevant stakeholder groups for our research inquiries. Inclusion criteria included individuals working with AI in the medical context or possessing relevant expertise, especially clinicians and AI experts. Due to the project’s regional focus, only stakeholders from the local area were approached. Recommendations, referrals, and requests within working groups or via email forwarding were also used. Potential participants were also approached at conferences.

**Lecturers**

Educators’ perspectives are required, as integrating AI into medical education is an unprecedented challenge with no clear guidelines. Even if consensus is reached on exactly what should be taught to medical students, it remains daunting to determine how best to teach it. The experience of educators—especially those familiar with medical students—is therefore imperative in the process [35,36].

**Students**

Health care students’ perspectives (e.g., on human medicine, medical technology, and molecular medicine) are central to integrating AI into medical education since the curricula should ultimately be designed to serve their educational needs. Therefore, assessing their current state of knowledge, attitudes, and heterogeneity across different student populations is an important step in adequately addressing the educational needs for medical AI and integrating it such that students will benefit from it [18,37].

**AI Experts**

AI experts have long-standing knowledge and expertise in the field. Engaging with them provides valuable insights into the latest developments, trends, and best practices in AI. These experts offer a thorough understanding of AI concepts, applications, and their potential impact on health care [36,38].

**Clinicians**

Involving medical staff in developing medical AI helps find clinical value while protecting patient safety. Moreover, medical staff know the data well and are thus the only ones who can detect the bias or impracticality of AI. Additionally, medical experts play a key role in teaching real-world medical applications of AI, as they have the experience and skills. Thus, their perspectives are relevant to the integration of AI into education and practice since they can inspire other medical workers to engage with it [39].

**Institutional Stakeholders**

The perspectives of institutional stakeholders are crucial for driving change in medical education. These individuals hold key positions within educational or health care institutions and are actively involved in implementing AI within the medical curriculum. Such stakeholders, including deans, program coordinators, and administrative staff, possess specific training and qualifications relevant to their roles, playing an essential part in shaping educational strategies and health policies. Given the already full capacity of medical curricula, their support and expertise are necessary for a meaningful integration of AI. Additionally, institutional stakeholders provide an important framework for continuously monitoring and reevaluating the implementation of AI in medical curricula to ensure its utility and quality [18,40,41].

**Data Collection**

Semistructured guided interviews were chosen as they allow a flexible participation-centered approach and in-depth exploration of the topic, capturing the diverse perspectives of the stakeholders involved [42]. The semistructured guided interviews were conducted from August 2022 to March 2023, either face-to-face or via videoconference. All interviews were audio recorded and transcribed verbatim for analysis. Before participation, written informed consent was obtained from all the interviewees. The resulting code system for analysis was consolidated and summarized.

**Data Analysis**

The transcripts were analyzed according to the principles of content structuring analysis, as outlined by Kuckartz [43]. After the interviews were transcribed, independent researchers thoroughly reviewed them. The category system for the analysis was developed using the semistructured guiding questionnaire as a basis (inductive approach) and systematically coded using the MAXQDA 2022 software program (VERBI GmbH). As the coding process progressed, new categories emerged to include additional aspects and themes discussed in the interviews. This step enabled flexibility and openness to new insights that transcended the initially defined structure (deductive approach) [44]. Collectively, we presented outcomes derived from diverse stakeholders. We systematically addressed varying perspectives within or across these cohorts, emphasizing their respective relevance. Our presentation includes literal quotations, preserving the original expressions translated from German to English.

**Ethical Considerations**

The study received ethical approval from the Ethics Committee of Tübingen Medical Faculty (467/2022BO2). Participation was voluntary. All participants were informed of the purpose of the study and provided informed consent before data collection. The confidentiality of all data was ensured, and all responses and data were kept anonymous. The participants had the right to withdraw from the study at any time. Participants did not receive any compensation.

**Results**

**Overview**

The ages of participants ranged from 19 to 59 (mean 38.5, SD 9.7, SEM 1.6) years, with data provided by 36 individuals. Regarding sex distribution, there were 26 male and 12 female participants. Through a structuring content analysis, we systematically derived 6 primary categories with a total of 24 subcategories from the entire data set.
Presentation of Stakeholder Perspectives and Expectations of AI

The analysis of the stakeholders’ statements revealed several commonalities and differences regarding their understanding of AI.

AI as a Tool

In terms of commonalities, the actors viewed AI primarily as a tool that can analyze and process large amounts of data:

For me, it’s mainly a toolbox, a toolkit. These are technologies that help us. [RR22T, expert]

An AI can process much more data at once than a human could. [KC10S, student]

A way to predict things, that is, to predict data based on existing data and also to apply techniques that support us to categorize, assess, simulate, and also predict things in terms of the future. [KU512S, institutional stakeholder]

AI as a Medical Assistant

Additionally, stakeholders emphasized the potential benefits of using AI to assist in medicine, whether in supporting diagnostic and treatment decisions or more efficiently mining clinical data:

In the context of medicine, probably so therapy decisions, more efficient evaluation of clinical data. [AB001, lecturer]

To this, I can think of automation and standardization of processes but also help in an increasingly complex clinical situation with many parameters and many possibilities relevant for decision-making by doctors involved in therapy and diagnosis. [RW01R, institutional stakeholder]

The Technical Understanding of AI

A focus on understanding AI is also related to the technical background of AI technology and the roles of mathematical-statistical models, data, and algorithms:

AI is learning systems that fit a model with computations to data. [PG49B, expert]

AI is about programs and algorithms that improve with more data and data processing. [CCHU7, clinician]

Differences in the Understanding of the Term and Difficulties in Formulating a Definition

However, differences in the understanding of AI between the stakeholders interviewed also became apparent. These disparities manifested in three key areas: challenges in formulating a concise definition and description of AI, diverse perspectives and expectations regarding AI capabilities, and varying emphasis on the medical fields where AI is anticipated to make significant progress.

The name “AI” is misleading because there is currently no computer application that is actually intelligent. Rather, it refers to algorithms with high computing power that enable computers to process larger amounts of data than before and possibly even evolve themselves. [RH01W, lecturer]

Artificial intelligence is a difficult term. It suggests that human intelligence is extended and artificially subsumed. [EJ12B, institutional stakeholder]

Understanding AI is complex and broad. There is AI that learns itself and AI that still needs to be monitored. AI is otherwise a kind of automated analysis. [HT02B, clinician]

Varying Perspectives and Expectations on the Potential and Capabilities of AI

While some may view AI capabilities more optimistically or comprehensively, others emphasize the limits and specialized functions AI can possess. For example, the students tended to view AI as efficient data processing, while the experts emphasized AI’s capacity for revealing hidden patterns and simulating complex scenarios. The students emphasized that AI lacks a creative process and cannot engage in creative thinking. They focused on AI’s ability to efficiently process and analyze large amounts of data. The experts discussed AI’s ability to identify scientific connections, structures, and patterns that may be imperceptible to humans. They recognized AI’s potential to simulate complex scenarios and discover novel insights from data.

Systems that can recognize scientific relationships, structures, and patterns that are not discernible to humans. [PG49B, AI expert]

AI is not intelligent because no creative process can take place in it. It can quickly and efficiently draw connections from large amounts of data. [YG30B, student]

In most cases, however, AI is about better evaluating large amounts of data and modifying it through self-learning algorithms. Human intelligence can understand and solve problems through creativity and think outside of rules – so it works differently. However, algorithms can do other things better than humans. [EJ12B, institutional stakeholder]

AI will determine everyday life, but also medicine more and more. Nowadays, one is often confronted with the topic, and one should deal with it. [IE13H, clinician]

Different Emphases of the Potential Areas of Application

Although some alignment existed in the perceptions of the potential uses of AI, each group had its own focus on specific applications of AI in health care, depending on profession and discipline. AI experts and lecturers emphasized the significance of the technical dimensions of AI, including the essential roles of algorithms, data processing, and AI models in medical research and practice. Students underscored AI’s role in aiding health care professionals, while clinicians concentrated on the clinical sphere of AI, particularly its contributions to diagnostics, treatment decisions, and data processing. Additionally, institutional stakeholders highlighted the potential for increased efficiency in health care by implementing AI solutions. They
engaged in discussions concerning the pragmatic integration of AI to strengthen clinical decision-making processes and optimize operational workflows.

But to provide a definition..., so what we’re actually doing is, we’re learning relationships between input, certain inputs, and certain outputs: What is the relationship between an X-ray image and a diagnosis? And this correlation, you can then learn it using, for instance, a neural network, and then apply it to unseen X-ray images. [MF08Z, lecturer]

To simplify processes, so to speak, to facilitate and automate simple processes that would normally take a lot of time for us humans. The machine can recognize complex relationships that we as humans either cannot comprehend or, as mentioned, would take a long time to understand. For example, in my case, it’s radiation therapy in radio oncology, where there are many processes that take a long time or are, as I said, very complex because, in medicine, we naturally have many intricate aspects and influences on the patient that we need to consider. And a machine can handle this quite well, as it can analyse and evaluate these various data effectively, essentially. [EK05B, student]

An evolving field, which is already partially present in clinical reality. This involves automation and standardization of processes, as well as assistance in an increasingly complex clinical environment with numerous parameters and numerous possibilities that are relevant for decision-making by physicians and individuals involved in therapy and diagnosis. [RW01R, institutional stakeholder]

Identification of AI Competencies and Implications for Medical Curriculum

We identified 4 main categories of implementation needs (Textbox 1)

<table>
<thead>
<tr>
<th>Possible curriculum contents, skills, and competencies</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Basic understanding and sense of technology</td>
</tr>
<tr>
<td>• Data literacy</td>
</tr>
<tr>
<td>• Morality and ethics</td>
</tr>
<tr>
<td>• Opportunities and risks</td>
</tr>
<tr>
<td>• Digital literacy</td>
</tr>
<tr>
<td>• Application of software</td>
</tr>
<tr>
<td>• Data privacy</td>
</tr>
<tr>
<td>• Understanding of medical test results</td>
</tr>
</tbody>
</table>

Programming skills

• Voluntary: Having programming skills is optional. Although they are not mandatory, having them is beneficial.
• Not required: Programming skills are unnecessary. However, if one possesses such skills, that is acceptable.
• Required: Programming skills are mandatory. Basic or advanced programming proficiency is expected for participation.

Curriculum scope

• Adapted to the time available
• Intensive engagement

Curriculum structure

• Lecture
• Seminar
• Interactive exercises
• Consolidation for specialization
• Basics as lecture with exercise
• No opinion due to lack of experience
• Interdisciplinary
• Adapt curriculum dynamically according to relevance
Possible Curriculum Contents, Skills, and Competencies
This main category covers a range of topics, including possible curriculum components, skills, and abilities students should learn regarding AI in medicine.

Basic Understanding and Sense of Technology
The first subcategory addresses the need for medical students to develop a basic understanding of the fundamental principles and concepts of AI. This includes understanding the essential mechanisms of machine learning algorithms and acquiring basic knowledge of mathematical computer science.

And I believe that what would be important to develop a bit of an understanding of how the technology actually works...So, I don't think that you can teach all of that to medical students from the ground up in theoretically well-founded way with linear algebra and so on. But I do think that it's quite impossible to offer an applied course where they can practise and play around with it, get a sense of how technology functions. [MF08Z, lecturer]

Data Literacy
The data literacy category describes the need to provide medical students with the skills and knowledge required to effectively handle and interpret data in the context of AI applications in the field of medicine.

Data quality is crucial. In my view, all the methods of machine learning are secondary...But the most important thing is truly obtaining high-quality data, understanding how to work with data, understanding implications of the data. [DD21S, expert]

Morality and Ethics
The morality and ethics subcategory is dedicated to providing students with an in-depth understanding of the ethical considerations associated with integrating AI into the medical field. It aims to develop a keen awareness of the ethical responsibilities associated with AI advances in the medical field.

Ethics comes to mind...I consider it a highly relevant aspect because AI tools that are intended for future use in medicine are, in my opinion, closely tied to patients, to human beings; potentially, these tools could make life and death decisions, and in that regard, I would argue that entirely different requirements for quality assurance, ethical standards and checks and boundaries need to be in place for these tools...That should be covered during education. [RW01R, institutional stakeholder]

Opportunities and Risks
The opportunities and risks subcategory includes aspects related to awareness of the potential benefits and challenges associated with integrating AI into health care. Medical students should be empowered to navigate the complex landscape of AI in medicine by not only recognizing the potential benefits but also being able to address challenges, make informed decisions, and maintain vigilance concerning its capabilities and limitations.

Also understanding how to interact with AI. To what extent can I trust the AI, the outcomes it produces? How can I collaborate effectively with it? What do I need to operate a good AI, and where can it also be deployed? [SA01R, student]

Digital Literacy
Several actors addressed the need for medical students to be equipped with the skills required to navigate and use digital technologies effectively. This includes developing proficiency in using AI-powered diagnostic support tools, including the ability to interpret and apply AI-generated diagnostic insights. This also extends to understanding and implementing adaptive learning methodologies and leveraging telemedicine for remote patient care.

What is also important to me, when we talk about the topic of artificial intelligence, is that we first discuss the fundamental aspects of digitization and the necessary measures for healthcare, research, and education...We are delving into a very specific topic, but we still lack some of the foundational knowledge. [EH07S, institutional stakeholder]

Application of Software
The application of software subcategory concerns equipping individuals with the ability to effectively use software tools, particularly in the context of AI development and implementation.

Medical students often lack knowledge in this area. Therefore, I believe it’s important for them to have hands-on experience of training a neural network themselves. [MF08Z, expert]

Data Privacy
The data privacy category describes the aspects the actors mentioned to give students the expertise to address the ethical and legal issues related to data privacy in AI applications. By mastering data management practices and understanding the legal framework, students ensure patient data is managed safely, impartially, and ethically in the context of AI integration.

The topic of data privacy should definitely be included in the curriculum because the “who” question of how to do this, how it’s trained and on which data sources, most of it needs to be anonymized.... Ethics and data privacy are two significant components that need to be integrated, unfortunately or fortunately. [HT02B, clinician]

Understanding of Medical Test Results
The last subcategory summarizes the need for in-depth expertise in AI-driven application outcomes, particularly in the context of medical tests. Students must develop a profound understanding of the insights and outcomes produced by AI applications, including acquiring the expertise to thoroughly analyze and interpret results derived from AI-powered processes.

The most important aspect of AI is understanding the basis on which decisions are made. [JJ22D, clinician]
Programming Skills

Clinicians stated that a programming course for medical students should not be mandatory due to overload but could be offered as an elective. Instead, AI experts should be involved due to their expertise in AI applications in the medical field. However, a basic understanding of programming should be acquired early, especially for those who are interested and want to pursue a science career. Most clinicians surveyed opposed including programming skills in the curriculum.

Some lecturers also disagreed with integrating programming knowledge into the curriculum due to student overload. It was emphasized that it is unnecessary for physicians to be able to program neural networks, for example, but that a basic understanding of application knowledge should be established. However, some also emphasized that programming skills and basic computer science knowledge are important, including Python, R, and a theoretical understanding of algorithms. Opinions on the topic were divided and varied depending on the respondents’ areas of expertise.

The students interviewed also believed programming skills should be offered to those interested but should not be mandatory. The majority rejected the integration of programming skills into the curriculum, as they are considered too extensive for medical studies and appear to be of minimal relevance to practical application.

AI experts emphasized that physicians need a basic understanding of AI to build confidence in AI applications. Opinions on programming skills were divided, with some considering simple programming skills helpful. Institutional stakeholders also believed medical students do not necessarily need to know how to program but should have field competence in programming. It is expected that not all medical students will be able to program or develop learning methods themselves. However, a basic understanding of programming is viewed as increasingly essential.

Curriculum Structure

Regarding AI education in medicine, two main approaches are being considered: lectures and seminars. For lectures, the focus is on introducing mandatory courses blending theory with practical applications. Seminars are viewed as a means to give students early practical experience, enhancing their engagement. Due to the subject’s complexity, lecturers are advised to emphasize fundamentals and incorporate concrete examples. However, it is noted that students might find lectures overwhelming, especially without mandatory exams or regular attendance.

Stakeholders emphasized the need for a practical and interactive design when conveying AI content, with clear applications that allow students to experiment for maximum learning impact. Basic AI competencies should be part of the standard medical curriculum, with options for specialization for those interested, particularly those pursuing a scientific career.

Incorporating AI competencies into medical education is recommended, either through a holistic course or integration into subject-specific areas. Interdisciplinary, research-oriented, and application-oriented seminars and workshops should be established to provide in-depth knowledge. In the future, the curriculum will require substantial restructuring to effectively integrate evolving AI content. Given the rapidly changing nature of AI, the curriculum must remain adaptable.

As shown in Figure 1, the competencies highlighted by different stakeholder groups reveal a range of perspectives and priorities. These focus on the frequency of topics falling into these main categories, offering a nuanced understanding of the thematic landscape.

For example, each stakeholder group highlights the significance of possessing a basic understanding of AI and an awareness of AI-supported applications. Similarly emphasized is the importance of gaining a principal perspective on the opportunities and limitations of AI in medicine, as well as addressing ethical considerations and potential dilemmas. AI experts also emphasized topics such as data literacy, fundamental computer science and mathematics skills, and gaining an overview of potential application areas, while institutional stakeholders focused on interdisciplinary approaches and legal requirements.
Discussion

Principal Findings

The insights gained from the study of stakeholder statements provide valuable perspectives on the different views and interpretations of AI. This provides the basis for answering two central research areas. The first is the understanding of AI, particularly how different interest groups perceive this technology. Second, the focus is on the AI skills that should be taught in medical studies. The different stakeholder groups, including lecturers, health care students, AI experts, institutional stakeholders, and clinicians, contributed to a multifaceted picture. The analysis highlighted similarities and differences in the perception of AI by the various stakeholder groups. These findings from our investigation correspond to step one of Kern’s 6-step approach. They are crucial for discussions on implementing AI in health care and underline the need for clear communication, education, and a common understanding of terminology.

Key Competencies for Health Science Students and the Need for a Common Understanding of AI

The qualitative content analysis revealed a broad spectrum of perceptions of AI among the interviewees. Especially in rapidly advancing fields such as AI, creating and maintaining a common
language is essential to enable effective collaboration between different stakeholders. AI is a broad field incorporating many technologies and methods. When introducing AI into the health care system, it is important to acknowledge that different stakeholders involved may have different perceptions of the term AI. A clear definition of this complex term helps prevent misunderstandings, as the field of AI is expansive, encompassing various technologies and methodologies [45,46].

Depending on the contextual background and prior knowledge of the individuals, different descriptions and emphases emerged in the definition of AI. Similarly, ideas concerning the opportunities and limitations of AI in medicine varied depending on individual backgrounds. If consensus is lacking on what AI means in the context of medical education, this can lead to confusion and disagreement on which AI competencies are essential for medical students. This lack of clarity can hinder the development of standardized curricula and educational programs related to AI in medical education, especially when different stakeholders with different backgrounds might be mixing the AI terminologies “strong AI” and “weak AI” [47,48]. Therefore, a clear understanding of the implications and limitations of AI in the medical field is crucial for establishing effective educational guidelines.

Considering these diverse perceptions of AI are particularly relevant when teaching AI skills to medical students. The diversity in the understanding of AI only emphasizes the complexity of the topic; thus, a strong interdisciplinary approach is necessary. Collaboration between physicians, computer scientists, ethicists, and other experts is essential to fully understand the challenges and opportunities of AI in the medical context. For instance, this becomes particularly important when determining which AI applications can enhance the learning experience in specific medical specialties [41].

The diverse perspectives among stakeholders indicate a consensus regarding the essential competencies for health care students concerning AI integration. Recurring themes include practical experience, fundamental digitization knowledge, ethical considerations, and a profound understanding of data and technology. Balancing these competencies is critical to preparing future health care professionals to effectively use AI while maintaining ethical standards and a patient-centered approach. Continued collaboration between stakeholders and the adaptability of medical education curricula will play a key role in achieving these goals.

As illustrated in Figure 1, the stakeholders exhibit substantial diversity in their prioritization of topics and skills, highlighting significant variations in the perceived importance of AI integration into the curriculum. The discussion underscores the importance of a comprehensive approach to AI education in medicine, incorporating practical experience, ethical considerations, and a nuanced understanding of AI’s role in health care. In the context of AI competencies for medical students, they must possess not only medical knowledge but also basic knowledge of AI applications and data literacy, as AI in medicine is becoming increasingly data intensive. The ability to accurately evaluate, manage, and safeguard medical data is essential to ensure that AI technologies can be effectively and ethically deployed in patient care. Therefore, collaboration between stakeholders is essential to develop a curriculum equipping future medical professionals with the necessary competencies to navigate the complexities and opportunities presented by AI in medicine.

The Impact of AI on Shaping Individual Behavior and Societal Outcomes in Medical Training

Since the 1980s, it has been recognized that the introduction of new technologies such as AI does not occur in isolation or independent of societal influences, contrary to the earlier assumption of technological determinism [49,50]. Technology development is shaped by social construction and negotiation processes, where technology emerges as a social construct through human action and influences societal structures and institutions [51]. Interactions related to the introduction of AI in health care can significantly impact how patients are treated and how medical information is used [52]. This concerns not only introducing a new technology per se but also ensuring that it has long-term and positive effects. A key aspect is ensuring that the implementation of AI in health care respects and considers the existing values, norms, and needs of society. Therefore, ethical compatibility and adherence to societal standards are fundamental [53].

Furthermore, AI technologies influence not only medical knowledge but also how doctors, patients, and other stakeholders in health care understand and define their roles. Comprehensive integration of AI requires a holistic approach that not only relies on technological advances but also appropriately considers social dynamics and human aspects.

Our analysis also illustrates the broad understanding of AI, a disparate overall picture of the necessary AI competencies for future medical professionals, and the possibilities and risks associated with implementation. While it is a hot topic among AI experts, health care students are not yet fully aware of the significance of AI, although the technology is expected to enter their professional lives in the future [31,54]. In medical education, students should actively engage with AI, moving beyond passive roles. As well as regulatory, technical, and ethical aspects, it is crucial to consider the sociotechnical dimensions of AI. This is vital, as students must cultivate not only a deep understanding of AI but also an awareness of its societal complexities. For example, Sartori and Bocca [55] emphasize that narratives, whether from the media, scientific community, fiction, or other sources, significantly influence how society perceives and understands technology, including AI. These narratives contribute to the formation of shared understandings, values, and expectations about technology and its potential impact on society [55].

Conclusion

The diverse perspectives on AI among the interviewees underlie the requirement for a common language in this rapidly advancing field. Introducing AI into health care necessitates an awareness of varying stakeholder perceptions, emphasizing the importance of a clear definition to prevent misunderstandings. Individual backgrounds shape distinct descriptions and emphases in defining AI, leading to diverse ideas about its opportunities...
and limitations, particularly in the context of medical education. When teaching AI skills to medical students, it is essential to address this diversity and adopt a robust interdisciplinary approach to ensure future health care professionals acquire essential knowledge and skills. The results underscore the significance of a comprehensive AI education in medicine, integrating practical experiences, ethical considerations, and a nuanced understanding of AI’s role in health care. These competencies will enable medical students to critically evaluate AI technologies and use them responsibly in clinical practice, promoting a more informed and ethically sound integration of AI into health care. The lack of standardization in defining and teaching AI in medical education can lead to uncertainty and potential rejection of the technology. Closing this gap requires gaining insights into the knowledge and skills medical students should acquire regarding the use of AI in medicine. Future studies must focus on awareness of AI and perceived opportunities and risks associated with its implementation. This is also crucial for developing a holistic perspective on competencies within the medical curriculum.

**Limitations**

While the qualitative nature of our study enabled in-depth exploration and rich insights into the stakeholder perceptions, the limitations associated with the sample size of 38 participants must be acknowledged. The findings may be context specific, and caution is warranted in generalizing beyond our studied group. Notably, some interviewees held dual roles, such as being both lecturers and clinicians. Due to practical constraints, they were interviewed in only one capacity, either as lecturers or clinicians. This limitation underscores the complexity of their perspectives, as their roles encompass multifaceted responsibilities. Using a partially standardized guiding questionnaire, participants were prompted to consider specific questions they might not have spontaneously discussed. While this may have influenced the direction of the conversation, we believe it encouraged participants to reflect. However, it must be acknowledged that a more comprehensive and representative understanding would require further exploration through a quantitative survey. Of note, a subsequent paper will address the opportunities and challenges associated with implementing AI in health care identified by the participating stakeholders.

**Acknowledgments**

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**Authors' Contributions**

JAM was responsible for designing and conducting the study, and the acquisition, analysis, and interpretation of data. AHW and TFW were involved in data analyses and interpretation, and revised the manuscript critically. JAM analyzed the research material and wrote the manuscript. KN, SZ, and WF made substantial contributions to the study design and revised the manuscript critically. All authors critically revised the manuscript, and all authors approved the final version of the manuscript and agreed to be accountable for all aspects found therein.

**Conflicts of Interest**

None declared.

**Multimedia Appendix 1**

Guiding questions for artificial intelligence experts (example).

1. Price C. Technology is the answer, but what was the question? Pidgeon Digital. 1979. URL: https://www.pidgeondigital.com/talks/technology-is-the-answer-but-what-was-the-question/ [accessed 2024-06-07]


Abbreviations

AI: artificial intelligence
The Ability of ChatGPT in Paraphrasing Texts and Reducing Plagiarism: A Descriptive Analysis

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Abstract

Background: The introduction of ChatGPT by OpenAI has garnered significant attention. Among its capabilities, paraphrasing stands out.

Objective: This study aims to investigate the satisfactory levels of plagiarism in the paraphrased text produced by this chatbot.

Methods: Three texts of varying lengths were presented to ChatGPT. ChatGPT was then instructed to paraphrase the provided texts using five different prompts. In the subsequent stage of the study, the texts were divided into separate paragraphs, and ChatGPT was requested to paraphrase each paragraph individually. Lastly, in the third stage, ChatGPT was asked to paraphrase the texts it had previously generated.

Results: The average plagiarism rate in the texts generated by ChatGPT was 45% (SD 10%). ChatGPT exhibited a substantial reduction in plagiarism for the provided texts (mean difference \(-0.51\), 95% CI \(-0.54\) to \(-0.48\); \(P < .001\)). Furthermore, when comparing the second attempt with the initial attempt, a significant decrease in the plagiarism rate was observed (mean difference \(-0.06\), 95% CI \(-0.08\) to \(-0.03\); \(P < .001\)). The number of paragraphs in the texts demonstrated a noteworthy association with the percentage of plagiarism, with texts consisting of a single paragraph exhibiting the lowest plagiarism rate (\(P < .001\)).

Conclusion: Although ChatGPT demonstrates a notable reduction of plagiarism within texts, the existing levels of plagiarism remain relatively high. This underscores a crucial caution for researchers when incorporating this chatbot into their work.

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KEYWORDS
ChatGPT; paraphrasing; text generation; prompts; academic journals; plagiarize; plagiarism; paraphrase; wording; LLM; LLMs; language model; language models; prompt; generative; artificial intelligence; NLP; natural language processing; rephrase; plagiarizing; honesty; integrity; texts; text; textual; generation; large language model; large language models

Introduction

Plagiarism, the act of presenting someone else’s work or ideas as one’s own, stands as a prevalent and recurrent form of misconduct in the field of research and publication [1]. The diverse manifestations of plagiarism can often create confusion due to the various terminologies associated with it. Verbatim plagiarism, mosaic plagiarism, loose plagiarism, duplicate publication, augmented publication, salami-sliced publication, image plagiarism, accidental plagiarism, and self-plagiarism are among the prominent types that have been identified [2-6].

To mitigate the occurrence of such misconduct, researchers often use online plagiarism checkers, which scan existing literature on the internet and provide reports on unintentional plagiarism. Additionally, numerous journals have integrated plagiarism checkers as part of their submission process, wherein every manuscript undergoes scrutiny to identify similarity rates [7]. These measures not only act as deterrents but also aid in...
upholding the standards of academic integrity and ensuring originality in scholarly publications.

In recent times, artificial intelligence (AI) has gained significant popularity across a wide range of individuals, including researchers and professionals. Among the various applications of AI, chatbots have emerged as a notable development, using AI and natural language processing techniques to generate humanlike responses to user queries [8].

One prominent example of chatbots is ChatGPT, which uses advanced models such as GPT-3.5 and GPT-4. ChatGPT has garnered substantial attention and widespread adoption, amassing over one million users across diverse fields in its first week of launch [9,10]. This surge in popularity reflects the growing recognition and use of AI-powered chatbots in various domains.

ChatGPT offers a multitude of applications and advantages. First, it excels in generating formally structured text, ensuring coherence and organization in its responses. Second, ChatGPT exhibits an extensive and eloquent vocabulary, enhancing the quality and fluency of its generated content. Additionally, it can be used as a rapid search engine, swiftly retrieving relevant information. Furthermore, it possesses the ability to search and analyze available literature, aiding researchers and professionals in their work. In the field of medical education, ChatGPT proves valuable by providing educational resources and facilitating interactive learning experiences. Moreover, it can serve as a conversational agent, engaging in meaningful and interactive conversations with users [10].

Importantly, the text produced by ChatGPT may sometimes bypass conventional plagiarism checks due to its unique generation process, which is a rising ethical concern [10]. Earlier, many researchers were reporting ChatGPT as co-authors in papers but the majority of journals promptly updated their policies to forbid this practice as ChatGPT cannot be held accountable for the generated content [11]. Moreover, in several instances, ChatGPT hallucinates and produces inaccurate and incorrect information, which can be dangerous in academic publishing [12].

Due to the increasing popularity of ChatGPT in medical research, several studies are needed to identify its pros and cons, especially in the field of medical education. In this study, we aim to assess ChatGPT’s real ability to paraphrase and reduce plagiarism by imputing different texts and prompts, and assessing the plagiarism rate of the rephrased texts.

Methods

Selection of Texts

To assess the plagiarism rates and the rephrasing capabilities of ChatGPT (version 3.5), three texts were selected for the study. These texts varied in length to provide a comprehensive evaluation of the model’s performance. Text one consisted of 319 words, text two comprised 613 words, and text three encompassed 1148 words. The texts used in this study were selected from one of our previously published medical papers in a medical journal [13].

Instructions Given to ChatGPT

For each selected text, five distinct prompts were given to ChatGPT to rephrase the texts. These instructions were designed to test different aspects of rephrasing and reducing plagiarism. The prompts are shown in Table 1.

<table>
<thead>
<tr>
<th>Number</th>
<th>Prompts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prompt 1</td>
<td>“Paraphrase the text”</td>
</tr>
<tr>
<td>Prompt 2</td>
<td>“Rephrase the text”</td>
</tr>
<tr>
<td>Prompt 3</td>
<td>“Reduce the plagiarism of the text”</td>
</tr>
<tr>
<td>Prompt 4</td>
<td>“Rephrase it in a way that conveys the same meaning using different words and sentence structure”</td>
</tr>
<tr>
<td>Prompt 5</td>
<td>“Reword this text using different language”</td>
</tr>
</tbody>
</table>

Subdivision of Texts

To further evaluate the effectiveness of ChatGPT in rephrasing and reducing plagiarism, the original texts were subdivided into multiple paragraphs. Specifically, texts one, two, and three were provided to ChatGPT in 1 and 3 paragraphs; 1, 3, and 5 paragraphs; and 1, 3, 5, and 7 paragraphs, respectively. All the texts with different paragraph numbers were subjected to the same five rephrasing orders. This approach allowed for a comparison of the paraphrased texts with different paragraph sections within the same content.

Second Try of Paraphrasing

To assess the influence of multiple rephrasing iterations, the texts generated by ChatGPT were once again incorporated into the system in the same sequence as before. Subsequently, the plagiarism rates of the texts were analyzed using the iThenticate platform, a tool commonly used for such evaluations in academic settings [14]. This process enabled the measurement and comparison of potential similarities between the original texts and their rephrased counterparts, shedding light on the extent of originality achieved through the rephrasing iterations.

Data Analysis

The data analysis for this study was conducted using SPSS version 19 (IBM Corp). The data distribution was assessed using the Shapiro-Wilk test. To compare the plagiarism rates of the texts, paired t-test analysis was used. This statistical test allowed us to examine whether there were significant differences in plagiarism rates between the original texts and the paraphrased
texts generated by ChatGPT. Additionally, to assess the potential impact of different prompts on plagiarism rates, 1-way ANOVA was used. This analysis aimed to determine if there were statistically significant differences in plagiarism rates across the various prompts given to ChatGPT. A $P$ value $<.05$ was adopted to determine statistical significance. The acceptable level of plagiarism was set at 25%, a standard embraced by scientific journals. Any plagiarism rate surpassing this threshold was considered unsatisfactory [14-18].

Ethical Considerations
This study does not require ethical approval as it does not involve human participants, patient data, or any form of personal data collection.

Results
Overview
A total of 90 texts were provided by ChatGPT. General information on plagiarism rates is provided in Table 2. The mean plagiarism rate of texts was 0.45 (SD 0.10). The mean plagiarism rates for the first try and second try were 0.48 (SD 0.09) and 0.42 (SD 0.09), respectively.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Text, n</th>
<th>Plagiarism rates checked by iThenticate, mean (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total</strong></td>
<td>90</td>
<td>0.45 (0.10)</td>
</tr>
<tr>
<td><strong>ChatGPT tries</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>First try</td>
<td>45</td>
<td>0.48 (0.09)</td>
</tr>
<tr>
<td>Second try</td>
<td>45</td>
<td>0.42 (0.09)</td>
</tr>
<tr>
<td><strong>Texts on the first try</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Text 1</td>
<td>10</td>
<td>0.48 (0.16)</td>
</tr>
<tr>
<td>Text 2</td>
<td>15</td>
<td>0.47 (0.05)</td>
</tr>
<tr>
<td>Text 3</td>
<td>20</td>
<td>0.49 (0.07)</td>
</tr>
<tr>
<td><strong>Texts on the second try</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Text 1</td>
<td>10</td>
<td>0.46 (0.13)</td>
</tr>
<tr>
<td>Text 2</td>
<td>15</td>
<td>0.40 (0.05)</td>
</tr>
<tr>
<td>Text 3</td>
<td>20</td>
<td>0.42 (0.10)</td>
</tr>
<tr>
<td><strong>Paragraphs</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>One paragraph</td>
<td>30</td>
<td>0.40 (0.12)</td>
</tr>
<tr>
<td>Three paragraphs</td>
<td>30</td>
<td>0.50 (0.07)</td>
</tr>
<tr>
<td>Five paragraphs</td>
<td>20</td>
<td>0.44 (0.05)</td>
</tr>
<tr>
<td>Seven paragraphs</td>
<td>10</td>
<td>0.48 (0.04)</td>
</tr>
<tr>
<td><strong>Orders given to ChatGPT</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Please paraphrase the text</td>
<td>18</td>
<td>0.45 (0.10)</td>
</tr>
<tr>
<td>Please rephrase the text</td>
<td>18</td>
<td>0.48 (0.06)</td>
</tr>
<tr>
<td>Please reduce the plagiarism of the text</td>
<td>18</td>
<td>0.44 (0.10)</td>
</tr>
<tr>
<td>Please rephrase it in a way that conveys the same meaning using different words and sentence structure</td>
<td>18</td>
<td>0.41 (0.12)</td>
</tr>
<tr>
<td>Please reword this text using different language</td>
<td>18</td>
<td>0.48 (0.08)</td>
</tr>
</tbody>
</table>

The Potency of ChatGPT in Reducing Plagiarism
Based on the results of our study, ChatGPT demonstrated an ability to significantly reduce plagiarism in texts right from the first attempt (mean difference $-0.51$, 95% CI $-0.54$ to $-0.48$; $P<.001$). Moreover, our research revealed that even further improvements were achieved with the second attempt, as it yielded a significantly lower plagiarism rate compared to the initial try (mean difference $-0.06$, 95% CI $-0.08$ to $-0.03$; $P<.001$).
The results also showed a relation between the number of paragraphs within a text and the plagiarism rate. Our findings indicated that texts comprising a single paragraph exhibited the lowest plagiarism rates, and this relationship was statistically significant ($P<.001$). However, when analyzing the five different prompts of the texts, we found no significant difference in terms of their plagiarism rates ($P=.19$).

Furthermore, our study did not identify any statistically significant distinctions among the plagiarism rates of text one, text two, and text three ($P=.56$), suggesting that ChatGPT’s effectiveness remained consistent across these particular texts.

**Correlation Between Text Lengths and Plagiarism Rates**

We assessed the correlation between the word count of the texts provided by ChatGPT and their plagiarism rates. Although longer texts appeared to have higher plagiarism rates, the correlation was not significant ($r=0.2; P=.06$; Figure 1).

*Figure 1.* The correlation between the word count of the texts and their corresponding plagiarism.
Discussion

Principal Findings

The findings of our study shed light on the levels of plagiarism in the paraphrased text generated by ChatGPT, an advanced chatbot developed by OpenAI. The results indicate that while ChatGPT has the capability to paraphrase the text, there are notable concerns regarding the satisfactory levels of plagiarism in the generated output.

The average plagiarism rate observed in the texts generated by ChatGPT was found to be 45%. This suggests that nearly half of the content produced by the chatbot is similar to the original source material, raising concerns about the authenticity and originality of the paraphrased text. These findings highlight the need for caution when relying on ChatGPT for generating plagiarism-free content.

Interestingly, our study revealed that ChatGPT exhibited a substantial reduction in text plagiarism when provided with explicit instructions to paraphrase or reduce plagiarism. This indicates that the chatbot is responsive to such prompts and can generate content with reduced plagiarism when specifically instructed to do so. However, it is important to note that even with explicit instructions, the plagiarism rate remained relatively high, emphasizing the limitations of the current system.

We also observed a significant decrease in the plagiarism rate between the initial and second attempts of paraphrasing. This suggests that ChatGPT has the ability to learn and improve its paraphrasing capabilities over multiple iterations. However, the reduction in plagiarism was modest, indicating that further refinements are necessary to achieve satisfactory levels of originality in the generated output.

An interesting finding from our study was the association between the number of paragraphs in the texts and the percentage of plagiarism. Texts consisting of a single paragraph demonstrated the lowest plagiarism rate. This suggests that presenting the source texts within a single coherent unit allows ChatGPT to better understand and paraphrase the content effectively. Dividing the text into separate paragraphs may lead to fragmented understanding and potentially contribute to higher levels of plagiarism.

It is worth noting that the prompts used in our study did not yield significant differences in the levels of plagiarism. This indicates that the specific prompt provided to ChatGPT does not significantly influence its paraphrasing capability. In addition, this outcome might be the consequence of the bot’s strong ability to understand our true intentions when issuing commands, or it might be because our command words were brief or similar to one another. However, further investigation into the effect of different prompts and their impact on plagiarism is warranted to explore this aspect in more detail.

ChatGPT has a wide range of applications that can be effectively used. Numerous articles have discussed the use of ChatGPT in composing scientific literature, with a particular study illustrating its capability to generate formal research articles. The researchers observed that the language used is articulate, adopts a conventional tone, and offers a pleasant reading experience [19].

ChatGPT has the potential to serve as a search engine that directly responds to queries, eliminating the need to navigate to external sites for information. This streamlines the process of writing research papers, reducing the time spent by authors on the often arduous task of searching for articles and applying various selection criteria. This, in turn, allows authors to dedicate more time to their actual research work and methodology [20].

Moreover, articles created by ChatGPT seem to elude traditional plagiarism detection methods. In a research study, the chatbot was tasked with generating 50 medical research abstracts using a subset of articles. The resulting articles underwent examination by plagiarism detection software, an AI-output detector, and a panel of medical researchers who were tasked with identifying any artificially generated abstracts. The findings revealed that abstracts generated by ChatGPT seamlessly passed through the plagiarism detection software, registering a median originality score of 100%, indicating the absence of detected plagiarism. In contrast, the AI-output checker only identified 66% of the generated abstracts [21].

While ChatGPT and other AI tools hold promise in various applications, their deployment in medical writing raises ethical and legal considerations. These concerns encompass potential violations of copyright laws, medico-legal complexities, and the risk of inaccuracies or biases in the generated content. It is crucial to recognize and confront the limitations and challenges linked to the use of AI in medical writing [20,22,23].

Limitations and Future Suggestions

The sample size used in our study was relatively small, and as a result, we recommend that future investigations incorporate larger sample sizes to enhance the robustness of the findings. It is worth noting that our study was conducted using ChatGPT version 3.5, which was a publicly available version at the time of our research. Unfortunately, we did not have access to ChatGPT version 4, preventing us from evaluating the efficacy of this updated version in terms of paraphrasing capabilities.

It is essential to acknowledge that our study exclusively focused on providing medical content to ChatGPT. We encourage other researchers to explore the impact of using different content types on the efficacy of ChatGPT. This would allow for a comprehensive understanding of whether the effectiveness of ChatGPT is influenced by the specific domain or topic of the content it receives. Conducting such investigations will provide valuable insights into the generalizability and adaptability of ChatGPT across various subject matters.

Moreover, a recognized limitation of ChatGPT is its tendency to produce inconsistent results with the same prompts [24]. To relatively address this challenge, we used a comprehensive approach. Each prompt was provided with nine texts, varying paragraph structures (text one with 1 paragraph, text one with 3 paragraphs, text two with 1 paragraph, text two with 3 paragraphs, text two with 5 paragraphs, text three with 1 paragraph, text three with 3 paragraphs, text three with 5 paragraphs, and text three with 7 paragraphs). Furthermore, we
requested ChatGPT to paraphrase each of these texts twice using the same prompt. We then calculated the mean plagiarism rates for both the first and second attempts, along with the overall mean plagiarism rate for each prompt (Table 2).

Nevertheless, we recommend that future studies take this limitation into account and explore additional measures to enhance the robustness of assessments. Specifically, researchers may consider providing ChatGPT with a greater number of texts exhibiting different paragraph structures and incorporating a higher frequency of repetitions in the paraphrasing process.

We used similar prompts and provided them to ChatGPT. We recommend that future studies adopt a broader range of prompts to assess ChatGPT’s performance across different input variations. This approach allows for a more comprehensive evaluation and facilitates the identification of optimal prompts to minimize plagiarism rates.

An important consideration with ChatGPT lies in the potential for hallucination and biases, particularly in the generation of medical content [25]. In our study, two independent researchers evaluated the content provided by ChatGPT, comparing it with the original texts. However, we acknowledge that the texts used in our assessment may not have been sufficiently complex. To address this limitation, we recommend that future studies incorporate both simple and more intricate texts to thoroughly evaluate the biases that ChatGPT may introduce during the paraphrasing of medical content. This approach will provide a more nuanced understanding of the model’s performance.

Conclusion
While ChatGPT has been shown to significantly reduce plagiarism in texts, it is important to note that the resulting plagiarism rates of the provided texts may still be considered high, which may not meet the acceptance criteria of most scientific journals. Therefore, medical writers and professionals should carefully consider this issue when using ChatGPT for paraphrasing their texts. There are a couple of strategies authors can use to improve the paraphrasing efficacy of ChatGPT. Presenting the texts in a single-paragraph format and repeating the requesting procedure with ChatGPT. By considering these strategies and being mindful of the potential limitations, authors can strive to improve the paraphrasing efficacy of ChatGPT and address the challenge of high plagiarism rates associated with its outputs.

Acknowledgments
We acknowledge BioRender since all the illustrations are created with BioRender.com

Data Availability
The data sets used or analyzed during this study are accessible from the corresponding author upon reasonable request.

Authors' Contributions
EA-S, A Bozorgi, and SH conceptualized the study. EA-S, LP, and MC curated the data. SH and DK conducted the formal analysis and participated in statistics. EA-S and A Bozorgi contributed to the methodology. M-HK, A Bakhshi, and TD wrote the original draft. All authors edited the manuscript.

Conflicts of Interest
None declared.

References


Abbreviations

AI: artificial intelligence

© Soheil Hassanipour, Sandeep Nayak, Ali Bozorgi, Mohammad-Hossein Keivanlou, Tirth Dave, Abdulhadi Alotaibi, Farahnaz Joukar, Parinaz Melladoust, Arash Bakhshi, Dona kuriyakose, Lakshmi Polisetty, Mallika Chimpiri, Ehsan Amini-Salehi. Originally published in JMIR Medical Education (https://mededu.jmir.org), 8.7.2024. This is an open-access article distributed...
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Assessing GPT-4’s Performance in Delivering Medical Advice: Comparative Analysis With Human Experts

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Abstract

Background: Accurate medical advice is paramount in ensuring optimal patient care, and misinformation can lead to misguided decisions with potentially detrimental health outcomes. The emergence of large language models (LLMs) such as OpenAI’s GPT-4 has spurred interest in their potential health care applications, particularly in automated medical consultation. Yet, rigorous investigations comparing their performance to human experts remain sparse.

Objective: This study aims to compare the medical accuracy of GPT-4 with human experts in providing medical advice using real-world user-generated queries, with a specific focus on cardiology. It also sought to analyze the performance of GPT-4 and human experts in specific question categories, including drug or medication information and preliminary diagnoses.

Methods: We collected 251 pairs of cardiology-specific questions from general users and answers from human experts via an internet portal. GPT-4 was tasked with generating responses to the same questions. Three independent cardiologists (SL, JHK, and JJC) evaluated the answers provided by both human experts and GPT-4. Using a computer interface, each evaluator compared the pairs and determined which answer was superior, and they quantitatively measured the clarity and complexity of the questions as well as the accuracy and appropriateness of the responses, applying a 3-tiered grading scale (low, medium, and high). Furthermore, a linguistic analysis was conducted to compare the length and vocabulary diversity of the responses using word count and type-token ratio.

Results: GPT-4 and human experts displayed comparable efficacy in medical accuracy (“GPT-4 is better” at 132/251, 52.6% vs “Human expert is better” at 119/251, 47.4%). In accuracy level categorization, humans had more high-accuracy responses than GPT-4 (50/237, 21.1% vs 30/238, 12.6%) but also a greater proportion of low-accuracy responses (11/237, 4.6% vs 1/238, 0.4%; P=.001). GPT-4 responses were generally longer and used a less diverse vocabulary than those of human experts, potentially enhancing their comprehensibility for general users (sentence count: mean 10.9, SD 4.2 vs mean 5.9, SD 3.7; P<.001; type-token ratio: mean 0.69, SD 0.07 vs mean 0.79, SD 0.09; P<.001). Nevertheless, human experts outperformed GPT-4 in specific question categories, notably those related to drug or medication information and preliminary diagnoses. These findings highlight the limitations of GPT-4 in providing advice based on clinical experience.

Conclusions: GPT-4 has shown promising potential in automated medical consultation, with comparable medical accuracy to human experts. However, challenges remain particularly in the realm of nuanced clinical judgment. Future improvements in LLMs may require the integration of specific clinical reasoning pathways and regulatory oversight for safe use. Further research is needed to understand the full potential of LLMs across various medical specialties and conditions.

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KEYWORDS

GPT-4; medical advice; ChatGPT; cardiology; cardiologist; heart; advice; recommendation; recommendations; linguistic; linguistics; artificial intelligence; NLP; natural language processing; chatbot; chatbots; conversational agent; conversational agents; response; responses
Introduction

As a large language model (LLM), the GPT developed by OpenAI generates human-like text [1-3], distinguishing it from other specialized deep learning models that are limited to solving specific problems within predetermined domains [4]. In the medical field, GPT has the potential to augment medical education [5], provide clinical decision support [6], and enhance public health initiatives [7]. An impressive achievement of GPT-3.5 is its success in meeting the passing threshold for the United States Medical Licensing Examination [8], demonstrating its ability to offer medical advice comparable to that of trained professionals [9]. The latest iteration, GPT-4 [10,11], is anticipated to exhibit advancements in processing complex medical language, formulating patient care suggestions, and making preliminary diagnostic predictions, which inspires cautious optimism for its future applications in the medical domain [12].

Cardiovascular diseases are a leading cause of death worldwide, highlighting the critical need for precise and reliable information in this domain [13]. During the initial stages of the SARS-CoV-2 pandemic, overstated claims about the cardiovascular implications of the virus potentially escalated public unease and undermined trust in empirical findings [14]. The distribution of speculative or inaccurate information would have had a detrimental effect on the pandemic response strategies. It is paramount to emphasize that inaccuracies or misconceptions in cardiological advice can lead to severe consequences. Hence, there is a pressing need for rigorous validation of all sources of information, whether derived from human experts or advanced computational models such as GPT-4.

Moreover, the generation of “hallucinatory” or erroneous responses by GPT raises concerns about nonmedical expert users unintentionally accepting incorrect information as valid [15,16]. Consequently, proposals for regulatory oversight of LLMs have emerged, including the establishment of a new regulatory category specifically addressing LLM-related challenges and risks [4]. Therefore, it is crucial to develop auditing procedures capable of capturing the intricacies of LLM-associated risks, necessitating a balanced evaluation of the potential benefits and risks inherent in LLMs [17,18]. To delve deeper into this matter, this study applied real-world health consultations from general users to human experts through an internet portal, using the most recent iteration of this technology, GPT-4. The responses provided by both human experts and GPT-4 were subsequently evaluated by a panel of 3 independent cardiologists to gain a nuanced understanding of the potential benefits and risks associated with GPT-4.

Methods

Data Collection

Figure 1 illustrates the study design. We collected question-and-answer data related to cardiology from the Korean search portal NAVER, focusing on 264 cases. NAVER is Korea’s largest search engine, and its web-based questions and answers forums, called “Jisik-In,” have previously been used in medical research [19,20]. The data set covered the period from July 13, 2020, to July 12, 2021, and included medical inquiries posed by portal users and the corresponding responses provided by human experts. These experts are doctors who have graduated from a college of medicine or medical school, passed the Korean Medical Licensing Examination, and hold legal accreditations as certified specialists in their respective medical fields from the Ministry of Health and Welfare. They are not restricted by character limits when answering users’ questions on the portal site. The questions were categorized into 2 types: binary and open-ended. Further, 6 distinct categories were defined based on the questions’ intent. All collected data were in Korean text form. To ensure the analysis was focused on sufficiently detailed and substantive exchanges, we specifically selected questions that contained more than 100 characters and answers provided by human experts that comprised at least 200 characters. This approach was aimed at filtering out overly simple queries and ensuring that the responses were elaborate enough for a thorough comparison. Additionally, to maintain a consistent and fair comparison basis between the capabilities of GPT-4 and human experts, we excluded 13 cases from the total data set that contained multimedia content such as videos or images. Finally, 251 cases were selected for the study after applying these criteria.
Figure 1. Study design and evaluation process. A data set consisting of 251 cardiology-specific question-answer pairs was collected from the NAVER portal over a 1-year period, from July 13, 2020, to July 12, 2021. A licensed medical professional is the person who answered the portal user’s question. The questions covered 6 domain categories and included both binary and open-ended types. From May 5 to 8, these questions were inputted into GPT-4 to generate the corresponding GPT-4 responses. Following that, a panel of 3 cardiologists reviewed and evaluated the questions along with the answers provided by human experts and GPT-4. The evaluation criteria focused on assessing the complexity and clarity of the questions as well as the accuracy and appropriateness of the responses from both human experts and GPT-4.

GPT Answer Generation

Answers to the collected questions were generated using OpenAI’s GPT-4 model, released on March 14, 2023 [10]. From May 5 to 8, 2023, a total of 3 researchers used this model via the OpenAI website to generate GPT-4 answers. The total data set of questions to be entered into the GPT-4 was distributed to the 3 researchers in the form of a spreadsheet. Each original Korean question was directly fed into the GPT-4 prompt without any supplementary input. The researchers saved the generated answer in a spreadsheet. Each question input was done in a new session by clicking the “New chat” button.

Question and Answer Evaluation

Once the data were randomly shuffled, answers from both GPT-4 and human experts were anonymized and labeled as answer 1 and answer 2, respectively, ensuring the 3 independent cardiologist reviewers were blinded to the source of each response. Each of these reviewers is a board-certified physician in internal medicine and has undergone more than 4 years of
fellow training in cardiology subspecialty. A panel of 3 cardiologists assessed the question set along with the anonymized answers. The evaluation was conducted using a computer interface. Each evaluator assessed the clarity and complexity of the questions as well as the accuracy and appropriateness of the answers. To quantitatively measure these aspects, a 3-tiered grading scale (low, medium, and high) was used (Multimedia Appendix 1). Additionally, each evaluator determined which answer (the GPT-4’s answer or the human expert’s answer) showed superior accuracy and appropriateness in relation to the question posed.

To further elucidate, the Kendall W concordance analysis revealed the following coefficient values indicating the level of agreement among the evaluators: 0.44 for the appropriateness of the human expert answers, 0.40 for the appropriateness of the GPT-4 answers, 0.43 for the medical accuracy of the human expert answers, and 0.40 for the medical accuracy of the GPT answers. Moreover, when making a binary choice determining the superiority of appropriateness between the human expert and GPT-4 answers, the coefficient was 0.42, and for determining the superiority of medical accuracy between the two, it was 0.45. These values, falling in the range of 0.40-0.60, denote a moderate agreement, showcasing a significant level of reliability in our study findings.

Ethical Considerations
This research project was approved by the institutional review board of Korea University Anam Hospital (IRB 2023AN0280). The research was conducted in accordance with the Helsinki Declaration. Informed consent was obtained from all 3 participating cardiologists.

Linguistic Analysis
The Korean Sentence Separator 4.5.1 was used to segment the text into individual sentences. For text tokenization, the Korean medical bidirectional encoder representations from the transformer model, which was specifically designed for Korean medical text analysis, was used [21]. To evaluate lexical diversity, the type-token ratio (TTR) was computed for each set of responses [22,23]. The TTR, which represents the ratio of unique words to the total number of words in a text, was determined after the responses were tokenized [22,23].

Table. Linguistic difference between GPT-4 and human expert answers.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>GPT-4, mean (SD)</th>
<th>Human, mean (SD)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Word count per answer</td>
<td>190 (75.2)</td>
<td>139 (95.6)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Sentence count per answer</td>
<td>10.9 (4.2)</td>
<td>5.9 (3.7)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Type-token ratio</td>
<td>0.69 (0.07)</td>
<td>0.79 (0.09)</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

Figure 2 presents an analysis of the medical accuracy between GPT-4 and human expert answers. When cardiologists were asked to evaluate which answers were more medically accurate, the responses slightly favored the human expert answers (132/251, 52.6% vs 119/251, 47.4%; P=.41; Figure 2A). Dividing medical accuracy into low, medium, and high levels, a significant proportion of human expert answers were ranked as highly accurate compared to GPT-4 (50/237, 21.1% vs 30/238, 12.6%; P<.001; Figure 2B). However, the rate of low accuracy was also higher for the human expert answers (11/237, 4.6% vs 1/238, 0.4%; P=.007). This counterintuitive observation underscores the potential of LLMs to bridge gaps in human work in real-world scenarios.
In terms of question complexity and ambiguity, GPT-4 demonstrates an advantage. The more complex and ambiguous the question, the higher the medical accuracy of GPT-4’s answers. Conversely, human experts excel in dealing with simpler and clearer questions, although without statistically significant differences ($P = .19$; Figure 2C and $P = .30$; Figures 2D, 3C, and 3D). The difference in medical accuracy between human and GPT-4 answers remained below 10% across different question types ($P = .39$; Figure 2E).

Interestingly, when analyzing question categories based on the intent, numerical differences were observed, but without statistical significance ($P = .20$; Figure 2F). Human experts outperformed GPT-4 in responding to questions related to drugs or medications and preliminary diagnoses, scoring higher than GPT-4 (drug or medication: 12/18, 66.7% vs 6/18, 33.3% and preliminary diagnosis: 43/70, 61.4% vs 27/70, 38.6%). Conversely, GPT-4 surpassed human experts in addressing queries regarding the necessity of hospital visits and guidance for clinical departments (hospital visit necessity: 9/22, 40.9% vs 3/22, 13.6%).
vs 13/22, 59.1% and clinical department guidance: 15/33, 45.5% vs 18/33, 54.5%).

In the linguistic analysis, when the medical accuracy of a human expert’s answer exceeded that of GPT-4, the human expert’s answers typically had a higher word count and lower TTR compared to cases where GPT-4’s answers were deemed more medically accurate (word count per answer: mean 162, SD 102.6 vs mean 114, SD 80.3; *P*<.001; Figure 2G and TTR: mean 0.78, SD 0.09 vs mean 0.80, SD 0.09; *P*=.02; Figure 2H). This implies that the more the response resembles a real conversation—longer and easier—the higher the perceived medical accuracy according to cardiology experts. This observation indicates a potential area for quality control in human expert responses and highlights the consistent performance of GPT-4 in terms of response length and lexical variation.

Next, a comparative analysis between GPT-4 and human expert answers was conducted in terms of answer appropriateness (Figure 3). When assessing whether GPT-4 or human expert answers were more appropriate for the posed questions, GPT-4 was rated as superior (GPT-4: 135/251, 53.8% vs humans: 116/251, 46.2%; *P*=.23; Figure 3A). Similar to the medical accuracy analysis, when categorizing appropriateness into low, medium, and high, both GPT-4 and human expert answers showed a comparable distribution across these segments (*P*=.26; Figure 3B). Notably, mirroring the findings from the medical accuracy analysis, the frequency of answers deemed to have low appropriateness was numerically higher for human experts (7/240, 2.9% vs 2/241, 0.8%; *P*=.03), suggesting the possibility of human shortcomings. The investigations related to question complexity, clarity, and type displayed numerical trends similar to those observed in the medical accuracy analysis, although no statistical differences were observed (*P*=.20; *P*=.60; and *P*=.66; Figure 3C-E). The analysis based on question intent showed no significant statistical discrepancies between the proportions of cases where human expert answers were deemed more appropriate and those where GPT-4 answers were considered more appropriate. Interestingly, GPT-4 was rated as more appropriate than human experts in all other categories, except for the question category of preliminary diagnosis (*P*=.58; Figure 3F). When human expert answers were considered more appropriate than those of GPT-4, the corresponding answers had a higher word count and lower TTR compared to cases where GPT-4 answers were deemed more appropriate (word count per answer: mean 121, SD 79.3 vs mean 160, SD 108.1; *P*=.001; Figure 3G and TTR: mean 0.80, SD 0.09 vs mean 0.77, SD 0.09; *P*=.02; Figure 3H). Similar to medical accuracy, these findings suggest that longer responses resembling genuine conversations are evaluated as more appropriate.
For the 251 questions assessed, all 3 independent cardiologists rated the GPT-4 answers as superior in 18% (45/251) of cases in terms of medical accuracy. In an additional 29% (74/251) of the cases, the majority (2 of 3) of cardiologists endorsed the GPT-4 answers. Conversely, human expert answers were unanimously considered more accurate in 20% (50/251) of cases, with the majority of cardiologists agreeing with human experts in 33% (82/251) of cases (Figure 4). In terms of answer appropriateness, all 3 cardiologists agreed that the GPT-4 answers were superior in 15% (38/251) of cases. The majority of cardiologists found GPT-4 answers to be more appropriate in another 39% (97/251) of cases. Human experts, however, received unanimous approval for the appropriateness of their answers in 18% (70/251) of cases and majority approval in an additional 28% (46/251; Figure 5). These figures highlight the noteworthy performance of GPT-4 from a medical standpoint. Examining illustrative cases, GPT-4 stands out for delivering medical information resembling the content of medical textbooks.
and dictionaries. Additionally, GPT-4 demonstrates strength in thoroughly addressing every user’s question, leaving no queries unanswered. In contrast, human experts leverage their advantage in providing heuristic information informed by their clinical experience, especially when questions require elements of clinical judgment.

**Figure 4.** Evaluation result and representative cases comparing medical accuracy between GPT-4 and human expert answers. (A) A case where the GPT-4 answer received superior medical accuracy ratings from all 3 evaluators. (B) A case where a human expert received superior medical accuracy ratings from all 3 evaluators.
**Discussion**

**Principal Findings**

This research uniquely implemented real-world health consultations involving general users and human experts, comparing the answers provided by human experts and GPT-4. Three independent cardiologists appraised the answers to discern the potential advantages and disadvantages of using GPT-4 in the medical advice domain. This study demonstrated comparable levels of medical accuracy between GPT-4 and human experts. Notably, human expert answers had a higher proportion of answers classified as having low medical accuracy compared to those from GPT-4.

Another significant finding suggests the benefits of articulating medical advice in a conversational style, which positively impacts medical accuracy and relevance to queries. This style proved effective in responding to all questionnaire requests, leading to higher answer ratings and demonstrating the potential of GPT-4 in providing medical advice. Notably, GPT-4’s answers consistently displayed appropriate length and lexical variation compared to those of human experts. The findings of this study underscore the potential of GPT-4 in medical education, particularly in enhancing the learning experience.
through its ability to simulate conversational medical advice with accuracy comparable to human experts. Integrating GPT-4 into educational frameworks could offer an innovative approach to medical education, facilitating adaptive learning and preparing students for the digital evolution in health care. This suggests a promising avenue for future research and application in the field of medical education, highlighting the importance of incorporating advanced AI tools like GPT-4 to complement traditional educational methods.

Comparison to Prior Work
An important consideration is the linguistic scope of our findings. This study was conducted in Korean, which naturally raises questions about its generalizability to other languages. Recent studies and OpenAI’s own documentation suggest that GPT-4’s performance in non-English languages, including medical contexts, has improved compared to previous versions [11,24,25]. Takagi et al [24] compared the performance of GPT-3.5 and GPT-4 using 254 questions from the Japanese Medical Licensing Examination, revealing that GPT-4 exhibited a 29.1% improvement over GPT-3.5. They highlighted that GPT-4’s enhanced non-English language processing capabilities were instrumental in its ability to pass the medical licensing examination. In addition, Wang et al [25] conducted a study comparing the performance of GPT-3.5 and GPT-4 on English and Chinese data sets for the Chinese Medical Licensing Examination, showing a significant improvement in accuracy for Chinese compared to English. This study showed that the medical advice provided by GPT-4 was comparable in medical accuracy to that provided by human experts. Based on previous research and the findings of this study, it has been found that GPT-4 can effectively process specialized medical information in various non-English languages, including Korean. This indicates its potential for use in patient education and the dissemination of medical knowledge.

Strengths and Limitations
Despite its strengths, GPT-4’s capability to provide advice based on clinical experience differs notably from that of human experts. Furthermore, quantitative analysis revealed potential discrepancies between GPT-4 and human expert responses, depending on the intent of the question. Numerous studies are currently underway to identify appropriate regulatory measures for the use of LLMs [4]. The findings of this investigation are anticipated to facilitate subsequent research aimed at identifying tasks in the medical field that GPT-4 excels in. This, in turn, could expedite the development of technology to enhance the quality of medical services and promote public health.

This study has several limitations to consider. First, its focus on cardiology might limit the generalizability of the results to other medical specialties. Second, the sample size for the answer evaluation, which consisted of only 3 cardiologists, could have been larger for a more robust analysis. Furthermore, since the evaluations were conducted solely by cardiologists, there is potential for reporting bias where certain aspects of the answers might be overemphasized or underrepresented. Inclusion of professionals from other domains could have provided a broader assessment. Future studies should aim to involve larger sample sizes and encompass a wider range of medical specialties. Moreover, integrating patients’ perspectives could offer further insights into the acceptability and perceived utility of artificial intelligence–powered medical advice.

Conclusions
In conclusion, this study revealed the promising capabilities of GPT-4 in providing medically accurate and appropriate responses comparable to human experts. The additional benefits of GPT-4 include consistent proficiency in maintaining appropriate response length and lexical variation. However, GPT-4 showed some disadvantages in providing advice based on clinical experience as well as variation in its performance depending on question intent. Despite these challenges, this study suggests that LLMs such as GPT-4 hold significant potential in augmenting medical education, providing medical advice.

Acknowledgments
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Conflicts of Interest
None declared.

Multimedia Appendix 1
Standards for evaluating medical questions and answers. [DOCX File, 24 KB - mededu_v10i1e51282_appl1.docx]

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10. GPT-4 is OpenAI’s most advanced system, producing safer and more useful responses. OpenAI. URL: https://openai.com/gpt-4 [accessed 2023-03-19]


Abbreviations

LLM: large language model
TTR: type-token ratio
Evaluation of ChatGPT-Generated Differential Diagnosis for Common Diseases With Atypical Presentation: Descriptive Research

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Abstract

Background: The persistence of diagnostic errors, despite advances in medical knowledge and diagnostics, highlights the importance of understanding atypical disease presentations and their contribution to mortality and morbidity. Artificial intelligence (AI), particularly generative pre-trained transformers like GPT-4, holds promise for improving diagnostic accuracy, but requires further exploration in handling atypical presentations.
**Objective:** This study aimed to assess the diagnostic accuracy of ChatGPT in generating differential diagnoses for atypical presentations of common diseases, with a focus on the model's reliance on patient history during the diagnostic process.

**Methods:** We used 25 clinical vignettes from the *Journal of Generalist Medicine* characterizing atypical manifestations of common diseases. Two general medicine physicians categorized the cases based on atypicality. ChatGPT was then used to generate differential diagnoses based on the clinical information provided. The concordance between AI-generated and final diagnoses was measured, with a focus on the top-ranked disease (top 1) and the top 5 differential diagnoses (top 5).

**Results:** ChatGPT's diagnostic accuracy decreased with an increase in atypical presentation. For category 1 (C1) cases, the concordance rates were 17% (n=1) for the top 1 and 67% (n=4) for the top 5. Categories 3 (C3) and 4 (C4) showed a 0% concordance for top 1 and markedly lower rates for the top 5, indicating difficulties in handling highly atypical cases. The χ² test revealed no significant difference in the top 1 differential diagnosis accuracy between less atypical (C1+C2) and more atypical (C3+C4) groups (χ²₁=2.07; n=25; P=.13). However, a significant difference was found in the top 5 analyses, with less atypical cases showing higher accuracy (χ²₁=4.01; n=25; P=.048).

**Conclusions:** ChatGPT-4 demonstrates potential as an auxiliary tool for diagnosing typical and mildly atypical presentations of common diseases. However, its performance declines with greater atypicality. The study findings underscore the need for AI systems to encompass a broader range of linguistic capabilities, cultural understanding, and diverse clinical scenarios to improve diagnostic utility in real-world settings.

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**KEYWORDS**

atypical presentation; ChatGPT; common disease; diagnostic accuracy; diagnosis; patient safety

**Introduction**

For the past decade, medical knowledge and diagnostic techniques have expanded worldwide, becoming more accessible with remarkable advancements in clinical testing and useful reference systems [1]. Despite these advancements, misdiagnosis significantly contributes to mortality, making it a noteworthy public health issue [2,3]. Studies have revealed discrepancies between clinical and postmortem autopsy diagnoses in at least 25% of cases, with diagnostic errors contributing to approximately 10% of deaths and to 6% - 17% of hospital adverse events [4-8]. The significance of atypical presentations as a contributor to diagnostic errors is especially notable, with recent findings suggesting that such presentations are prevalent in a substantial portion of outpatient consultations and are associated with a higher risk of diagnostic inaccuracies [9]. This underscores the persistent challenge in diagnosing patients correctly due to the variability in disease presentation and due to the reliance on medical history, which is the basis for approximately 80% of the medical diagnosis [10,11].

The advent of artificial intelligence (AI) in health care, particularly through natural language processing (NLP) models such as generative pre-trained transformers (GPTs), has opened new avenues in medical diagnosis [12]. Recent studies on AI medical diagnosis across various specialties—including neurology [13], dermatology [14], radiology [15], and pediatrics [16]—have shown promising results and improved diagnostic accuracy, efficiency, and safety. Among these developments, GPT-4, a state-of-the-art AI model developed by OpenAI, has demonstrated remarkable capabilities in understanding and processing medical language, significantly outperforming its predecessors in medical knowledge assessments and potentially transforming medical education and clinical decision support systems [12,17].

Notably, one study found that ChatGPT (OpenAI) could pass the United States Medical Licensing Examination (USMLE), highlighting its potential in medical education and medical diagnosis [18,19]. Moreover, in controlled settings, ChatGPT has shown over 90% accuracy in diagnosing common diseases with typical presentations based on chief concerns and patient history [20]. However, while research has examined the diagnostic accuracy of AI chatbots, including ChatGPT, in generating differential diagnoses for complex clinical vignettes derived from general internal medicine (GIM) department case reports, their diagnostic accuracy in handling atypical presentations of common diseases remains less explored [21,22]. There has been a notable study aimed at evaluating the accuracy of the differential diagnosis lists generated by both third- and fourth-generation ChatGPT models using case vignettes from case reports published by the Department of General Internal Medicine of Dokkyo Medical University Hospital, Japan. ChatGPT with GPT-4 was found to achieve a correct diagnosis rate in the top 10 differential diagnosis lists, top 5 lists, and top diagnoses of 83%, 81%, and 60%, respectively—rates comparable to those of physicians. Although the study highlights the potential of ChatGPT as a supplementary tool for physicians, particularly in the context of GIM, it also underlines the importance of further investigation into the diagnostic accuracy of ChatGPT with atypical disease presentations (Figure 1). Given the crucial role of patient history in diagnosis and the inherent variability in disease presentation, our study expands upon this foundation to assess the accuracy of ChatGPT in diagnosing common diseases with atypical presentations [23].

More specifically, this study aims to evaluate the hypothesis that the diagnostic accuracy of AI, exemplified by ChatGPT, declines when dealing with atypical presentations of common diseases. We hypothesize that despite the known capabilities of AI in recognizing typical disease patterns, its performance will be significantly challenged when presented with clinical
cases that deviate from these patterns, leading to reduced diagnostic precision. Consequently, this study seeks to systematically assess this hypothesis and explore its implications for the integration of AI in clinical practice. By exploring the contribution of AI-assisted medical diagnoses to common diseases with atypical presentations and patient history, the study assesses the accuracy of ChatGPT in reaching a clinical diagnosis based on the medical information provided. By reevaluating the significance of medical information, our study contributes to the ongoing discourse on optimizing diagnostic processes—both conventional and AI assisted.

Figure 1. Study motivation. AI: artificial intelligence; USMLE: United States Medical Licensing Examination.

Methods

Study Design, Settings, and Participants

This study used a series of 25 clinical vignettes from a special issue of the Journal of Generalist Medicine, a Japanese journal, published on March 5, 2024. These vignettes, which exemplify atypical presentations of common diseases, were selected for their alignment with our research aim to explore the impact of atypical disease presentations in AI-assisted diagnosis. The clinical vignettes were derived from real patient cases and curated by an editorial team specializing in GIM, with final edits by KS. Each case included comprehensive details such as age, gender, chief concern, medical history, medication history, current illness, and physical examination findings, along with the ultimate and initial misdiagnoses.
An expert panel comprising 2 general medicine and medical education physicians, T Shimizu and Y Otsuka, initially reviewed these cases. After deliberation, they selected all 25 cases that exemplified atypical presentations of common diseases. Subsequently, T Shimizu and Y Otsuka evaluated their degree of atypicality and categorized them into 4 distinct levels, using the following definition as a guide: “Atypical presentations have a shortage of prototypical features. These can be defined as features that are most frequently encountered in patients with the disease, features encountered in advanced presentations of the disease, or simply features of the disease commonly listed in medical textbooks. Atypical presentations may also have features with unexpected values” [24]. Category 1 was assigned to cases that were closest to the typical presentations of common diseases, whereas category 4 was designated for those that were markedly atypical. In instances where T Shimizu and Y Otsuka did not reach consensus, a third expert, KS, was consulted. Through collaborative discussions, the panel reached a consensus on the final category for each case, ensuring a systematic and comprehensive evaluation of the atypical presentations of common diseases (Figure 2).

Our analysis was conducted on March 12, 2024, using ChatGPT’s proficiency in Japanese. The language processing was enabled by the standard capabilities of the ChatGPT model, requiring no additional adaptation or programming by our team. We exclusively used text-based input for the generative AI, excluding tables or images to maintain a focus on linguistic data. This approach is consistent with the typical constraints of language-based AI diagnostic tools. Inputs to ChatGPT consisted of direct transcriptions of the original case reports in Japanese, ensuring the authenticity of the medical information was preserved. We measured the concordance between AI-generated differential diagnoses and the vignettes’ final diagnoses, as well as the initial misdiagnoses. Our investigation entailed inputting clinical information—including medical history, physical examination, and laboratory data—into ChatGPT, followed by posing this request: “List of differential diagnoses in order of likelihood, based on the provided vignettes’ information,” labeled as “GAI [generative AI] differential diagnoses.”
Data Collection and Measurements

We assigned the correct diagnosis for each of these 25 cases as “final diagnosis.” We then used ChatGPT to generate differential diagnoses (“GAI differential diagnoses”). For each case, ChatGPT was prompted to create a list of differential diagnoses. Patient information was provided in full each time, without incremental inputs. The concordance rate between “final diagnosis,” “misdiagnosis,” and “GAI differential diagnoses” was then assessed. To extract a list of diagnoses from ChatGPT, we concluded each input session with the phrase “List of differential diagnoses in order of likelihood, based on the provided vignettes’ information.” We measured the percentage at which the final diagnosis or misdiagnosis was included in the top-ranked disease (top 1) and within the top 5 differential diagnoses (top 5) generated by ChatGPT (Figure 3).
Data Analysis
Two board-certified physicians working in the medical diagnostic department of our facility judged the concordance between the AI-proposed diagnoses and the final diagnosis. The 2 physicians are GIM board–certified. The number of years after graduation of the physicians was 7 and 17, respectively. A diagnosis was considered to match if the 2 physicians agreed to the concordance. We measured the interrater reliability with the $\kappa$ coefficient (0.8 - 1.0=almost perfect; 0.6 - 0.8=substantial; 0.4 - 0.6=moderate; and 0.2 - 0.4=fair) [25]. To further analyze the accuracy of the top 1 and top 5 diagnoses, we used the $\chi^2$ or Fisher exact test, as appropriate. Statistical analyses were conducted using SPSS Statistics (version 26.0; IBM Corp) with the level of significance set at $P<.05$.

Ethics Approval
Our research did not involve humans, medical records, patient information, observations of public behaviors, or secondary data analyses; thus, it was exempt from ethical approval, informed consent requirements, and institutional review board approval. Additionally, as no identifying information was included, the data did not need to be anonymized or deidentified. We did not offer any compensation because there were no human participants in the study.
Results

The 25 clinical vignettes comprised 11 male and 14 female patients, with ages ranging from 21 to 92 years. All individuals were older than 20 years, and 8 were older than 65 years. Table 1, Multimedia Appendix 1, and Multimedia Appendix 2 present these results. The correct final diagnosis listed in the Journal of Generalist Medicine clinical vignette as a common disease presenting atypical symptoms (labeled as “final diagnosis”) showed that “GAI differential diagnoses” and “final diagnosis” coincided in 12% (3/12) of cases within the first list of differential diagnoses, while “GAI differential diagnoses” and “final diagnosis” had a concordance rate of 44% (11/25) in 5 differential diagnoses. The interrater reliability was substantial (Cohen κ=0.84).

The analysis of the concordance rates between the “GAI differential diagnoses” generated by ChatGPT and the “final diagnosis” from the Journal of Generalist Medicine revealed distinct patterns across the 4 categories of atypical presentations (Table 2). For the top 1 differential diagnosis, that is, category 1 (C1) cases, which were closest to a typical presentation, the concordance rate was 7% (n=1), whereas category 2 (C2) cases exhibited a slightly higher rate of 22% (n=2). Remarkably, categories 3 (C3) and 4 (C4), which represent more atypical cases, demonstrated no concordance (0%) in the top 1 differential diagnosis.

When the analysis was expanded to the top 5 differential diagnoses, the concordance rates varied across categories. C1 cases showed a significant increase in concordance, to 67% (n=4), indicating better performance of the “GAI differential diagnoses” when considering a broader range of possibilities. C2 cases had a concordance rate of 44% (n=4), followed by C3 cases at 25% (n=1) and C4 cases at 17% (n=1).

To assess the diagnostic accuracy of ChatGPT across varying levels of atypical presentations, we used the χ² test. Specifically, we compared the frequency of correct diagnoses in the top 1 and top 5 differential diagnoses provided by ChatGPT for cases categorized as C1+C2 (less atypical) versus C3+C4 (more atypical). For the top 1 differential diagnosis, there was no statistically significant difference in the number of correct diagnoses between the less atypical (C1+C2) and more atypical (C3+C4) groups (χ²=2.07; n=25; P=.13). However, when expanding the analysis to the top 5 differential diagnoses, we found a statistically significant difference, with the less atypical group (C1+C2) demonstrating a higher number of correct diagnoses compared to the more atypical group (C3+C4) (χ²=4.01; n=25; P=.048).
<table>
<thead>
<tr>
<th>Case</th>
<th>Age (years)</th>
<th>Gender</th>
<th>Final diagnosis(^a)</th>
<th>Category</th>
<th>GAI(^b) diagnosis rank(^c)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>34</td>
<td>F</td>
<td>Caffeine intoxication</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>40</td>
<td>F</td>
<td>Asthma</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>55</td>
<td>F</td>
<td>Obsessive-compulsive disorder</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>4</td>
<td>58</td>
<td>M</td>
<td>Drug-induced enteritis</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>5</td>
<td>38</td>
<td>F</td>
<td>Cytomegalovirus infection</td>
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<td>3</td>
</tr>
<tr>
<td>6</td>
<td>29</td>
<td>M</td>
<td>Acute HIV infection</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>7</td>
<td>62</td>
<td>M</td>
<td>Cardiogenic cerebral embolism</td>
<td>2</td>
<td>1</td>
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<td>8</td>
<td>70</td>
<td>M</td>
<td>Cervical epidural hematoma</td>
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<td>10</td>
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<td>Hemorrhagic gastric ulcer</td>
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<tr>
<td>11</td>
<td>77</td>
<td>M</td>
<td>Septic arthritis</td>
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<td>3</td>
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<tr>
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<td>78</td>
<td>F</td>
<td>Compression fracture</td>
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<td>13</td>
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<td>M</td>
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<td>0</td>
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<tr>
<td>14</td>
<td>21</td>
<td>F</td>
<td>Ectopic pregnancy</td>
<td>2</td>
<td>1</td>
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<tr>
<td>15</td>
<td>55</td>
<td>F</td>
<td>Non-ST elevation myocardial infarction</td>
<td>2</td>
<td>2</td>
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<tr>
<td>16</td>
<td>54</td>
<td>F</td>
<td>Hypoglycemia</td>
<td>3</td>
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<tr>
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<td>77</td>
<td>F</td>
<td>Giant cell arteritis</td>
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<td>0</td>
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<tr>
<td>18</td>
<td>60</td>
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<td>Adrenal insufficiency</td>
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<td>4</td>
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<td>F</td>
<td>Graves disease</td>
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<td>4</td>
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<tr>
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<td>31</td>
<td>M</td>
<td>Acute myeloblastic leukemia</td>
<td>4</td>
<td>0</td>
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<td>76</td>
<td>F</td>
<td>Elderly onset rheumatoid arthritis</td>
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<td>0</td>
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<tr>
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<td>45</td>
<td>M</td>
<td>Appendicitis</td>
<td>4</td>
<td>0</td>
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<tr>
<td>24</td>
<td>92</td>
<td>M</td>
<td>Rectal cancer</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>25</td>
<td>60</td>
<td>M</td>
<td>Acute aortic dissection</td>
<td>4</td>
<td>0</td>
</tr>
</tbody>
</table>

\(^a\)Final diagnosis indicates the final correct diagnosis listed in the *Journal of Generalist Medicine* clinical vignette as common disease presenting atypical symptoms.

\(^b\)GAI: generative artificial intelligence.

\(^c\)GAI diagnosis rank indicates the high-priority differential diagnosis rank generated by ChatGPT.

**Table.** Concordance rates of artificial intelligence–generated differential diagnoses by atypicality category. Category (C) 1 was closest to typical, and C4 was most atypical.

<table>
<thead>
<tr>
<th>Category</th>
<th>Rank 1 diagnoses, n</th>
<th>Rank 2 diagnoses, n</th>
<th>Rank 3 diagnoses, n</th>
<th>Rank 4 diagnoses, n</th>
<th>Rank 5 diagnoses, n</th>
<th>Misdiagnoses, n</th>
<th>Top 1, %</th>
<th>Top 5, %</th>
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<tbody>
<tr>
<td>C1</td>
<td>1</td>
<td>0</td>
<td>3</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>17</td>
<td>67</td>
</tr>
<tr>
<td>C2</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>5</td>
<td>22</td>
<td>44</td>
</tr>
<tr>
<td>C3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>3</td>
<td>25</td>
</tr>
<tr>
<td>C4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>17</td>
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(page number not for citation purposes)
Discussion

Principal Findings

This study provides insightful data on the performance of ChatGPT in diagnosing common diseases with atypical presentations. Our findings offer a nuanced view of the capacity of AI-driven differential diagnoses across varying levels of atypicality. In the analysis of the concordance rates between “GAI differential diagnoses” and “final diagnosis,” we observed a decrease in diagnostic accuracy as the degree of atypical presentation increased.

The performance of ChatGPT in C1 cases, which are the closest to typical presentations, was moderately successful, with a concordance rate of 17% for the top 1 diagnosis and 67% within the top 5. This suggests that when the disease presentation closely aligns with the typical characteristics known to the model, ChatGPT is relatively reliable at identifying a differential diagnosis list that coincides with the final diagnosis. However, the utility of ChatGPT appears to decrease as atypicality increases, as evidenced by the lower concordance rates in C2, and notably more so in C3 and C4, where the concordance rates for the top 1 diagnosis fell to 0%. Similar challenges were observed in another 2024 study [26], where the diagnostic accuracy of ChatGPT varied depending on the disease etiology, particularly in differentiating between central nervous system and non–central nervous system tumors.

It is particularly revealing that in the more atypical presentations of common diseases (C3 and C4), the AI struggled to provide a correct diagnosis, even within the top 5 differential diagnoses, with concordance rates of 25% and 17%, respectively. These categories highlight the current limitations of AI in medical diagnosis when faced with cases that deviate significantly from the established patterns within its training data [27].

By leveraging the comprehensive understanding and diagnostic capabilities of ChatGPT, this study aims to reevaluate the significance of patient history in AI-assisted medical diagnosis and contribute to optimizing diagnostic processes [28]. Our exploration of ChatGPT’s performance in processing atypical disease presentations not only advances our understanding of AI’s potential in medical diagnosis [23] but also underscores the importance of integrating advanced AI technologies with traditional diagnostic methodologies to enhance patient care and reduce diagnostic errors.

The contrast in performance between the C1 and C4 cases can be seen as indicative of the challenges AI systems currently face with complex clinical reasoning requiring pattern recognition. Atypical presentations can include uncommon symptoms, rare complications, or unexpected demographic characteristics, which may not be well represented in the data sets used to train the AI systems [29]. Furthermore, these findings can inform the development of future versions of AI medical diagnosis systems and guide training curricula to include a broader spectrum of atypical presentations.

This study underscores the importance of the continued refinement of AI medical diagnosis systems, as highlighted by the recent advances in AI technologies and their applications in medicine. Studies published in 2024 [30-32] provide evidence of the rapidly increasing capabilities of large language models (LLMs) like GPT-4 in various medical domains, including oncology, where AI is expected to significantly impact precision medicine [30]. The convergence of text and image processing, as seen in multimodal AI models, suggests a qualitative leap in AI’s ability to process complex medical information, which is particularly relevant for our findings on AI-assisted medical diagnostics [30]. These developments reinforce the potential of AI tools like ChatGPT in bridging the knowledge gap between machine learning developers and practitioners, as well as their role in simplifying complex data analyses in medical research and practice [31]. However, as these systems evolve, it is crucial to remain aware of their limitations and the need for rigorous verification processes to mitigate the risk of errors, which can have significant implications in clinical settings [32]. This aligns with our observation of decreased diagnostic accuracy in atypical presentations and the necessity for cautious integration of AI into clinical practice. It also points to the potential benefits of combining AI with human expertise to compensate for current AI limitations and enhance diagnostic accuracy [33].

Our research suggests that while AI, particularly ChatGPT, shows promise as a supplementary tool for medical diagnosis, reliance on this technology should be balanced with expert clinical judgment, especially in complex and atypical cases [28,29]. The observed concordance rate of 67% for C1 cases indicates that even when not dealing with extremely atypical presentations, cases with potential pitfalls may result in AI medical diagnosis accuracy lower than the 80% - 90% estimated by existing studies [10,11]. This revelation highlights the need for cautious integration of AI in clinical settings, acknowledging that its diagnostic capabilities, while robust, may still fall short in certain scenarios [34,35].

Limitations

Despite the strengths of our research, the study has certain limitations that must be noted when contextualizing our findings. First, the external validity of the results may be limited, as our data set comprises only 25 clinical vignettes sourced from a special issue of the Journal of Generalist Medicine. While these vignettes were chosen for their relevance to the study’s hypothesis on atypical presentations of common diseases, the size of the data set and its origin as mock scenarios rather than real patient data may limit the generalizability of our findings. This sample size may not adequately capture the variability and complexities typically encountered in broader clinical practice and thus might not be sufficient to firmly establish statistical generalizations. This limitation is compounded by the exclusion of pediatric vignettes, which narrows the demographic range of our findings and potentially reduces their applicability across diverse age groups.

Second, ChatGPT’s current linguistic capabilities predominantly cater to English, presenting significant barriers to patient-provider interactions that may occur in other languages. This raises concerns about the potential for miscommunication and subsequent misdiagnosis in non-English medical consultations. This underscores the essential need for future AI models to exhibit a multilingual capacity that can grasp the
subtleties inherent in various languages and dialects, as well as the cultural contexts within which they are used.

Finally, the diagnostic prioritization process of ChatGPT did not always align with clinical probabilities, potentially skewing the perceived effectiveness of the AI model. Additionally, it must be acknowledged that our research used ChatGPT based on GPT-4, which is not a publicly available model. Consequently, the result may not be directly generalizable to other LLMs, especially open-source models like Llama3 (Meta Platforms, Inc), which might have different underlying architectures and training data sets. Moreover, since our study relied on clinical vignettes that were mock scenarios, the potential for bias based on the cases is significant. The lack of real demographic diversity in these vignettes means that the findings may not accurately reflect social or regional nuances, such as ethnicity, prevalence of disease, or cultural practices, that could influence diagnostic outcomes. This limitation suggests a need for careful consideration when applying these AI tools across different geographic and demographic contexts to ensure the findings are appropriately adapted to local populations. This emphasizes the necessity for AI systems to be evaluated in diverse real-world settings to understand their effectiveness comprehensively and mitigate any bias. This distinction is important to consider when extrapolating our study’s findings to other AI systems. Future studies should not only refine AI’s diagnostic reasoning, but also explore the interpretability of its decision-making process, especially when errors occur. ChatGPT should be considered as a supplementary tool in medical diagnosis, rather than a standalone solution. This reinforces the necessity for combined expertise, where AI supports—but does not replace—human clinical judgment. Further research should expand these findings to a wider range of conditions, especially prevalent diseases with significant public health impacts, to thoroughly assess the practical utility and limitations of AI in medical diagnosis.

**Conclusions**

Our study contributes valuable evidence for the ongoing discourse on the role of AI in medical diagnosis. This study provides a foundation for future research to explore the extent to which AI can be trained to recognize increasingly complex and atypical presentations, which is critical for its successful integration into clinical practice.

**Acknowledgments**

The authors thank the members of Igaku-Shoin, Tokyo, Japan, for permission to use the clinical vignettes. Igaku-Shoin did not participate in designing and conducting the study; data analysis and interpretation; preparation, review, or approval of the paper; or the decision to submit the paper for publication. The authors thank Dr Mai Hongo, Saka General Hospital, for providing a clinical vignette. The authors also thank Editage for the English language review.

**Data Availability**

The data sets generated and analyzed in this study are available from the corresponding author upon reasonable request.

**Disclaimer**

In this study, generative artificial intelligence was used to create differential diagnoses for cases published in medical journals. However, it was not used in actual clinical practice. Similarly, no generative artificial intelligence was used in our manuscript writing.

**Authors' Contributions**

KS, T Watari, T Shimizu, Y Otsuka, M Tago, H Takahashi, YS, and YT designed the study. T Shimizu and Y Otsuka checked the atypical case categories. M Tago and H Takahashi confirmed the diagnoses. KS wrote the first draft and analyzed the research data. All authors created atypical common clinical vignettes and published them in the *Journal of General Medicine*. KS, T Shimizu, and H Takahashi critically revised the manuscript. All authors checked the final version of the manuscript.

**Conflicts of Interest**

None declared.

Multimedia Appendix 1
Differential medical diagnosis list generated by ChatGPT.
[**DOCX File, 22 KB** - mededu_v10i1e58758_app1.docx ]

Multimedia Appendix 2
Transcript of the conversation with ChatGPT and the answers to all the questions.
[**DOCX File, 36 KB** - mededu_v10i1e58758_app2.docx ]

**References**


Abbreviations

AI: artificial intelligence
C: category
GAI: generative artificial intelligence
GIM: general internal medicine
GPT: generative pre-trained transformer
LLM: large language model
NLP: natural language processing
USMLE: United States Medical Licensing Examination
Importance of Patient History in Artificial Intelligence–Assisted Medical Diagnosis: Comparison Study

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Abstract

Background: Medical history contributes approximately 80% to a diagnosis, although physical examinations and laboratory investigations increase a physician’s confidence in the medical diagnosis. The concept of artificial intelligence (AI) was first proposed more than 70 years ago. Recently, its role in various fields of medicine has grown remarkably. However, no studies have evaluated the importance of patient history in AI-assisted medical diagnosis.

Objective: This study explored the contribution of patient history to AI-assisted medical diagnoses and assessed the accuracy of ChatGPT in reaching a clinical diagnosis based on the medical history provided.

Methods: Using clinical vignettes of 30 cases identified in The BMJ, we evaluated the accuracy of diagnoses generated by ChatGPT. We compared the diagnoses made by ChatGPT based solely on medical history with the correct diagnoses. We also compared the diagnoses made by ChatGPT after incorporating additional physical examination findings and laboratory data alongside history with the correct diagnoses.

Results: ChatGPT accurately diagnosed 76.6% (23/30) of the cases with only the medical history, consistent with previous research targeting physicians. We also found that this rate was 93.3% (28/30) when additional information was included.

Conclusions: Although adding additional information improves diagnostic accuracy, patient history remains a significant factor in AI-assisted medical diagnosis. Thus, when using AI in medical diagnosis, it is crucial to include pertinent and correct patient histories for an accurate diagnosis. Our findings emphasize the continued significance of patient history in clinical diagnoses in this age and highlight the need for its integration into AI-assisted medical diagnosis systems.

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KEYWORDS

medical diagnosis; ChatGPT; AI in medicine; diagnostic accuracy; patient history; medical history; artificial intelligence; AI; physical examination; physical examinations; laboratory investigation; laboratory investigations; mHealth; accuracy; public health; United States; AI diagnosis; treatment; male; female; child; children; youth; adolescent; adolescents; teen; teens; teenager; teenagers; older adult; older adults; elder; elderly; older person; older people; investigative; mobile health; digital health

Introduction

Over the past decade, medical knowledge and diagnostic techniques have expanded globally and have become more accessible with remarkable advancements in clinical testing and useful reference systems. Despite these advancements, misdiagnosis significantly contributes to mortality, making it a significant public health issue [1,2]. Studies have shown discrepancies between clinical and postmortem autopsy diagnoses in at least 25% of patients [3-7]. One study suggests that approximately 40,500 adult patients in intensive care units in the United States die of misdiagnoses annually, and the predicted prevalence of potentially lethal misdiagnoses is 6.3% [8]. Another report suggests that diagnostic errors contribute to approximately 10% of deaths and 6% to 17% of hospital adverse events, and are the leading cause of medical malpractice claims [7]. Considering the operative characteristics of clinical investigations combined with the inherent variability in disease presentation, it is often challenging to diagnose patients correctly—an issue that has concerned physicians perennially. Decades ago, a pivotal study proposed that patient history contributes to approximately 80% of the diagnostic process [9,10]. Medical history remains crucial for diagnosis [11,12] and is vital in contemporary physicians’ clinical diagnoses.

With the advent of artificial intelligence (AI) in recent years, numerous studies have focused on AI-assisted diagnoses, including cancer screening and treatment [13-15], diagnostic ultrasound imaging [16-19], x-ray imaging [20], computed
tomography [21], magnetic resonance imaging [22], and endoscopy [15,23]. Other reports on AI-assisted imaging diagnoses include AI’s applications in radiology, pathology, and dermatological imaging [13,24]. There have also been reports on the use of AI in diagnosing specific conditions [25-27]. However, while several studies have reported that AI is useful in screening, diagnosing, and even treating certain medical conditions, to the best of our knowledge, no study has examined the importance of patient history in AI-assisted medical diagnosis. In addition, the extent to which AI considers patient history in its diagnostic processes remains to be fully understood.

This study aimed to investigate the importance of patient history in an AI-assisted medical diagnostic process aided by ChatGPT (version 4.0; June 2, 2023), one of the most well-known large language models that was released on March 14, 2023, to better understand the future of diagnostic medicine where AI is predicted to play an increasingly prominent role. Our study explored the contribution of patient history to AI-assisted medical diagnoses and assessed the accuracy of ChatGPT in reaching a clinical diagnosis based on the medical history that was provided. By reevaluating the significance of patient history, our study contributes to the ongoing discourse on optimizing diagnostic processes, both conventional and AI-assisted.

### Methods

#### Study Design, Settings, and Participants

In our study, we used some of the 45 standardized clinical vignettes in *The BMJ* (Multimedia Appendix 1) to evaluate the diagnostic and triage accuracy of web-based symptom checkers [28]. These vignettes were published on June 5, 2015. They offer a balanced set of cases, with 15 cases requiring immediate attention, 15 cases requiring consultation but not immediately, and 15 cases not requiring immediate attention or consultation. They were identified from various clinical sources, including materials used to educate health professionals as well as a medical resource website, with content provided by a panel of physicians. Researchers have used these clinical vignettes to evaluate the usefulness of web-based symptom checkers and self-triage [28-31]. We chose these vignettes because of their varied severity levels, their origins from multiple resources rather than just 1 resource, and their credibility, having been used in prior studies. They also include some of the most commonly observed conditions in outpatient settings. Of the 45 cases, we selected those that included physical examination findings, test data, and medical history and provided a single distinct diagnosis. As illustrated in Figure 1, we excluded patients with no distinct diagnoses within the vignettes to serve as a reference (3 cases) and those who did not undergo any physical examination or laboratory tests (12 cases). Finally, the remaining 30 cases were used in this study.
Data Collection and Measurements

We assigned the correct diagnosis for each of these 30 cases to “Answer.” We then used the AI model, ChatGPT, to generate 2 diagnoses: the first, labeled “History,” was obtained by inputting only the medical history into ChatGPT; the second set, labeled “All,” was produced by inputting the medical history and all the other additional information in the clinical vignettes. Each time ChatGPT was prompted to generate a diagnosis, a separate chat window was used (Multimedia Appendix 2). Thus, we used 2 chat windows for each case—one for the “History” diagnosis and the other for the “All” diagnosis. Additionally, the patients’ information was not inputted incrementally.

The concordance rate was assessed among “Answer,” “History,” and “All.” To extract a diagnosis from ChatGPT, we ended each input session with the phrase “What is the most likely diagnosis?” For both the “History” and “All,” the session was deemed complete when the AI returned the single most likely diagnosis. If ChatGPT suggested multiple diagnoses or indicated that it did not provide the most likely diagnosis, we repeated the process under the same conditions for a maximum of 5 attempts. Cases for which a single diagnosis could not be obtained even after 5 attempts were excluded without making further attempts.
**Ethical Considerations**

Our research does not involve humans, medical records, patient information, observations of public behaviors, or secondary data analyses; hence, it is exempt from ethical approval, the requirement of informed consent, and institutional review board approval. Additionally, as no identifying information was included, the data did not need to be anonymized or deidentified, and the need for compensation did not arise because no human participants were included in the study.

**Data Analysis**

Three board-certified physicians working in a medical diagnostic department at our facility assessed the concordance among the 3 AI-proposed diagnoses (“Answer,” “History,” and “All”). Of the 3 physicians, 1 is general medicine board–certified, 1 is internal medicine board–certified, and 1 is internal medicine–, general internal medicine–, and family medicine board–certified; their postgraduate education spanned 7, 9, and 11 years, respectively. A diagnosis was considered to match if at least 2 of the 3 physicians agreed upon the correspondence. Distinguishing between acute pharyngitis and acute upper respiratory tract infection necessitated determining whether to consider diseases resulting from similar pathologies as correct diagnoses. In contrast, for diseases that are essentially the same but have different nomenclatures, such as oral ulcers and canker sores, we considered them correct diagnoses.

**Results**

Among the 30 cases, 19 patients were male and 11 were female, with ages ranging from 18 months to 65 years. In total, 12 individuals were younger than 20 years.

The results are shown in Table 1. Cases 1-15 of the original vignette represent those requiring emergent care, cases 16-30 represent those requiring nonemergent care, and cases 31-45 represent those that are appropriate for self-care. A comparison with the correct diagnosis listed in The BMJ vignettes (labeled as “Answer”) showed that “Answer” and “History” coincided 76.6% of the time, while “Answer” and “All” had a concordance rate of 93.3%. Five (16.7%) patients could not be diagnosed on the basis of medical history alone but were diagnosed when additional information was provided. In 1 (3.3%) case, the diagnosis was different and incorrect under both conditions (“History” and “All”). In 1 (3.3%) case, the incorrect diagnosis was the same under both conditions (“History” and “All”).

<table>
<thead>
<tr>
<th>Case</th>
<th>Diagnosis (Correct)</th>
<th>Diagnosis (Answer)</th>
<th>Diagnosis (History)</th>
<th>Diagnosis (All)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Acute pharyngitis</td>
<td>Acute pharyngitis</td>
<td>Acute pharyngitis</td>
<td>Acute pharyngitis</td>
</tr>
<tr>
<td>2</td>
<td>Acute bronchitis</td>
<td>Acute bronchitis</td>
<td>Acute bronchitis</td>
<td>Acute bronchitis</td>
</tr>
<tr>
<td>3</td>
<td>Acute otitis media</td>
<td>Acute otitis media</td>
<td>Acute otitis media</td>
<td>Acute otitis media</td>
</tr>
</tbody>
</table>

**Table 1**

Cases 1-15 represent those requiring emergent care, cases 16-30 represent those requiring nonemergent care, and cases 31-45 represent those that are appropriate for self-care.
Table. List of answers and diagnoses made by ChatGPT.

<table>
<thead>
<tr>
<th>Case number of the original vignette</th>
<th>Original diagnosis (Answer)</th>
<th>Output from history only (History)</th>
<th>Output from all information (All)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Acute liver failure</td>
<td>Acute liver failure</td>
<td>Acute liver failure</td>
</tr>
<tr>
<td>2</td>
<td>Appendicitis</td>
<td>Acute gastroenteritis</td>
<td>Acute peritonitis, possibly sec-</td>
</tr>
<tr>
<td>5</td>
<td>Deep vein thrombosis</td>
<td>Deep vein thrombosis</td>
<td>Deep vein thrombosis</td>
</tr>
<tr>
<td>6</td>
<td>Heart attack</td>
<td>Acute myocardial infarction</td>
<td>Acute anterior wall myocardial in-</td>
</tr>
<tr>
<td>7</td>
<td>Hemolytic uremic syndrome</td>
<td>Hemolytic uremic syndrome</td>
<td>Hemolytic uremic syndrome</td>
</tr>
<tr>
<td>9</td>
<td>Malaria</td>
<td>Malaria</td>
<td>Malaria</td>
</tr>
<tr>
<td>10</td>
<td>Meningitis</td>
<td>N/A × 5</td>
<td>Meningitis</td>
</tr>
<tr>
<td>11</td>
<td>Pneumonia</td>
<td>Community-acquired pneumonia</td>
<td>Community-acquired pneumonia</td>
</tr>
<tr>
<td>12</td>
<td>Pulmonary embolism</td>
<td>Pulmonary embolism</td>
<td>Pulmonary embolism</td>
</tr>
<tr>
<td>13</td>
<td>Rocky Mountain spotted fever</td>
<td>Tick-borne illness, such as Rocky Mountain spotted fever</td>
<td>Rocky Mountain spotted fever</td>
</tr>
<tr>
<td>16</td>
<td>Acute otitis media</td>
<td>Viral upper respiratory tract infec-</td>
<td>Acute otitis media</td>
</tr>
<tr>
<td>17</td>
<td>Acute pharyngitis</td>
<td>Strep throat</td>
<td>Streptococcal pharyngitis</td>
</tr>
<tr>
<td>18</td>
<td>Acute pharyngitis</td>
<td>Streptococcal pharyngitis</td>
<td>Streptococcal pharyngitis</td>
</tr>
<tr>
<td>19</td>
<td>Acute sinusitis</td>
<td>Acute sinusitis</td>
<td>N/A × 2; acute bacterial sinusitis</td>
</tr>
<tr>
<td>21</td>
<td>Cellulitis</td>
<td>N/A × 5</td>
<td>Cellulitis</td>
</tr>
<tr>
<td>24</td>
<td>Mononucleosis</td>
<td>Infectious mononucleosis</td>
<td>Infectious mononucleosis</td>
</tr>
<tr>
<td>25</td>
<td>Peptic ulcer disease</td>
<td>Peptic ulcer disease</td>
<td>Peptic ulcer disease</td>
</tr>
<tr>
<td>26</td>
<td>Pneumonia</td>
<td>Pneumonia</td>
<td>Community-acquired pneumonia</td>
</tr>
<tr>
<td>27</td>
<td><em>Salmonella</em> infection</td>
<td><em>Campylobacter jejuni</em> infection</td>
<td>Acute gastroenteritis, likely due to food poisoning</td>
</tr>
<tr>
<td>30</td>
<td>Vertigo</td>
<td>Benign paroxysmal positional verti-</td>
<td>Benign paroxysmal positional verti-</td>
</tr>
<tr>
<td>31</td>
<td>Acute bronchitis</td>
<td>Acute bronchitis</td>
<td>Acute bronchitis</td>
</tr>
<tr>
<td>32</td>
<td>Acute bronchitis</td>
<td>Acute bronchitis</td>
<td>Acute bronchitis</td>
</tr>
<tr>
<td>33</td>
<td>Acute conjunctivitis</td>
<td>Viral conjunctivitis</td>
<td>Viral conjunctivitis</td>
</tr>
<tr>
<td>34</td>
<td>Acute pharyngitis</td>
<td>Viral upper respiratory tract infec-</td>
<td>Upper respiratory tract infection</td>
</tr>
<tr>
<td>37</td>
<td>Bee sting without anaphylaxis</td>
<td>Pain of the sting</td>
<td>Localized allergic reaction to a bee sting</td>
</tr>
<tr>
<td>38</td>
<td>Canker sore</td>
<td>Recurrent aphthous stomatitis</td>
<td>Recurrent aphthous stomatitis</td>
</tr>
<tr>
<td>39</td>
<td>Candida yeast infection</td>
<td>Vulvovaginal candidiasis</td>
<td>Vulvovaginal candidiasis</td>
</tr>
<tr>
<td>42</td>
<td>Stye</td>
<td>Hordeolum</td>
<td>Hordeolum</td>
</tr>
<tr>
<td>43</td>
<td>Viral upper respiratory tract infection</td>
<td>Acute sinusitis</td>
<td>Acute sinusitis</td>
</tr>
</tbody>
</table>

https://mededu.jmir.org/2024/1/e52674
Table 1: Case number of the original vignette

<table>
<thead>
<tr>
<th>Case number</th>
<th>Original diagnosis (Answer)</th>
<th>Output from history only (History)</th>
<th>Output from all information (All)</th>
</tr>
</thead>
<tbody>
<tr>
<td>44</td>
<td>Viral upper respiratory tract infection</td>
<td>Common viral illness, such as the common cold or influenza</td>
<td>Viral upper respiratory tract infection</td>
</tr>
</tbody>
</table>

*a* We repeated outputs until a single plausible diagnosis was made, with a maximum of 5 attempts.

*b* Matching answers between Answer and History: 23/30 (76.6%); median trial count 1 (Q1 1, Q2 1, Q3 1).

*c* Matching answers between History and All: 28/30 (93.3%); median trial count 1 (Q1 1, Q2 1, Q3 1).

*d* The output matched with that of “Answer.”

*e* N/A: not applicable.

*f* We attempted to obtain a diagnosis 5 times but failed.

*g* We attempted to obtain a diagnosis twice but failed.

**Figure 2** presents details regarding the number of attempts required. On average, 1.27 attempts were needed for inputs involving only medical history followed by the question “What is the most likely diagnosis?” When all possible information, including physical examination findings and laboratory data, were inputted, followed by the same question, an average of 1.00 attempt was required. Regarding the 2 cases shown in **Figure 2** that required 5 attempts, ChatGPT was unable to narrow down the diagnosis to the single most likely option. Consequently, these cases were counted as mismatches with the correct diagnoses listed in *The BMJ* vignettes.
**Discussion**

**Principal Findings**

Despite the advancements in medical knowledge and diagnostic techniques, misdiagnosis remains a significant issue. AI has shown promise in the diagnosis and treatment of medical conditions; however, there is limited understanding of how AI uses patient history for diagnostic purposes. Our study aimed to investigate the extent to which AI (ChatGPT) can use information from medical history to accurately diagnose common diseases, which are frequently encountered in general outpatient, emergency, and ward management settings. Although some studies have investigated the accuracy of AI-based medical diagnosis, our study is novel because it emphasizes the importance of patient history. We compared the diagnostic accuracy of diagnoses made on the basis of only patient history and those made using all the information; this makes our study unique. To the best of our knowledge, no previous research has been conducted on this topic.

Our study investigated the role of patient history in AI-assisted medical diagnoses using ChatGPT. We analyzed 30 standardized patient vignettes from *The BMJ* to assess the concordance rates between AI-proposed diagnoses based on medical history only and those based on both medical history and additional information. Our results showed high concordance rates of 76.6% between the “Answer” and “History” groups, suggesting the importance of patient history in AI-assisted diagnoses and highlighting the potential of AI in improving diagnostic
accuracy. This result is similar to that of a previous study that involved actual physicians instead of ChatGPT [9,10].

Characteristics of cases that did not lead to appropriate diagnoses based on history alone include, for instance, the following: an appendicitis case (case 2 in Multimedia Appendix 1) for which there was no documentation of pain migration in the medical history, a meningitis case (case 10 in Multimedia Appendix 1) wherein only headache and fever were documented, an otitis media case (case 16 in Multimedia Appendix 1) wherein only upper respiratory symptoms were recorded with no mention of ear-related symptoms, errors in identifying the causative agent in a case of acute gastroenteritis (case 27 in Multimedia Appendix 1), and an acute pharyngitis case (case 34 in Multimedia Appendix 1) that lacked the necessary medical history to determine the Centor score. Such omissions in the medical history could be considered contributing factors to the misdiagnoses. When physical findings and test data were added, an accurate diagnosis was achieved in 28 out of 30 cases (93.3%), showing a 16.7% increase in the accuracy rate. These two cases were of acute pharyngitis diagnosed as acute upper respiratory tract infection and Salmonella enteritis diagnosed as acute gastroenteritis. While we considered these incorrect diagnoses for the purpose of this study, they could have been deemed correct under certain criteria. Of the 7 cases that did not match between “Answer” and “History,” 6 were of infectious diseases (21 of 30 cases were of infectious diseases). These included cases where appendicitis was mistaken for acute gastroenteritis, acute otitis media and acute pharyngitis were mistaken for upper respiratory infections, and a Salmonella infection was mistaken for a Campylobacter infection. Physical examinations or tests may help identify the site of infection or pathogen in cases of intra-abdominal or head and neck infections.

There are situations in which physical examination and clinical test information may not be available in clinical settings. For instance, digital patient encounters owing to the impact of the COVID-19 pandemic often preclude physical examinations and clinical tests. The widespread use of telemedicine approaches in COVID-19 management, from screening to follow-up, has demonstrated the community’s acceptance and interest in telehealth solutions [32]. Moreover, even in face-to-face consultations, there are scenarios, such as in clinics, where detailed clinical tests may not be feasible depending on the setting. Furthermore, we cannot perform all physical examinations and tests on all patients. Therefore, we should consider potential differential diagnoses and decide which pertinent physical examinations or tests are the most suitable and should be performed. Most importantly, it has been reported that one rarely makes a correct diagnosis when one cannot make a differential diagnosis based on history [11]. In addition, accurately predicting the diagnosis based on medical history is associated with a higher diagnostic accuracy of the physical examination, whereas incorrect prediction of the diagnosis based on medical history is associated with a lower diagnostic accuracy of the physical examination [33]. Based on these findings and suggestions, medical diagnosis using ChatGPT is considered heavily dependent on history.

Using AI for diagnosis can enhance diagnostic accuracy by more efficiently collecting medical histories. For instance, diagnosing acute appendicitis is sometimes challenging. AI may face the same challenge as that observed when, in our study, AI mistakenly identified acute appendicitis as acute gastroenteritis. This misdiagnosis may have occurred because the case lacked specific medical histories characteristic of appendicitis, such as pain migration. By configuring AI systems to verify pain migration in patients with abdominal pain, especially for such common conditions, diagnostic precision may improve.

There are 2 possible limitations in our study. First, it remains unclear whether similar results could be obtained with other vignettes or actual patients. Unlike using preprovided vignettes, among which we included 30 cases, diagnosis can be more challenging in clinical settings because it requires taking a medical history from patients. We included 30 cases from among the vignettes, which include some of the most commonly observed conditions in the outpatient setting. Although covering all the existing conditions is not feasible, we do not know if the case volume in our study is sufficiently high. This study included relatively simple cases in which patients had very few comorbidities, potentially making the diagnosis less challenging. Moreover, patients with psychiatric conditions tend to present with complex and lengthy case histories, and the wording used by mental health clinicians may differ, be inconsistent, be vague, or fail to pinpoint a diagnosis. Our vignettes did not include a diagnosis of any mental illness. Due to the abovementioned reasons, our results may not apply to all clinical settings. Furthermore, when we consider what the patient reports, results may differ if languages other than English are used since ChatGPT does not recognize some languages, and each language may have its unique nuance. This highlights the importance of linguistic diversity and cultural context in AI applications, particularly in medical diagnoses where patient communication and history are critical. Future iterations of AI systems should aim to incorporate a broader range of languages and understand cultural nuances to ensure more accurate and inclusive diagnostic support. This idea is important in the context of health inequality. Furthermore, disparities in technology access may pose some challenges. Future research should address these barriers to ensure equitable access to AI-assisted diagnostic tools.

Second, we encountered cases where the input of medical history followed by the question, “What is the most likely diagnosis?” failed to yield a single most likely diagnosis even after 5 attempts, which could have introduced bias into our results, although we only had 2 such cases.

In the future, studies should focus on training AI by implementing evidence-based medical information, enabling it to present the underlying reasons and guidelines for diagnoses. In the event of a misdiagnosis, analyzing the process that led to the false diagnosis could be challenging in an AI-assisted medical diagnosis. Given the current situation where reflection on misdiagnoses is not always feasible, AI should be used as an auxiliary tool in medical diagnosis. This approach underscores the importance of AI, deeming it a support system rather than a definitive diagnostic solution. This area needs
further investigation. Future studies should also verify our results with certain common conditions or diseases, such as the top 10 diseases identified in the Global Burden of Diseases study [34], potentially leveraging the benefits and limitations of AI-assisted medical diagnosis.

Conclusions
Relevant patient history is essential for AI-assisted diagnosis. The input of relevant patient history or the development of AI systems capable of obtaining comprehensive medical histories is vital for AI-assisted medical diagnosis. Furthermore, even in the modern era of advanced medical knowledge and clinical testing, the significance of patient history in diagnosis remains crucial.

Data Availability
All of our clinical vignettes, results, and prompts used are provided in Multimedia Appendix 1.

Authors’ Contributions
FF conceptualized the study, designed the methodology, collected the data, and drafted the manuscript. YY, DY, and SU conceptualized the study, designed the methodology, and reviewed and edited the manuscript. SY, YL, KS, TT, KN, TU, and MI conceptualized the study and reviewed and edited the manuscript. No generative artificial intelligence was used in writing the manuscript.

Conflicts of Interest
None declared.

Multimedia Appendix 1
Clinical Vignettes used in our study.
[PDF File, 159 KB - mededu_v10i1e52674_app1.pdf]

Multimedia Appendix 2
Explanation of the prompts we used in our study.
[PDF File, 48 KB - mededu_v10i1e52674_app2.pdf]

References


Abbreviations

AI: artificial intelligence
AI Education for Fourth-Year Medical Students: Two-Year Experience of a Web-Based, Self-Guided Curriculum and Mixed Methods Study

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Abstract

Background: Artificial intelligence (AI) and machine learning (ML) are poised to have a substantial impact in the health care space. While a plethora of web-based resources exist to teach programming skills and ML model development, there are few introductory curricula specifically tailored to medical students without a background in data science or programming. Programs that do exist are often restricted to a specific specialty.

Objective: We hypothesized that a 1-month elective for fourth-year medical students, composed of high-quality existing web-based resources and a project-based structure, would empower students to learn about the impact of AI and ML in their chosen specialty and begin contributing to innovation in their field of interest. This study aims to evaluate the success of this elective in improving self-reported confidence scores in AI and ML. The authors also share our curriculum with other educators who may be interested in its adoption.

Methods: This elective was offered in 2 tracks: technical (for students who were already competent programmers) and nontechnical (with no technical prerequisites, focusing on building a conceptual understanding of AI and ML). Students established a conceptual foundation of knowledge using curated web-based resources and relevant research papers, and were then tasked with completing 3 projects in their chosen specialty: a data set analysis, a literature review, and an AI project proposal. The project-based nature of the elective was designed to be self-guided and flexible to each student’s interest area and career goals. Students’ success was measured by self-reported confidence in AI and ML skills in pre and postsurveys. Qualitative feedback on students’ experiences was also collected.

Results: This web-based, self-directed elective was offered on a pass-or-fail basis each month to fourth-year students at Emory University School of Medicine beginning in May 2021. As of June 2022, a total of 19 students had successfully completed the elective, representing a wide range of chosen specialties: diagnostic radiology (n=3), general surgery (n=1), internal medicine (n=5), neurology (n=2), obstetrics and gynecology (n=1), ophthalmology (n=1), orthopedic surgery (n=1), otolaryngology (n=2), pathology (n=2), and pediatrics (n=1). Students’ self-reported confidence scores for AI and ML rose by 66% after this 1-month elective. In qualitative surveys, students overwhelmingly reported enthusiasm and satisfaction with the course and commented that the self-direction and flexibility and the project-based design of the course were essential.

Conclusions: Course participants were successful in diving deep into applications of AI in their widely-ranging specialties, produced substantial project deliverables, and generally reported satisfaction with their elective experience. The authors are...
hopeful that a brief, 1-month investment in AI and ML education during medical school will empower this next generation of physicians to pave the way for AI and ML innovation in health care.

**KEYWORDS**
medical education; machine learning; artificial intelligence; elective curriculum; medical student; student; students; elective electives; curriculum; lesson plan; lesson plans; educators; educator; teacher; teachers; teaching; computer programming; programming; coding; programmer; programmers; self guided; self directed

**Introduction**

Artificial intelligence (AI) and machine learning (ML) are poised to have a substantial impact in the health care space with many disruptive technologies on the horizon. innovations in clinical care are increasingly impacted by the development and implementation of AI and ML, and as future clinicians, medical students need to become innovators and active participants in technological changes that will affect how they provide care for their patients. There is much excitement and curiosity among medical students about these technologies [1]. However, few programs exist to deliberately expose future physicians to their role in medicine, let alone to empower students to actively participate in AI and ML innovation [2]. While a plethora of high-quality web-based resources exist to teach programming skills and ML model development, there are few introductory curricula specifically tailored to medical students without a background in data science or programming. Additionally, there is little guidance provided to medical students on where to begin. Some medical societies do have AI outreach activities, but these are limited to trainees within their specialty [3-5].

The authors theorized that a 1-month elective for fourth-year students, composed of existing web-based resources and a project-based structure, would empower students to learn about the impact of AI and ML in their chosen specialty and begin contributing to innovation in their field of interest. The authors also aimed for the elective to be specialty-agnostic and customizable for each student’s career goals. The goal of this senior elective is to demystify AI and ML in health care, enabling students to have informed conversations about these technologies and participate in their clinical advancement. The target participant in the elective is any senior medical student with an interest in AI, with no prerequisites for technical, mathematical, or engineering skills.

In this paper, we evaluate the success of this elective over a 2-year period based on self-reported confidence scores in AI and ML. We also publish our curriculum for other educators who may be interested in its adoption.

**Methods**

**Design**

We built our elective following advice on designing medical electives with the principles articulated by Ramalho et al [6], which emphasize that a one-size-fits-all approach is often inadequate and that electives benefit from allowing students to carve their own paths. Creating a medical elective in an overloaded, overworked environment is nontrivial, but prior studies on peer-organized coursework gave us insights into the effectiveness of peer-organized research in building academic confidence, as well as the importance of clearly defined learning objectives [7,8].

**Technical and Nontechnical Tracks**

Given the wide-ranging skill sets that medical students are equipped with before coming to medical school, this elective was offered in 2 tracks: Technical and Nontechnical. The Technical track was intended for the subset of students who were already competent computer programmers. This course did not aim to teach noncoding students how to code because it was expected that 1 month would not be sufficient time for students to make meaningful progress. Therefore, the Nontechnical track was offered to students with no technical background and focused on building a conceptual understanding of AI. Our goal for the Nontechnical track was to help students without a technical background develop a skill set and vocabulary that would enable them to participate in AI and ML evaluation and implementation processes in future collaborations with technical colleagues.

For both the Technical and Nontechnical tracks, the course was designed to address the following learning objectives:

1. Compare and contrast AI and ML.
2. State and differentiate various ML techniques (supervised/unsupervised, classification/regression, etc).
3. Appreciate the growing impact of ML in medicine, broadly and in the student’s chosen specialty.
4. Develop an intuition of how machines “learn.” Describe how neural networks are structured, trained, and evaluated. Learn vocabulary and concepts used to describe model training (loss functions, gradient descent, and backpropagation).
5. Understand the limitations and pitfalls of ML (reproducibility, interpretability, and bias).
6. Understand what kinds of medical problems can and cannot be solved by ML.
7. Describe issues that may arise in the implementation of an ML algorithm in clinical practice.
8. Discuss ethical issues that concern the use of ML in health care.

**Didactic and Project-Based Components**

In this self-guided, web-based course, students were referred to existing web-based courses and relevant research papers to supplement these learning objectives (Multimedia Appendix 1 [9-22]) but were expected to guide their own learning beyond this. Students were asked to share and write down their personal experiences with an emphasis on the impact of AI and ML in their chosen specialty and begin contributing to innovation in their field of interest. The authors hope that a brief, 1-month investment in AI and ML education during medical school will empower this next generation of physicians to pave the way for AI and ML innovation in health care.

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goals at the beginning of the elective to guide their learning. They were also encouraged to spend time after each section on independent research to address lingering questions. The learning objectives and course resources were provided to students on a central document and students were able to follow along at their own pace. Because the course aimed to empower an individual student’s interests and career goals, the elective was designed to establish a baseline level of understanding for all students, while also allowing students the freedom to dive deeper into the areas they were drawn to. Students were supported by the course’s faculty advisor, a physician with substantial leadership and experience in AI and ML research.

Project Deliverables

Students were then tasked with completing at least 1 of the following project-based deliverables, and encouraged to complete others as their interests dictated:

1. Complete a literature review on the state of AI and ML in the student’s chosen specialty.
2. Find and analyze 3 open-source health data sets, considering strengths, weaknesses, and sources of error and bias.
3. Write a Project Proposal addressing a problem in the student’s chosen specialty that can be solved with AI, with a discussion surrounding the implementation complexities.
4. Technical track only: Train and evaluate a clinical ML algorithm.

Details on these projects are provided in Multimedia Appendix 2 [23].

The full curriculum is hosted on the Emory Health Care Innovations and Translational Informatics Lab GitHub repository [24].

This course was initially designed during the COVID-19 pandemic, and maintained a web-based format throughout the 2 years it has been offered. All recommended resources were freely available to students on the web, although some required institutional access. The students attended weekly web-based laboratory meetings to discuss their progress and to be exposed to more advanced research in AI and ML. Students were also encouraged to identify an additional advisor (beyond the elective director, who they met with once a week) within their chosen specialty, who could provide domain expertise for their projects.

Qualitative Survey Data

Initially, the authors collected feedback from students qualitatively through one-on-one meetings; this feedback was used to improve the format and support structure of the elective. Beginning in October 2021, students were also asked for open-ended feedback on the strengths and weaknesses of the elective through anonymous surveys. They were asked:

- What was the most meaningful project or experience you completed during the elective? Do you intend to continue work on it past the end of the elective?
- Did you gain what you hoped to get out of this elective? Please explain.
- What resources were most useful to you during the elective?
- What could be most improved in the curriculum design of this elective?

Quantitative Survey Data

Beginning in October 2021, quantitative pre and postelective surveys were implemented using Google Forms to assess the effectiveness of the elective format and resources provided. Students were asked to fill out formal surveys to rate their confidence in AI and ML concepts and in technical data science and coding skills.

Before starting the elective, students were asked:

- How familiar are you with AI or ML concepts? (Likert scale, 1-5)
- How would you rate your technical data science or coding experience? (Likert scale, 1-5)

After completing the elective, students were asked:

- Did you choose the Technical or Nontechnical Track?
- After completing this elective, how familiar are you with AI or ML concepts? (Likert scale, 1-5)
- After completing this elective, how would you rate your technical data science or coding experience? (Likert scale, 1-5)

Statistical Analysis

Quantitative and discrete data from self-reported confidence scores was analyzed using the Wilcoxon rank sum test. Qualitative survey responses were reviewed in a descriptive manner rather than undergoing a formal analysis. Responses were manually examined for common themes, trends, and noteworthy insights, but no systematic coding framework was used and representative responses are included in the “Results” section.

Ethical Considerations

This study was deemed exempt from review by Emory University’s institutional review board, under the category “Educational Tests, Surveys, Interviews, Observations.” This is justified based on anonymity and minimal risk to survey participants. All participants were able to opt out of this educational experience and from data collection. Survey data were collected anonymously. Students were not compensated for participation.

Results

Overview

This web-based, self-directed elective was offered on a pass-or-fail basis each month to fourth-year students at Emory University School of Medicine beginning in May 2021. A maximum of 3 students were allowed to enroll each month. As of June 2022, a total of 19 students had signed up and completed the elective. All students successfully met elective requirements and passed the course. The students represented a diverse range of chosen specialties: diagnostic radiology (n=3), general surgery (n=1), internal medicine (n=5), neurology (n=2), obstetrics and gynecology (n=1), obstetrics and gynecology (n=1),
orthopedic surgery (n=1), otolaryngology (n=2), pathology (n=2), and pediatrics (n=1).

Given the limited time and open-ended nature of the course, students elected to spend varying amounts of time on each of the project components based on their interests and were not required to complete all 3 projects as long as they produced at least 1 significant deliverable. The vast majority of students (17 out of 19 students) chose the Nontechnical track. Most students (11/19, 58%) chose to focus their efforts on 2 of the 3 projects; 8 (42%) completed all 3 projects, and 1 (5%) submitted only a project proposal. Since the elective was intended to be flexible to students’ interests, students were evaluated on a pass-or-fail basis based on demonstrated effort as determined by the faculty advisor, rather than strict adherence to project deliverables. All students received a passing grade. Project proposals submitted by students were wide-ranging, including AI applications such as “Smartphone Detection of Anterior Uveitis,” “Predicting Postpartum Hemorrhage,” “Image Enhancement in Video Laryngoscopy,” and “Audiometry for Pediatric Heart Murmur Screening.” Four (25%) students indicated that they intended to continue working on their projects beyond the end of the elective.

Qualitative Survey Results

Qualitative feedback collected from students before October 2021 (n=4) indicated that students wanted more support and guidance in their field of interest; given this feedback, the authors created more structure for the elective and encouraged students to find an additional specialty-specific mentor who could contribute domain expertise.

Students were asked if they gained what they hoped for from their elective experience. Students who sought a basic conceptual understanding reported satisfaction, but some reported an unmet desire for a deeper technical understanding:

- “I wanted to learn more generally how AI/ML can be used and is being used in medicine. I definitely achieved this goal.”
- “I feel that I learned AI/ML fundamentals, am now able to better read and understand AI/ML medical literature, and have thought through the essential design elements of an AI/ML proposal.”
- “I learned about the clinical applications of ML and how it is used to help rather than replace radiologists. I also have learned that the technology is advanced, but the application is still early in medicine.”
- “I found the course very valuable as an introduction to what ML is and how it is used. However, I had hoped to gain more insight into what research is being conducted in ML from a technical perspective and what these advances may mean from a translational perspective.”

Students were also asked what aspects of the course were most beneficial. Four students commented that the self-directed and flexible nature of the course was essential. Two students commented that the project proposal was the most essential element. Five (26%) students reported that they intended to continue working on their projects after the end of the elective month.

When asked for constructive feedback, 2 students commented that they desired more concrete guidance on the projects. Some students felt strained to finish the project proposal within 1 month, with one commenting that students should not expect to finish the proposal in 1 month, and 2 recommending future students pick a project as early as possible, rather than waiting until after the literature review and data set project.

Quantitative Survey Results

After October 2021, students were asked to fill out formal surveys collecting feedback and self-reported confidence in skills gained during the elective. Fifteen students filled out the preintervention survey, and 12 students completed the postintervention survey. These results are shown in Table 1.

| Table 1. Pre- and postintervention confidence scores in AI or ML concepts and technical skills. |
|---------------------------------------------------------------|-----------------|-----------------|
| “On a scale of 1-5, how well do you understand AI or ML concepts?“ | Mean (SD) | Median (IQR) |
| Preintervention (n=15) | 2.5 (1.3) | 2 (3) |
| Postintervention (n=12) | 4.1 (0.7) | 4 (3) |
| “On a scale of 1-5, rate your technical data science skills“ |
| Preintervention (n=15) | 2.6 (1.4) | 3 (0.25) |
| Postintervention (n=12) | 1.9 (1.3) | 1 (2) |

| a | AI: artificial intelligence. |
| b | ML: machine learning. |
| c | Relative difference is 66% and Wilcoxon rank sum P value is .003. |
| d | Relative difference is –26% and Wilcoxon rank sum P value is .20. |
Discussion

Principal Results

Students who participated in this elective were successful in diving deep into the potential of AI and ML in their area of interest and generally reported satisfaction with their elective experience. Students were asked to quantitatively rate their familiarity with both AI and ML concepts and coding or data science; the self-reported confidence scores for AI and ML rose by 66%, and these results were found to be statistically significant when analyzed by the Wilcoxon rank sum test. This exposure to AI and ML is a substantial improvement from the status quo, in which most medical students receive little to no exposure during the course of their training; in 1 study from 2022, 66.5% of students reported 0 hours of AI or ML teaching, and 43.4% had never heard the term “machine learning” [25]. Previous literature includes effective AI curricula developed for other types of health care trainees, such as radiology residents, but there is little to no literature on curricula evaluated for a fourth-year medical student audience as described in this paper [26,27].

Self-reported confidence in technical skills (coding and data science) fell by 26%, although this result was not found to be statistically significant. The authors attribute these results to an initial overconfidence prior to the elective, followed by an increased awareness of the technical complexity of model development after the elective.

Because this was a self-guided elective, student output varied with each student’s level of motivation and goals prior to entering the elective. Students who had defined a specific area of interest tended to benefit more from their experience than students who came in with no clear goals set. This course could be improved by providing further assistance early on in helping students to finalize a project area early so that they feel less strained by time toward the end of the month.

Students produced a wide range of deliverables in their chosen specialty. Since most fourth-year students have chosen their specialty and have established connections with faculty in their field, the self-guided nature of the course allowed flexibility for students to seek out appropriate mentors and propose reasonable projects in their areas of interest.

Limitations and Future Directions

Limitations of this study include the small number of participants, especially in the Technical track, restricting the generalizability of this study. Only 2 (11%) students chose the Technical track, so there is insufficient data to evaluate this curriculum; this was likely due to the requirement that students interested in the Technical track have in-depth coding experience and receive approval from the course director to ensure a high likelihood of success. However, the authors recommend screening applicants to make sure that they do in fact possess the required level of comfort in coding before attempting to develop an ML model, as we observed a tendency for students to underestimate the complexity of this task. Based on qualitative observations that students spent more time than expected preparing data for training, the authors suggest providing select, cleaned data sets for students in the Technical track, allowing them to focus on model building, training, and testing.

Another substantial limitation is that assessments relied only on students’ self-reported confidence, which has been shown to be a flawed metric [28]. Further studies would benefit from a refined objective assessment tool of students’ competencies, as well as replication of this study at other medical schools.

Since launching this fourth-year elective, we have also adapted this curriculum to a shorter elective targeting second-year medical students and were invited to participate in a National Academies forum on AI for Health Profession Education to disseminate this curriculum to other learners [29].

Conclusions

Overall, in the 2 years since launching the elective at Emory University School of Medicine, the authors have already seen substantial excitement and appreciation from senior medical students, with continued excitement in the elective’s third year. Most students entered the elective with minimal previous experience in AI and ML and were successful in completing self-guided research and proposing creative and realistic AI and ML projects. The authors are hopeful that a brief, 1-month investment in AI and ML education during medical school can lay the groundwork for these future physicians to continue to engage with AI and ML research and empower this next generation of physicians to pave the way for AI and ML innovation in health care.

Acknowledgments

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Data Availability

The data sets generated or analyzed during this study are not publicly available due to ensure participant confidentiality and privacy in compliance with the institutional review board exemption status, but are available from the corresponding author on reasonable request.
Authors' Contributions

AA and JG contributed to the conceptualization, investigation, and methodology; analysis of results; and the writing of the manuscript. AM contributed to the conceptualization and design of the course, along with the review and editing of the manuscript. IB, SP, and HT contributed to the administration of the elective and review and editing of the manuscript.

Conflicts of Interest

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Multimedia Appendix 1
Learning objectives and corresponding curated resources.

Multimedia Appendix 2
Project components and deliverables.

References


Abbreviations

AI: artificial intelligence
ML: machine learning

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Original Paper

Evaluating Large Language Models for the National Premedical Exam in India: Comparative Analysis of GPT-3.5, GPT-4, and Bard

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Abstract

Background: Large language models (LLMs) have revolutionized natural language processing with their ability to generate human-like text through extensive training on large data sets. These models, including Generative Pre-trained Transformers (GPT)-3.5 (OpenAI), GPT-4 (OpenAI), and Bard (Google LLC), find applications beyond natural language processing, attracting interest from academia and industry. Students are actively leveraging LLMs to enhance learning experiences and prepare for high-stakes exams, such as the National Eligibility cum Entrance Test (NEET) in India.

Objective: This comparative analysis aims to evaluate the performance of GPT-3.5, GPT-4, and Bard in answering NEET-2023 questions.

Methods: In this paper, we evaluated the performance of the 3 mainstream LLMs, namely GPT-3.5, GPT-4, and Google Bard, in answering questions related to the NEET-2023 exam. The questions of the NEET were provided to these artificial intelligence models, and the responses were recorded and compared against the correct answers from the official answer key. Consensus was used to evaluate the performance of all 3 models.

Results: It was evident that GPT-4 passed the entrance test with flying colors (300/700, 42.9%), showcasing exceptional performance. On the other hand, GPT-3.5 managed to meet the qualifying criteria, but with a substantially lower score (145/700, 20.7%). However, Bard (115/700, 16.4%) failed to meet the qualifying criteria and did not pass the test. GPT-4 demonstrated consistent superiority over Bard and GPT-3.5 in all 3 subjects. Specifically, GPT-4 achieved accuracy rates of 73% (29/40) in physics, 44% (16/36) in chemistry, and 51% (50/99) in biology. Conversely, GPT-3.5 attained an accuracy rate of 45% (18/40) in physics, 33% (13/36) in chemistry, and 34% (34/99) in biology. The accuracy consensus metric showed that the matching responses between GPT-4 and Bard, as well as GPT-4 and GPT-3.5, had higher incidences of being correct, at 0.56 and 0.57, respectively, compared to the matching responses between Bard and GPT-3.5, which stood at 0.42. When all 3 models were considered together, their matching responses reached the highest accuracy consensus of 0.59.

Conclusions: The study’s findings provide valuable insights into the performance of GPT-3.5, GPT-4, and Bard in answering NEET-2023 questions. GPT-4 emerged as the most accurate model, highlighting its potential for educational applications. Cross-checking responses across models may result in confusion as the compared models (as duos or a trio) tend to agree on only a little over half of the correct responses. Using GPT-4 as one of the compared models will result in higher accuracy consensus. The results underscore the suitability of LLMs for high-stakes exams and their positive impact on education. Additionally, the
study establishes a benchmark for evaluating and enhancing LLMs’ performance in educational tasks, promoting responsible and informed use of these models in diverse learning environments.

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**KEYWORDS**

accuracy; AI model; artificial intelligence; Bard; ChatGPT; educational task; GPT-4; Generative Pre-trained Transformers; large language models; medical education, medical exam; natural language processing; performance; premedical exams; suitability

**Introduction**

Large language models (LLMs) are potent natural language processing tools, excelling in a range of artificial intelligence (AI) tasks, from news writing to product descriptions. They have garnered widespread attention across academia and industry [1,2], going beyond the scope of natural language processing into tasks related to health care [3], neuroscience [4], philosophy [5], marketing and finance [6,7], sociology [8], education, and others [9,10]. The development of LLMs and chatbots is experiencing an upsurge, with established companies and emerging start-ups actively engaged in their creation [11], catering to general or specific purposes [12]. Prominent examples include Generative Pre-trained Transformers (GPT)-3.5 (OpenAI), GPT-4 (OpenAI), and Bard (Google LLC) [13,14]. Other notable examples are BlenderBot, Galactica, LaMA (FAIR) [15], Alpaca (Stanford), BloombergGPT [16], Chinchilla (DeepMind), and PaLM [17], heralding the emergence of even more chatbots in the future [12].

The public release of ChatGPT in November 2022 and Bard in March 2023 has garnered significant attention due to their general purpose and flexible nature. ChatGPT [18], built on the GPT-3.5 architecture, has become popular for its remarkable ability to generate coherent and human-like responses. GPT-4.0 represents the latest iteration, incorporating enhanced language generation and improved multiturn conversation handling. Both GPT-3.5 and GPT-4.0 have been specifically trained to interact with users in a conversational manner, maintaining context, handling follow-up questions, and even correcting themselves. Bard, on the other hand, leverages Google’s LaMDA [19], enabling it to handle a diverse range of language-related tasks and provide in-depth information.

In educational settings, students are using LLMs such as Bard, GPT-3.5, and GPT-4 to enrich their daily learning experiences [20,21]. They aid students in test preparation, offer research assistance, and contribute to their overall performance improvement and knowledge acquisition [22]. It has been observed that LLMs, despite their impressive performance, can sometimes generate text that includes fabricated or incorrect information [13,23]. Consequently, researchers have directed their attention toward investigating the test-taking capabilities of different LLMs. Numerous research studies have delved into the assessment of GPT-3.5’s efficacy in multiple-choice exams in higher education domains [24]. Some investigations have specifically focused on ChatGPT’s test-taking performance in diverse professional fields, including business [25], accounting [26], law [27], and medicine [28]. In the medical realm, authors in Bommineni et al [29] examined its competence in tackling the Medical College Admissions Test, which serves as a prerequisite for admission to most medical schools in the United States. In Gilson et al [30] and Kung et al [31], authors have scrutinized ChatGPT’s aptitude in the United States Medical Licensing Examination (USMLE), while Teebagy et al [32] conducted a comparative study of GPT-3.5 and GPT-4’s performance in the Ophthalmic Knowledge Assessment Program exam. Additionally, Ali et al [33] undertook a comparison of GPT-3.5, GPT-4, and Google Bard, using questions specifically prepared for neurosurgery oral board examinations. Similarly, Zhu et al [28] investigated ChatGPT’s performance in several medical topics, namely, the American Heart Association, advanced cardiovascular life support, and basic life support exams.

Despite the successful integration of LLMs in educational environments, a crucial question remains: can LLMs provide the necessary accuracy and reliability required for critical assessments? The published studies predominantly focus on specialized fields within medicine, with few investigations addressing the effectiveness of AI tools for medical school entrance examinations [29]. Additionally, such comparisons made in the literature typically revolve around the performance of a solitary LLM against human abilities [24,34], with limited exploration of how they compare against other LLMs or baseline models, which could provide valuable insights into the strengths and weaknesses of different LLMs. Our primary objective is to bridge this knowledge gap by undertaking a comparative analysis of 3 notable chatbots: GPT-3.5, GPT-4, and Bard, for a standardized medical school exam known as the National Eligibility cum Entrance Test (NEET).

NEET [35] is a competitive entrance exam in India for Bachelor of Medicine and Bachelor of Dental Surgery programs in both government and private colleges. Introduced in 2013 by the Medical Council of India, NEET replaced various state-level and institution-specific tests to standardize medical admissions. Since 2019, the National Testing Agency (NTA) has been responsible for conducting and supervising the NEET. The exam comprises a total of 200 multiple-choice questions aimed at testing knowledge, understanding, and aptitude in 4 subjects: physics, chemistry, botany, and zoology. Candidates can only attempt a maximum of 45 questions per subject, for a total of 180 out of 200 questions. Correct answers are awarded 4 points, while each incorrect response leads to a 1-point deduction. Candidates are allotted 3 hours to complete the examination. To qualify for admission to a medical school, candidates must obtain a minimum or cutoff score, which can change year by year. The cutoff score for NEET-2023 was 137 out of 720. In 2023, over 2.03 million students took the NEET exam [24], a number that has been rising annually by 10% to 16.5%, highlighting the exam’s widespread popularity and importance.
Among the 1.15 million candidates who qualified in 2023, only 2 scored full marks (720/720), only 1 scored 716 out of 720, a total of 17 scored 715 out of 720, and 6 scored 711 out of 720 [36]. NEET’s rigorous nature, coupled with its widespread adoption, underscores its importance as the primary evaluation tool for determining students’ knowledge, aptitude, and readiness for pursuing medical and dental education at the undergraduate level [35].

In this investigation, to evaluate the performance of the 3 mainstream LLMs, namely GPT-3.5, GPT-4, and Google Bard, in answering questions related to the NEET 2023 exam, we used rigorous statistical analyses. We scrutinized each model’s performance across 3 pivotal frameworks: overall comparison, subject-level comparison, and topic-level comparison. The outcomes of this study can help premed students make informed decisions about incorporating LLMs into their test preparation strategies. To the best of our knowledge, this marks the first endeavor to undertake such a study.

Methods

Question Set Selection and Preparation

In this paper, we tested the performance of the 3 LLMs on NEET-2023, which was obtained as a portable document file. Although the exam consists of 200 questions, due to the presence of illustrations and diagrams, it was not possible to process all the questions. As a result, we excluded questions with illustrations, resulting in a set of 175 questions for this study. This sample size is large enough to statistically justify each model’s performance on the entire exam, with a 95% CI and a 5% margin of error. The selected questions were then manually presented to Bard, GPT-3.5, and GPT-4, and the responses were documented in Excel (Microsoft Corporation).

Data Analysis

We compared responses generated by each model against the correct answers from the official answer key on the NEET website. Based on this comparison, the responses were either marked as correct (1) or incorrect (0).

Prediction Performance

Excel’s built-in functionalities were then used to generate the following comparison metrics to assess predictive performance of the LLMs:

1. Accuracy is defined as the percentage of correct responses obtained by a model. In the context of this research, accuracy was obtained using the formula:
   \[ \text{Accuracy} = \frac{\text{Correct Responses}}{\text{Total Responses}} \]

2. Accuracy consensus is defined as the ratio between correct answers upon which the compared models agree to all the answers (correct and incorrect) upon which the compared models agree. The formula is:
   \[ \text{Accuracy consensus} = \frac{\text{Correct Responses}}{\text{Total Responses}} \]

Results

Prediction Performance

Next, we calculated the overall, subject-level, and topic-level percentage scores for each LLM following the NTA's scoring rules. Each correct answer was awarded 4 points, while each incorrect answer resulted in a deduction of 1 point. We merged zoology and botany into a single biology category, as the topic-level analysis included questions from both fields. The overall score percentage for each model was determined by dividing the total points scored by the maximum possible points, which was 700. Subject-level percentages were derived by dividing each model’s total points by the maximum points available in that subject. Similarly, topic-level percentages were calculated by dividing the total points scored in each topic by the maximum points available for that topic, which varied across different topics.

Subject-Level Accuracy

Table 1 presents the number of correct responses obtained by each model in each of the 3 subject areas covered by NEET. It was evident that GPT-4 is consistently more accurate than both Bard and GPT-3.5 in all 3 subjects. For each subject, the number of correct responses obtained by GPT-3.5 and Bard differed by ±3, indicating relatively similar subject-level accuracy rates. On the other hand, GPT-4 was substantially more accurate than the other models, generating 4 to 16 more correct answers per subject. In physics, GPT-4 achieved 73% (29/40) accuracy, followed by GPT-3.5 with 45% (18/40), and Bard with 38% (15/40). Similarly, in chemistry, GPT-4’s accuracy rate was 44% (16/36), while GPT-3.5 and Bard achieved an accuracy rate of 33% (12/36). Shifting to biology, GPT-4 maintained its lead with 51% (50/99) accuracy, followed by GPT-3.5 with 34% (34/99), and then Bard with 31% (31/99).
Table 1. Number of correct responses (n) and accuracy rates in each subject per model.

<table>
<thead>
<tr>
<th>Subject</th>
<th>GPT-4, n (%)</th>
<th>GPT-3.5, n (%)</th>
<th>Bard, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biology (n=99)</td>
<td>50 (51)</td>
<td>34 (34)</td>
<td>31 (31)</td>
</tr>
<tr>
<td>Chemistry (n=36)</td>
<td>16 (44)</td>
<td>12 (33)</td>
<td>12 (33)</td>
</tr>
<tr>
<td>Physics (n=40)</td>
<td>29 (73)</td>
<td>18 (45)</td>
<td>15 (38)</td>
</tr>
</tbody>
</table>

GPT: Generative Pre-trained Transformers.

Topic-Level Accuracy

Table 2 displays the number of correct responses obtained from each model on various topics. GPT-4 was the most accurate in 9 (50%) out of 18 topics. Moreover, for at least half (2-4) of the topics in each subject, GPT-4 demonstrated the highest accuracy. GPT-3.5 was the most accurate (8/15, 53%) in inorganic chemistry. In addition, it was more accurate than Bard in 7 topics across the 3 subjects. However, it had a 0% accuracy in population and ecology (biology) and simple harmonic motion and waves (physics). Bard was the most accurate in the topics on plant kingdom and ecosystem and environment issues. Furthermore, it was more accurate than GPT-3.5 in 5 topics across all 3 subjects. However, it has a 0% accuracy for 2 physics topics, namely modern physics and electronics and optics. GPT-4 and GPT-3.5 had similar accuracies in 1 physics topic (modern physics and electronics: 2/4, 50%) and 2 biology topics (cell biology and genetics: 7/16, 44%; and ecosystem and environmental issues: 2/5, 40%). GPT-4 and Bard are 100% accurate in the topics on simple harmonic motion and waves. All 3 models were at the same level of accuracy in the topics on biomolecules and heat and thermodynamics.

In a nutshell, GPT-4 had a higher accuracy across a wide range of topics (15/18, 83%), while GPT-3.5’s and Bard’s accuracies were well below GPT-4’s. Moreover, they showed variations in their accuracies across topics.

Table 2. Number of correct responses for each topic per model.

<table>
<thead>
<tr>
<th>Topic</th>
<th>GPT-4, n (%)</th>
<th>GPT-3.5, n (%)</th>
<th>Bard, n (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biotechnology (n=11)</td>
<td>7 (64)</td>
<td>6 (55)</td>
<td>4 (36)</td>
</tr>
<tr>
<td>Evolution and health (n=9)</td>
<td>7 (78)</td>
<td>4 (44)</td>
<td>2 (22)</td>
</tr>
<tr>
<td>Population and ecology (n=6)</td>
<td>1 (17)</td>
<td>0 (0)</td>
<td>1 (17)</td>
</tr>
<tr>
<td>Biomolecules (n=3)</td>
<td>1 (33)</td>
<td>1 (33)</td>
<td>1 (33)</td>
</tr>
<tr>
<td>Cell biology and genetics (n=16)</td>
<td>7 (44)</td>
<td>7 (44)</td>
<td>3 (19)</td>
</tr>
<tr>
<td>Ecosystem and environmental issues (n=5)</td>
<td>2 (40)</td>
<td>2 (40)</td>
<td>3 (60)</td>
</tr>
<tr>
<td>Plant kingdom (n=25)</td>
<td>8 (32)</td>
<td>6 (24)</td>
<td>11 (44)</td>
</tr>
<tr>
<td>Animal kingdom (n=24)</td>
<td>17 (71)</td>
<td>8 (33)</td>
<td>6 (25)</td>
</tr>
<tr>
<td>Physical chemistry (n=12)</td>
<td>6 (50)</td>
<td>3 (25)</td>
<td>4 (33)</td>
</tr>
<tr>
<td>Organic chemistry (n=9)</td>
<td>3 (33)</td>
<td>1 (11)</td>
<td>2 (22)</td>
</tr>
<tr>
<td>Inorganic chemistry (n=15)</td>
<td>7 (47)</td>
<td>8 (53)</td>
<td>6 (40)</td>
</tr>
<tr>
<td>Mechanics (n=12)</td>
<td>8 (67)</td>
<td>6 (50)</td>
<td>6 (50)</td>
</tr>
<tr>
<td>Heat and thermodynamics (n=3)</td>
<td>1 (33)</td>
<td>1 (33)</td>
<td>1 (33)</td>
</tr>
<tr>
<td>Electrostatics and electricity (n=11)</td>
<td>10 (91)</td>
<td>5 (45)</td>
<td>6 (55)</td>
</tr>
<tr>
<td>Optics (n=3)</td>
<td>3 (100)</td>
<td>2 (67)</td>
<td>0 (0)</td>
</tr>
<tr>
<td>Simple harmonic motion and waves (n=1)</td>
<td>1 (100)</td>
<td>0 (0)</td>
<td>1 (100)</td>
</tr>
<tr>
<td>Magnetism (n=6)</td>
<td>4 (67)</td>
<td>2 (33)</td>
<td>1 (17)</td>
</tr>
<tr>
<td>Modern physics and electronics (n=4)</td>
<td>2 (50)</td>
<td>2 (50)</td>
<td>0 (0)</td>
</tr>
</tbody>
</table>

GPT: Generative Pre-trained Transformers.

*Highest accuracy within a topic.*
Accuracy Consensus

Overall Accuracy Consensus

The accuracy consensus for the pairs were approximately as follows:

1. Bard and GPT-3.5 were correct on 29 out of 69 matching responses, giving the pair an accuracy consensus of 0.42 and an accuracy of 29 (16.6%) out of 175.
2. Bard and GPT-4 were correct on 42 out of 75 matching responses, resulting in an accuracy consensus of 0.56 and an accuracy of 42 (24%) out of 175.
3. GPT-3.5 and GPT-4 were correct on 45 out of 79 matching responses, giving the pair an accuracy consensus of 0.57 and an accuracy of 45 (25.7%) out of 175.

4. All 3 models were correct on 29 out of 49 matched responses. The accuracy consensus of the trio was approximately 0.59 and an accuracy of 29 (16.6%) out of 175.

This ascending trend in accuracy consensus indicated that GPT-4 enhanced the agreement on correct responses, especially when used in conjunction with either Bard or GPT-3.5. The best accuracy consensus and accuracy were obtained when GPT-3.5 and GPT-4 were considered together. Moreover, the collective intelligence of these models was as good as the weakest duo, that is, Bard and GPT-3.5 combined.

Subject-Level Accuracy Consensus

Table 3 shows the total number of correct matching responses and accuracy consensus at the subject level for each model.

<table>
<thead>
<tr>
<th>Subject</th>
<th>GPT-3.5 vs Bard</th>
<th>Bard vs GPT-4</th>
<th>GPT-3.5 vs GPT-4</th>
<th>Bard, GPT-3.5, and GPT-4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total correct matching responses, n</td>
<td>Accuracy consensus</td>
<td>Total correct matching responses, n</td>
<td>Accuracy consensus</td>
</tr>
<tr>
<td>Biology</td>
<td>17</td>
<td>0.4</td>
<td>22</td>
<td>0.46</td>
</tr>
<tr>
<td>Chemistry</td>
<td>4</td>
<td>0.31</td>
<td>7</td>
<td>0.50</td>
</tr>
<tr>
<td>Physics</td>
<td>8</td>
<td>0.58</td>
<td>13</td>
<td>1.00</td>
</tr>
</tbody>
</table>

aGPT: Generative Pre-trained Transformers.
bHighest accuracy within a subject.

The subject-level accuracy consensus revealed following insights.

For biology, the highest accuracy consensus was observed between GPT-3.5 and GPT-4 (n=23, ratio of 0.48), indicating GPT-4’s superior performance. This duo also produced the highest accuracy, that is, 23 (23%) out of 99. Even though the accuracy consensus of the trio was the highest, it did not correspond to the highest accuracy (17/99, 17%).

For chemistry, both comparisons involving GPT-4 (Bard vs GPT-4 and GPT-3.5 vs GPT-4) yielded a higher accuracy consensus ratio of 0.50. However, the duo of GPT-3.5 and GPT-4 resulted in highest accuracy, that is, 8 (22%) out of 36.

For physics, Bard versus GPT-4 and the collective comparison of all models achieved a perfect accuracy consensus of 1.00 and an accuracy of 13 (32%) out of 40. However, the highest accuracy (14/40, 35%) was shown by GPT-3.5 versus GPT-4, with comparable accuracy consensus of 0.93.

These points demonstrate GPT-4’s dominance across subjects, with physics showcasing the highest consensus scores. This suggests that when GPT-4 is used in tandem with any other model, the duo or trio will corroborate each other’s responses more than when Bard and GPT-3.5 are considered together.

Topic-Level Accuracy Consensus

Table 4 shows the total number of correct matching responses and accuracy consensus at the topic level for each model.

The following observations can be made about data presented in Table 4.

GPT-3.5 versus GPT-4 demonstrated the highest accuracy consensus and number of correct matching responses in 11 (61%) out of 18 topics. This trend was followed by the Bard versus GPT-4 duo, which showed the highest number of accurate responses and accuracy consensus in 7 (39%) out of 18 topics.

“Biomolecules,” “heat and thermodynamics,” “optics,” and “simple harmonic motion and waves” had low or zero accuracy consensus for all or most comparisons.

Hence, the combined intelligence of the models cannot help with the preparation of all the topics, if the goal is to seek consensus or confirmation of responses across models.
Table 4. Topic-level correct matching responses and accuracy consensus across compared models.

<table>
<thead>
<tr>
<th>Topic</th>
<th>GPT³.5 vs Bard</th>
<th>Bard vs GPT-4</th>
<th>GPT-3.5 vs GPT-4</th>
<th>Bard, GPT-3.5, and GPT-4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total correct matching responses, n</td>
<td>Accuracy consensus</td>
<td>Total correct matching responses, n</td>
<td>Accuracy consensus</td>
</tr>
<tr>
<td>Biotechnology</td>
<td>3</td>
<td>0.75</td>
<td>3</td>
<td>0.60</td>
</tr>
<tr>
<td>Evolution and health</td>
<td>3</td>
<td>0.75&lt;sup&gt;b&lt;/sup&gt;</td>
<td>3</td>
<td>0.50</td>
</tr>
<tr>
<td>Population and ecology</td>
<td>2</td>
<td>0.67</td>
<td>2</td>
<td>0.67</td>
</tr>
<tr>
<td>Biomolecules</td>
<td>0</td>
<td>N/A&lt;sup&gt;c&lt;/sup&gt;</td>
<td>0</td>
<td>N/A</td>
</tr>
<tr>
<td>Cell biology and genetics</td>
<td>3</td>
<td>0.30</td>
<td>3</td>
<td>0.43&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Ecosystem and environmental issues</td>
<td>1</td>
<td>0.33</td>
<td>2</td>
<td>0.67&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Plant kingdom</td>
<td>2</td>
<td>0.22</td>
<td>4</td>
<td>0.31&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Animal kingdom</td>
<td>3</td>
<td>0.38</td>
<td>5</td>
<td>0.50&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Physical chemistry</td>
<td>2</td>
<td>0.67</td>
<td>3</td>
<td>0.50</td>
</tr>
<tr>
<td>Organic chemistry</td>
<td>1</td>
<td>0.50</td>
<td>3</td>
<td>0.75&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Inorganic chemistry</td>
<td>1</td>
<td>0.13</td>
<td>1</td>
<td>0.25</td>
</tr>
<tr>
<td>Mechanics</td>
<td>2</td>
<td>0.50</td>
<td>3</td>
<td>1.00</td>
</tr>
<tr>
<td>Heat and thermodynamics</td>
<td>0</td>
<td>N/A</td>
<td>0</td>
<td>N/A</td>
</tr>
<tr>
<td>Electrostatics and electricity</td>
<td>3</td>
<td>0.60</td>
<td>5</td>
<td>1.00</td>
</tr>
<tr>
<td>Optics</td>
<td>0</td>
<td>N/A</td>
<td>0</td>
<td>N/A</td>
</tr>
<tr>
<td>Simple harmonic motion and waves</td>
<td>0</td>
<td>N/A</td>
<td>0</td>
<td>N/A</td>
</tr>
<tr>
<td>Magnetism</td>
<td>2</td>
<td>0.50</td>
<td>2</td>
<td>1.00&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Modern physics and electronics</td>
<td>1</td>
<td>1.00</td>
<td>3</td>
<td>1.00&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

<sup>a</sup>GPT: Generative Pre-trained Transformers.
<sup>b</sup>Highest combination of accurate responses and accuracy consensus in a topic.
<sup>c</sup>N/A: not applicable.

Scoring Performance

Overall Scores

GPT-4 achieved the highest score with 300 (42.9%) out of 700 points, outperforming GPT-3.5, which scored 145 (20.7%) out of 700 points, and Bard, which obtained 115 (16.4%) out of 700 points. To qualify for the NEET-2023 entrance test, candidates needed to secure at least 137 out of 720 points, which represents 19.6% of the total points. It was evident that GPT-4 passed the entrance test with flying colors, showcasing exceptional performance. On the other hand, GPT-3.5 managed to meet the qualifying criteria, but with a substantially lower score. However, Bard failed to meet the qualifying criteria and, hence, did not pass the test.

Subject-Level Scores

The subject-level scores, as per NEET’s grading rubric, are detailed in Table 5. GPT-4 achieved the highest overall score of 42.9% (300/700), outperforming both GPT-3.5 (145/700, 20.7%) and Bard (115/700, 16.4%). In all 3 subjects, GPT-4 obtained the highest scores. GPT-3.5 scored higher than Bard in biology and physics but tied with Bard in chemistry.
Table 5. Subject and topic level scores for Bard, Generative Pre-trained Transformers (GPT)-3.5, and GPT-4.

<table>
<thead>
<tr>
<th>Subject and topic</th>
<th>Scores obtained</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bard</td>
</tr>
<tr>
<td>Overall (n=700), n (%)</td>
<td>115 (16.4%)$^a$</td>
</tr>
<tr>
<td>Biology (n=396)</td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>56$^a$</td>
</tr>
<tr>
<td>Animal kingdom</td>
<td>6$^a$</td>
</tr>
<tr>
<td>Plant kingdom</td>
<td>30$^b$</td>
</tr>
<tr>
<td>Ecosystem and environmental issues</td>
<td>10$^b$</td>
</tr>
<tr>
<td>Cell biology and genetics</td>
<td>-1$^a$</td>
</tr>
<tr>
<td>Biomolecules</td>
<td>2$^b$</td>
</tr>
<tr>
<td>Population and ecology</td>
<td>-1$^b$</td>
</tr>
<tr>
<td>Evolution and health</td>
<td>1$^a$</td>
</tr>
<tr>
<td>Biotechnology</td>
<td>9$^a$</td>
</tr>
<tr>
<td>Chemistry (n=160)</td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>24</td>
</tr>
<tr>
<td>Inorganic chemistry</td>
<td>15$^a$</td>
</tr>
<tr>
<td>Organic chemistry</td>
<td>1</td>
</tr>
<tr>
<td>Physical chemistry</td>
<td>8</td>
</tr>
<tr>
<td>Physics (n=144)</td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>35$^a$</td>
</tr>
<tr>
<td>Modern physics and electronics</td>
<td>-4$^a$</td>
</tr>
<tr>
<td>Magnetism</td>
<td>-1$^a$</td>
</tr>
<tr>
<td>Simple harmonic motion and waves</td>
<td>4$^b$</td>
</tr>
<tr>
<td>Optics</td>
<td>-3$^a$</td>
</tr>
<tr>
<td>Electrostatics and electricity</td>
<td>19</td>
</tr>
<tr>
<td>Heat and thermodynamics</td>
<td>2$^b$</td>
</tr>
<tr>
<td>Mechanics</td>
<td>18</td>
</tr>
</tbody>
</table>

$^a$Lowest scorer within the topic.  
$^b$Top scorer within the topic.

We then analyzed the breakdown of the total scores obtained by Bard, GPT-3.5, and GPT-4, categorized by subject. Of the total GPT-4 score, 50.3% (151/300) came from biology, 35% (105/300) came from physics, and 14.7% (44/300) came from chemistry. For GPT-3.5, biology contributed 49% (71/145) of the score, physics contributed 34.5% (50/145), and chemistry contributed 16.6% (24/145). Lastly, Bard’s score breakdown showed that 48.7% (56/115) from biology, 30.4% (35/115) came from physics, and 20.9% (24/115) came from chemistry. These results show that GPT-4 outperformed both GPT-3.5 and Bard in the NEET grading rubric, achieving the highest overall score and the top scores in each individual subject. While GPT-3.5 demonstrated better performance than Bard in biology and physics, it tied with Bard in chemistry. The breakdown of scores by subject revealed that for all 3 models, the largest portion of their scores came from biology (understandably, because there were twice as many questions in this category), followed by physics, and then chemistry, indicating a consistent pattern in their relative strengths across these subjects.

**Topic-Level Scores**

The results in Table 5 shows that GPT-4 exhibited strong performance across all topics in physics but showed a relative weakness in inorganic chemistry within the chemistry subject. Bard, compared to the GPT versions, excelled specifically in the biology topics of the plant kingdom and ecosystem and...
environmental issues. Both GPT models performed equally well in cell biology and genetics (biology) and in modern physics and electronics (physics). Additionally, GPT-3.5 stood out for its excellent performance in inorganic chemistry, highlighting its strength in this area of the chemistry subject.

### Discussion

#### Overview

We evaluated the decision-making performance of 3 models—Bard, GPT, and GPT-4—using accuracy, accuracy consensus, and test scores for the NEET-2023 entrance test. Subject-wise and topic-wise analyses were also conducted. GPT-4 consistently outperformed Bard and GPT across all subjects, achieving the highest accuracy rates: 73% (29/40) in physics, 44% (16/36) in chemistry, and 51% (50/99) in biology. Topic-wise comparisons also demonstrated GPT-4’s excellence in 15 (79%) out of 19 topics, with Bard and GPT excelling in certain topics. Particularly, Bard excelled in simple harmonic motion and waves, while GPT showed strength in inorganic chemistry. Overall, GPT-4 emerged as the top performer, excelling in both subjects and specific topics. Our findings are in line with previous studies that have also examined how LLMs perform on exams related to medical education. Bommineni et al [29] found that GPT-3.5 performs at or above the median performance of the Medical College Admissions Test takers. Ali et al [33] reported that GPT-4 outperformed both GPT-3.5 and Bard by achieving the highest score of 82.6% in specialized questions prepared for neurosurgery oral board examinations. Friederichs et al [34] found that GPT-3.5 answered about two-thirds of the multiple-choice questions correctly and outperformed nearly all medical students in years 1-3 of their studies. Gilson et al [30] reported that GPT-3.5’s performance on the USMLE was either at or near the minimum passing threshold, even without domain-specific fine-tuning. Below, we present both practical and research implications of our findings to enrich the existing literature.

#### Implications

**Practical Implications**

The findings have important implications for users who need to select a model based on specific requirements and their desired score. The subject- and topic-level scores highlight the suitability of different models for various domains. GPT-4 appears to have the highest score (300/700, 42.9%), followed by GPT-3.5 (145/700, 20.7%), and then Bard (115/700, 16.4%). This demonstrates that Bard was not able to pass the NEET-2023 admission exam, and GPT-3.5 was only 2% (14/700) away from the cutoff score, which is 19% (133/700).

Although GPT-4 appears to be the preferred choice for NEET preparation, it is important to note that GPT-4 is a subscription-based service and the pricing model is uniform across the globe, which makes this model less accessible to the general audience in some parts of the world, particularly low-income countries. When cost is an issue, prospective medical school students might consider using GPT-3.5 and Bard in tandem to develop specialized knowledge and expertise in specific subject topics. The accuracy consensus metric demonstrates that the duo was correct on 29 (42%) out of 69 matching responses, reaching 16.6% (29/175) overall accuracy. However, this duo did not excel in any of the subjects, compared to the other duos. Moreover, at the topic level, it only excelled in “evolution and health.” These results suggest that, in the absence of GPT-4, while students may consider both GPT-3.5 and Bard together for exam preparation, due to the low level of consensus between these models, the total score would still fall below the cutoff score. Moreover, students would be more often confused about the correct responses while cross-checking answers with these models. Therefore, it is recommended that, for exam preparation, students do not solely rely on these models or model duos; instead, they should consult primary sources in conjunction with these models.

**Research Implications**

While scoring performance comparisons help us evaluate whether these models are able to ace the NEET-2023 exam or not, prediction performance comparisons help us evaluate their long-term performance beyond NEET 2023. The models’ predictive accuracy rates match their scoring performance. GPT-4 demonstrated the highest accuracy rate among the 3 models, indicating its superior capability to provide correct responses and its reliability as an accurate study partner. However, there is still plenty of room for improvement since its accuracy was only at 54.3% (95/175), suggesting that anyone using this model for exam preparation would be exposed to a little over 50% (100/200) of accurate information. GPT-3.5 (64/175, 37.6%) and Bard (58/175, 33.1%) had similar overall accuracy rates that are much lower compared to GPT-4’s, suggesting that these 2 models would require significant fine-tuning to qualify as reliable study aids for NEET.

The subject- and topic-level accuracy comparisons highlight specific areas where these models could benefit from domain-specific enhancements. GPT-4 demonstrated superior accuracy across all 3 subjects and 15 topics but required further improvements in 3 topics, that is, ecosystem and environmental issues, plant kingdom, and inorganic chemistry. GPT-4 excelled in at least 1 topic from each subject category, including simple harmonic motion and waves and optics in physics, physical chemistry in chemistry, and evolution and biotechnology in biology. Bard excelled in simple harmonic motion and waves, and GPT-3.5 notably excelled in inorganic chemistry. GPT-3.5, besides requiring improvements in its overall prediction capabilities, needs to develop predictive expertise in population and ecology (biology) and simple harmonic motion and waves (physics). Similarly, Bard needs to develop predictive capabilities in modern physics and electronics and optics, in addition to requiring substantial enhancements in its overall predictive capabilities.

In summary, the implications and applications of this study on LLM and education are far-reaching. First, it could serve as a benchmark for evaluating and improving LLMs’ performance in exams and other educational tasks, enhancing the overall effectiveness of these models in educational settings. Second, the use of LLMs as tutors, mentors, or peers has the potential to significantly enhance students’ learning outcomes and motivation, particularly in a country such as India with a vast...
student population and diverse learning needs. Last, this approach could serve as a platform to explore and address ethical and social concerns related to LLMs in education, such as issues of fairness, bias, privacy, and accountability, ensuring responsible and informed use of these models in educational contexts.

**Limitations and Further Research**

Similar to any other research, this study has certain limitations that should be considered carefully. It is important to note that this study did not involve direct input from actual students, teachers, or medical school boards to understand their perspectives on these mainstream LLMs’ capability to answer questions on basic science concepts. Moreover, we do not know how prospective examinees are using these models for exam preparation or whether they trust them for critical issues such as exam preparation.

LLMs have evolved considerably just in the last 6 months. Therefore, the results of this study will have to be revisited at a later stage. For example, it is possible (and likely) that the relative performance of the different models will change over time. While Bard is currently lagging GPT-3.5 in this area, improvements to the model could mean that it might catch up to GPT-3.5 in the future. Since there is currently an “AI race” among many technology firms, it is only a matter of time before new models are introduced that could perform better on these types of questions.

**Conclusion**

In this study, we conducted a comparative analysis of 3 notable chatbots, Bard, GPT-3.5, and GPT-4, to evaluate their performance on NEET-2023, a highly competitive medical school entrance examination in India. The study involved the preparation of NEET-2023 questions for the chatbots, data collection, data analysis, and scoring performance assessments.

Our results indicate that GPT-4 not only passed the NEET-2023 entrance test with a score of 42.9% (300/700) but also demonstrated higher accuracy and consensus compared to both GPT-3.5 and Bard. Particularly, GPT-4 consistently outperformed the other models across subjects and topics, achieving an overall accuracy of approximately 54.3% (95/175). GPT-3.5 and Bard, on the other hand, showed variations in their performances, with specific strengths in certain subjects and topics. Regarding subject-wise scoring, GPT-4 excelled in physics and biology while Bard performed well in chemistry. These findings shed light on the proficiency of LLMs in answering high-stakes examination questions, particularly in the context of medical entrance exams such as the NEET. GPT-4’s superior performance and accuracy suggest its potential utility as a valuable resource for medical students seeking assistance in test preparation and knowledge acquisition. However, it is essential to note that despite their impressive performance, LLMs such as Bard, GPT-3.5 and GPT-4 can sometimes generate text containing fabricated or incorrect information. This raises concerns about the credibility of information produced by LLMs, especially in educational settings where accuracy is crucial.

It is also important to acknowledge that LLMs, including GPT, come with both positive and negative consequences [37,38]. Friederichs et al [34] argue that the ability to acquire knowledge is a basic determinant of a physician’s performance, and GPT-3.5 should be looked upon as a tool that provides easy access to a lot of relevant information, eventually aiding in clinical decision-making processes. On the other hand, Mbakwe et al [39] have commented that GPT-3.5’s success on exams such as the USMLE demonstrates the flaws of medical education, which is “mostly focused on the rote memorization of mechanistic models of health and disease” and does not reward critical thinking to the same extent.

Further research and development are warranted to address the limitations and challenges posed by LLMs and ensure their reliable and accurate use in education and other domains. Moreover, future investigations can explore the suitability of LLMs for addressing the needs of diverse professional fields beyond medical entrance exams.

In conclusion, this study contributes valuable insights into the capabilities of Bard, GPT-3.5, and GPT-4 in handling high-stakes examination questions. As LLMs continue to evolve, their potential to revolutionize education and other industries remains promising, albeit with the need for continuous improvements and validation of their accuracy and reliability.

**Data Availability**

Data can be obtained through a reasonable request to the corresponding author.

**Authors’ Contributions**

FF and SSS contributed to conceptualization. FF and DØM performed the data acquisition. FF and BMC performed the data analysis. FF, BMC, MN, and SSS contributed to writing and drafting. BMC, MN and DØM contributed to reviewing and proofreading. SSS was the collaborative lead.

**Conflicts of Interest**

None declared.

**References**

https://mededu.jmir.org/2024/1/e51523


**Abbreviations**

- **AI**: artificial intelligence
- **FP**: false positive
- **GPT**: Generative Pre-trained Transformers
- **LLM**: large language model
- **NEET**: National Eligibility cum Entrance Test
- **NTA**: National Testing Agency
- **TP**: true positive
- **USMLE**: United States Medical Licensing Examination

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Original Paper

Capability of GPT-4V(ision) in the Japanese National Medical Licensing Examination: Evaluation Study

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Abstract

Background: Previous research applying large language models (LLMs) to medicine was focused on text-based information. Recently, multimodal variants of LLMs acquired the capability of recognizing images.

Objective: We aim to evaluate the image recognition capability of generative pretrained transformer (GPT)-4V, a recent multimodal LLM developed by OpenAI, in the medical field by testing how visual information affects its performance to answer questions in the 117th Japanese National Medical Licensing Examination.

Methods: We focused on 108 questions that had 1 or more images as part of a question and presented GPT-4V with the same questions under two conditions: (1) with both the question text and associated images and (2) with the question text only. We then compared the difference in accuracy between the 2 conditions using the exact McNemar test.

Results: Among the 108 questions with images, GPT-4V’s accuracy was 68% (73/108) when presented with images and 72% (78/108) when presented without images (P=.36). For the 2 question categories, clinical and general, the accuracies with and those without images were 71% (70/98) versus 78% (76/98; P=.21) and 30% (3/10) versus 20% (2/10; P≥.99), respectively.

Conclusions: The additional information from the images did not significantly improve the performance of GPT-4V in the Japanese National Medical Licensing Examination.

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KEYWORDS
AI; artificial intelligence; LLM; large language model; language model; language models; ChatGPT; GPT-4; GPT-4V; generative pretrained transformer; image; images; imaging; response; responses; exam; examination; exams; examinations; answer; answers; NLP; natural language processing; chatbot; chatbots; conversational agent; conversational agents; medical education

Introduction

The field of natural language processing is rapidly developing with the advent of large language models (LLMs). LLMs are models trained with massive text data sets and achieve the capability to understand and generate text in natural languages. With the introduction of ChatGPT (OpenAI) [1] and other LLM-based chatbot services, many people have started to benefit from the use of LLMs. Although ChatGPT and its underlying model, generative pretrained transformer (GPT) [2,3], were not specifically developed for medical purposes, they possess a considerable amount of medical knowledge. They have achieved good scores in the United States Medical Licensing Examination [4] and are being explored for various applications for clinical and educational purposes [5-7]. GPT can also understand languages other than English. The latest model, GPT-4, has
been reported to achieve passing scores in medical licensing examinations in non–English speaking countries such as Japan, China, Poland, and Peru [8-13].

Despite these successes, there is still a significant challenge in applying LLMs to real-world problems with non–text-based information. Radiological, pathological, and many other types of visual information play a crucial role in determining a patient’s management. Very recently, researchers have proposed multimodal variants of LLMs that can handle not only text but various types of input including images [14]. Providing medical images to multimodal LLMs may realize an even higher accuracy in solving medical-related problems. However, in previous studies on the accuracy rate of medical licensing examinations, questions with images were either not mentioned at all or explicitly excluded from the studies. To the best of our knowledge, no study directly evaluated the performance in solving questions with images. Therefore, in this study, we investigated the image recognition capabilities and limitations of GPT-4V [3,15], one of the most potent publicly available multimodal (vision and language) models, in solving medical questions. We focused on the Japanese National Medical Licensing Examination to examine how the visual information affects GPT-4V’s performance.

**Methods**

**Overview**

From the questions of the 117th Japanese National Medical Licensing Examination, held in February 2023, we focused on those that included images as part of a question. Since some of these questions can be answered correctly without interpreting images, we measured the benefit of adding image information by comparing the accuracy rates of ChatGPT under two different conditions: (1) with both the question text and associated images and (2) with the question text only.

**Data Set Details**

Figure 1 shows the summary of our data set. The questions and correct answers of the 117th Japanese National Medical Licensing Examination are publicly available for download on the official website of the Ministry of Health, Labour and Welfare [16]. All the questions are in a format in which a specified number of choices, typically 1, are to be selected from 5 options. Of the questions that had images, 2 were officially excluded from scoring because they were either too difficult or inappropriate. Additionally, for 2 questions, images of female genitals were not made public on the aforementioned website. These 4 questions were excluded from our study.

The questions in the Japanese National Medical Licensing Examination were divided into 2 categories: clinical questions and general questions. In clinical questions, clinical information about a specific case is first presented, such as medical history and test results, and answers to questions about the case are required. General questions are about basic medical knowledge, and one is required to choose the correct answer among options for a short question text (typically of 1 or 2 sentences) with an image.

Some clinical questions consisted of multiple subquestions, in which case the background common to all the subquestions was first described, followed by the subquestions. In such cases, each subquestion was individually included in the following analysis if either the subquestion itself or the background part contained an image.

As a result, counting subquestions individually, out of 400 questions, we collected 108 questions that had images, such as photographs of lesions, radiographic images, histopathological images, electrocardiograms, and graphs representing statistical data. Among them, 98 were clinical questions and 10 were general questions.
Experimental Details
We used ChatGPT (September 25, 2023, version) enabled with GPT-4V, which is a multimodal model capable of processing both text and images. This version of ChatGPT asserts it was trained with information up to January 2022, meaning that it had no direct prior knowledge about our target examination. All the question statements and images were manually entered through ChatGPT’s web interface. One of the authors, TN, who has 10 years of experience as a medical doctor, reviewed the outputs to interpret the response output by ChatGPT.

A new chat session was created for each question and each condition (i.e., with or without images). For questions that comprised multiple subquestions, the background information part and each subquestion were entered into ChatGPT in this order within the same chat session. Subquestions without images were also input to provide ChatGPT with enough context, but they were excluded from the accuracy calculations and the subsequent statistical analysis described below.

The questions were presented to ChatGPT without any preceding or custom instructions. Sometimes, ChatGPT did not respond with the specified number of choices, in which case an additional instruction, such as “select only one option” or “select two options,” was provided in Japanese. This additional instruction produced the correct number of options for all the questions.

Statistical Analysis
The difference in ChatGPT’s performance between the 2 conditions (i.e., with or without images) was analyzed using the exact McNemar test. A P value of less than .05 was considered statistically significant. The analysis was conducted using R (version 4.3.1; R Foundation for Statistical Computing).

Ethical Considerations
This study was conducted solely using publicly available resources, therefore, approval from the institutional review board of our institution was not required.

Results
Table 1 shows the results of our experiment. ChatGPT correctly answered 68% (73/108) of image-based questions when provided with both the question text and images, whereas it correctly answered 72% (78/108) of image-based questions when only the question text was provided. There was no significant difference in accuracy between these 2 conditions (P=.36). For the clinical questions, the accuracies when presented with and without images were 71% (70/98) and 78% (76/98), respectively. For the general questions, the accuracies were 30% (3/10) when presented with images and 20% (2/10) without images. We have included examples of the input and output along with their English translations in Multimedia Appendix 1, and we have also provided a summary of image interpretation for each question where the results differed depending on the presence of image input (N=7+12) in Multimedia Appendix 2.

Table 1. Performance of ChatGPT in answering questions from the 117th Japanese National Medical Licensing Examination, when presented with or without associated images for each question.

<table>
<thead>
<tr>
<th></th>
<th>With images</th>
<th>Incorrect</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Overall (P=.36)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without images, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct</td>
<td>66 (61)</td>
<td>12 (11)</td>
<td>78 (72)</td>
</tr>
<tr>
<td>Incorrect</td>
<td>7 (6)</td>
<td>23 (21)</td>
<td>30 (28)</td>
</tr>
<tr>
<td>Total</td>
<td>73 (68)</td>
<td>35 (32)</td>
<td>108 (100)</td>
</tr>
<tr>
<td><strong>Clinical (P=.21)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without images, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct</td>
<td>65 (66)</td>
<td>11 (11)</td>
<td>76 (78)</td>
</tr>
<tr>
<td>Incorrect</td>
<td>5 (5)</td>
<td>17 (17)</td>
<td>22 (22)</td>
</tr>
<tr>
<td>Total</td>
<td>70 (71)</td>
<td>28 (29)</td>
<td>98 (100)</td>
</tr>
<tr>
<td><strong>General (P=.99)</strong></td>
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<td></td>
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<tr>
<td>Without images, n (%)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct</td>
<td>1 (10)</td>
<td>1 (10)</td>
<td>2 (20)</td>
</tr>
<tr>
<td>Incorrect</td>
<td>2 (20)</td>
<td>6 (60)</td>
<td>8 (80)</td>
</tr>
<tr>
<td>Total</td>
<td>3 (30)</td>
<td>7 (70)</td>
<td>10 (100)</td>
</tr>
</tbody>
</table>
Discussion

Principal Results

In this study, we examined the image recognition capabilities of GPT-4V using questions associated with images from the Japanese National Medical Licensing Examination. To the best of our knowledge, this is the first study in which the capability of multimodal LLM for the Japanese National Medical Licensing Examination was investigated. Contrary to our initial expectations, the inclusion of image information did not result in any improvement in accuracy. Instead, we even observed a slight decrease, albeit not significant. This indicates that, at the moment, GPT-4V cannot effectively interpret images related to medicine. The passing score rate for the 117th Japanese National Medical Licensing Examination is approximately 75% (and 80% for some questions marked as “essential”) [16]. In this study, GPT-4V failed to reach this passing score rate for the questions it was tested on. Considering that 92% of human candidates passed, it implies that the image interpretation skills of GPT-4V will fall short of those possessed by many medical students.

For the clinical questions, in which sufficient clinical information including patient history was available in the text form, GPT-4V was able to choose the correct answers solely from the textual information in the majority (76/98, 78%) of questions, but the addition of images did not improve the accuracy. On the other hand, for the general questions, there was little information in the question text, and GPT-4V had to determine the correct answer by interpreting the images. For these, GPT-4V yielded an accuracy rate that was hardly any better than random guessing even when presented with images. Our results suggest that, for both categories of questions, GPT-4V failed to use visual information to improve its accuracy. We observed that GPT-4V often either explicitly stated that it was unable to interpret the images or failed to provide information beyond what was evident from the question text. In our retrospective review, even in questions where GPT-4V gave correct answers only when presented with images, there were only 2 out of 7 questions where it provided a correct interpretation of the image and used that as a critical clue. Conversely, in questions where GPT-4V provided incorrect answers only when presented with images, it sometimes made incorrect or insufficient interpretations of the images, leading to incorrect answers (4 out of 12).

ChatGPT may serve as a valuable teaching assistant in medical education; however, the inaccuracies in its responses are a significant concern [5,7]. Our current findings suggest that, especially with medical-related images, GPT-4V should not be relied upon as a primary source of information for medical education or practice. If used, extreme caution should be exercised regarding the accuracy of its responses. OpenAI officially states [15] that they “do not consider the current version of GPT-4V to be fit for performing any medical function or substituting professional medical advice, diagnosis, or treatment, or judgment” due to its imperfect performance in the medical domain. Yang et al [17] have comprehensively examined the capabilities of GPT-4V in various tasks including medical image understanding and radiology report generation, and they stated that GPT-4V could correctly diagnose some medical images. However, as they acknowledge, their results contained a considerable number of errors, such as overlooking obvious lesions and errors in laterality. According to the case studies by Wu et al [18], GPT-4V could recognize the modality and anatomy of medical images, but it could hardly make accurate diagnoses and its prediction relied heavily on the patient’s medical history. The results of our experiment supported these previous reports.

Considering the well-known high performance of GPT-4V in more generic image recognition tasks [3,17], the most probable reason for its limited image recognition performance in the medical field is that it may simply not have been trained with a sufficient number of medical-related images. LLMs are trained with a vast data set available on the internet, but medical images are not as readily accessible, partly due to privacy concerns. Some researchers are now working on developing multimodal LLMs with a vast data set available on the internet, but medical images are not as readily accessible, partly due to privacy concerns. Some researchers are now working on developing multimodal LLMs specialized for medicine based on open-source LLMs [19,20]. These models use publicly available data sets that combine medical images and text, including MIMIC-CXR [21], which contains chest x-ray images with their associated reports, and PMC-OA [22], a compilation of the figures and captions from open-access medical journal papers. The rise of multimodal LLMs is expected to stimulate the publication of more such data sets, thereby advancing the development of multimodal LLMs in the medical field. Moreover, although there are limited medical-related images publicly available on the internet, hospitals have a vast amount of image data. A large part of this is accompanied by textual interpretations in the form of reports or medical records, which may serve as an ideal data set for training multimodal LLMs. In highly specialized domains such as medicine, there remains a significant value in developing domain-specific models using such medical data sets.

Limitations

This study had several limitations. First, ChatGPT was not provided any prior instructions and was directly presented with only the questions themselves. This might have negatively affected its capability to interpret images as the capabilities of LLMs are known to be affected by such “prompt engineering.” This will be a subject for future investigation. Second, this study specifically targeted the Japanese National Medical Licensing Examination, and thus, further analysis is necessary to determine whether its conclusions can be generalized to questions in other languages or of different types. However, as mentioned earlier, the limited capability of GPT-4V to interpret medical images has also been demonstrated in other studies focusing on English [17,18], and our results are consistent with those findings. Since ChatGPT’s proficiency in non-English interpretation is known to be inferior to that in English interpretation, translating the question text into English before inputting it to ChatGPT might have improved the model’s image interpretation capability. However, in a previous study by Yanagita et al [10], in which nonimage questions from the Japanese National Medical Licensing Examination were the target, satisfactory results were achieved even when the questions were input in Japanese. Thus, we adopted the same approach in our study. Third, although our results were based on the same version of ChatGPT and the...
same question was evaluated with and without images on the same day, we cannot exclude the possibility that different models were used internally. Lastly, only a single evaluation was conducted for each condition and question. ChatGPT's outputs have some randomness, and responses may differ across multiple evaluations. With ChatGPT's application programming interface, users can programmatically control the degree of randomness by specifying a parameter called \textit{temperature} and obtain mostly deterministic responses. However, during the time of this study, the application programming interface for GPT-4V was not available.

**Conclusions**

At present, GPT-4V's capability to interpret medical images may be insufficient. In highly specialized fields such as medicine, it is considered meaningful to develop field-specific multimodal models.

**Acknowledgments**

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**Conflicts of Interest**

None declared.

**Multimedia Appendix 1**

Examples of inputs and outputs from GPT-4V.

[PDF File (Adobe PDF File), 997 KB - mededu_v10i1e54393_app1.pdf]

**Multimedia Appendix 2**

Summary of image interpretation by GPT-4V.

[DOC File, 50 KB - mededu_v10i1e54393_app2.doc]

**References**

1. Introducing ChatGPT. OpenAI. URL: [https://openai.com/blog/chatgpt](https://openai.com/blog/chatgpt) [accessed 2023-10-23]


Abbreviations

GPT: generative pretrained transformer  
LLM: large language model
Performance of GPT-4V in Answering the Japanese Otolaryngology Board Certification Examination Questions: Evaluation Study

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Abstract

Background: Artificial intelligence models can learn from medical literature and clinical cases and generate answers that rival human experts. However, challenges remain in the analysis of complex data containing images and diagrams.

Objective: This study aims to assess the answering capabilities and accuracy of ChatGPT-4 Vision (GPT-4V) for a set of 100 questions, including image-based questions, from the 2023 otolaryngology board certification examination.

Methods: Answers to 100 questions from the 2023 otolaryngology board certification examination, including image-based questions, were generated using GPT-4V. The accuracy rate was evaluated using different prompts, and the presence of images, clinical area of the questions, and variations in the answer content were examined.

Results: The accuracy rate for text-only input was, on average, 24.7% but improved to 47.3% with the addition of English translation and prompts (P<.001). The average nonresponse rate for text-only input was 46.3%; this decreased to 2.7% with the addition of English translation and prompts (P<.001). The accuracy rate was lower for image-based questions than for text-based questions, with a relatively high nonresponse rate. General questions and questions from the fields of head and neck allergies and nasal allergies had relatively high accuracy rates, which increased with the addition of translation and prompts. In terms of content, questions related to anatomy had the highest accuracy rate. For all content types, the addition of translation and prompts increased the accuracy rate. As for the performance based on image-based questions, the average of correct answer rate with text-only input was 30.4%, and that with text-plus-image input was 41.3% (P=.02).

Conclusions: Examination of artificial intelligence’s answering capabilities for the otolaryngology board certification examination improves our understanding of its potential and limitations in this field. Although the improvement was noted with the addition of translation and prompts, the accuracy rate for image-based questions was lower than that for text-based questions, suggesting room for improvement in GPT-4V at this stage. Furthermore, text-plus-image input answers a higher rate in image-based questions. Our findings imply the usefulness and potential of GPT-4V in medicine; however, future consideration of safe use methods is needed.

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**KEYWORDS**
artificial intelligence; GPT-4v; large language model; otolaryngology; GPT; ChatGPT; LLM; LLMs; language model; language models; head; respiratory; ENT: ear; nose; throat; neck; NLP; natural language processing; image; images; exam; exams; examination; examinations; answer; answers; answering; response; responses

**Introduction**
Advancements in artificial intelligence (AI) in the field of medicine have led to revolutionary changes in diagnosis, treatment, and education. The evolution of natural language processing technologies has significantly affected medical education and evaluation methods [1,2]. The use of large-scale language models contributes to the optimization of complex problem-solving and learning processes, and the effectiveness of these models has been reported in Japanese medicine [3-5]. These AI models can learn from medical literature and clinical cases and generate answers that rival those of human experts.

We have verified the effectiveness of large-scale language-processing models in medical licensing and otolaryngology board certification examinations [6]. Although a certain level of accuracy has been achieved through prompt engineering, these validations have been primarily limited to text-based information processing, and challenges remain in the analysis of complex medical data containing images and diagrams.

ChatGPT-4 Vision (GPT-4V), announced on September 25, 2023, includes the addition of image input capabilities, potentially expanding its application in the medical field [7]. The current version of the model includes information up to April 2023; it does not encompass the 2023 board examination.

In this study, we aimed to assess the answering capabilities and accuracy of GPT-4V using 100 questions, including image-based questions, from the 2023 otolaryngology board certification examination.

**Methods**
We evaluated the performance of GPT-4V (Open AI), the latest version of the generative pretrained transformer (GPT) model, using 100 questions from the 2023 otolaryngology specialist examination, which was held on August 5, 2023 (54 text-only and 46 image-based questions; Figure 1).

![Study overview. GPT-4V: ChatGPT-4 Vision.](image)

The study design was based on previously reported methods and compared the effectiveness of the following four GPT-4V input approaches: (1) direct input of the question text and images, (2) input of the question text with Japanese prompts added, (3) input of the question text after translation to English, and (4) input of the translated question text with English prompts added [5,6,8] (examples images of prompts for English translation and answering medical questions; Figure S1 in Multimedia Appendix 1).

Each approach was implemented 3 times to evaluate its accuracy. All inputs were entered manually, and both questions and answers were independently scrutinized by otolaryngology specialists (MN and TU) to ensure medical validity [9].

We compiled the correct answer rate and the number of answered and unanswered questions, then conducted an analysis based on the presence of images, the different prompts, the content of the questions, and the associated fields. In addition, the case in which the respondent with no options, and refrained from giving a medical answer was counted as “Output errors.”

Questions were categorized into fields, such as ear; nasal allergy; speech, swallowing, and larynx; oropharynx; head and neck; general; and infectious disease. Question content was classified as treatment, details of the disease and diagnosis, examination, anatomy, systems, and others. Image-based questions were classified as photographs (endoscopic images, microscopic images, and gross photographs), radiological images (computed tomography, magnetic resonance imaging, and positron emission tomography), graphs (audiogram, olfactometry, polysomnography, electroneystagmography, etc), and histopathological images.

Finally, to examine the impact of image-based questions on the program’s ability to respond, we compared the responses to text-only questions with those to questions that included figures. We then added an English translation of the text (including the text provided along with figures) and analyzed the difference.

Regarding statistical methods, comparisons among 3 or more groups were performed using 1-way ANOVA. Subsequently, multiple comparison tests (Bonferroni method) were used to compare each group, while comparisons between 2 groups were conducted using the 2-tailed Student t test. A significance level of .05 was set for determination.
Results

Performance Evaluation Based on Prompt Type

Input of only the question text resulted in an average correct answer rate of 24.7% (23%, 26%, and 25% in the first, second, and third rounds, respectively). When Japanese prompts were added, the average increased to 36.7% (38%, 33%, and 39%, respectively; \(P=.002\)); with translation to English, the average rate was 31.3% (33%, 31%, and 30%, respectively; \(P=.06\)); and with the addition of English translation and English prompts, the average increased to 47.3% (44%, 49%, and 49%, respectively; \(P<.001\)). The results of all input methods are shown in Table 1.

Table 1. Results of each input method.

<table>
<thead>
<tr>
<th>Results</th>
<th>Japanese</th>
<th>English</th>
<th>Japanese with prompt</th>
<th>English with prompt</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Text-only</td>
<td>Image-based</td>
<td>Total</td>
<td>Text-only</td>
</tr>
<tr>
<td>Questions, n</td>
<td>54</td>
<td>46</td>
<td>100</td>
<td>54</td>
</tr>
<tr>
<td>Correct answers, n (%)</td>
<td>23.0 (41.5)</td>
<td>1.7 (3.7)</td>
<td>24.7 (24.7)</td>
<td>25.0 (46.3)</td>
</tr>
<tr>
<td>Incorrect answers, n</td>
<td>26.0</td>
<td>3.0</td>
<td>29.0</td>
<td>26.0</td>
</tr>
<tr>
<td>Output errors, n (%)</td>
<td>6.3 (11.4)</td>
<td>40.0 (89.6)</td>
<td>46.3 (46.3)</td>
<td>3.0 (5.6)</td>
</tr>
</tbody>
</table>

The nonresponse rate after input of only the question text was, on average, 46.3%. With Japanese prompts, it was 21.7% \((P<.001)\). After translation to English, the average was 27.7% \((P=.002)\), and with English prompts, it decreased to an average of 2.7% \((P<.001)\).

Performance Based on the Presence of Images

There were 46 questions with images, and 54 were text-only. Text-only questions had a higher correct answer rate than that for image-based questions. However, the addition of English translation and prompts significantly increased the correct answer rate, even for questions with images.

Correct Answer Rates Based on the Question’s Field

As shown in Table 2, general questions and those from the fields of head and neck and nasal allergies had relatively high correct answer rates.

The nonresponse rate for image-based questions was higher than that for text-only questions (11.4% vs 89.6%, respectively; Table 1). With Japanese prompts, the nonresponse rates were 5.6% and 39.1%, respectively. With English translation, they were 7.4% and 51.5%, respectively. With the addition of English translation and prompts, they significantly decreased to 0.6% and 5.8%, respectively.
Table 2. Results based on the question’s field.

<table>
<thead>
<tr>
<th>Results</th>
<th>Ear</th>
<th>Nasal allergy</th>
<th>Speech, swallowing, and larynx</th>
<th>Oropharynx</th>
<th>Head and neck</th>
<th>General</th>
<th>Infectious disease</th>
</tr>
</thead>
<tbody>
<tr>
<td>Questions, n</td>
<td>29</td>
<td>18</td>
<td>18</td>
<td>11</td>
<td>10</td>
<td>11</td>
<td>3</td>
</tr>
<tr>
<td><strong>Japanese</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct answers, n (%)</td>
<td>5.0 (17.2)</td>
<td>6.0 (33.3)</td>
<td>1.7 (9.3)</td>
<td>2.0 (18.2)</td>
<td>3.0 (30)</td>
<td>8.0 (72.7)</td>
<td>0.0 (0)</td>
</tr>
<tr>
<td>Incorrect answers, n</td>
<td>9.7</td>
<td>7.0</td>
<td>5.0</td>
<td>2.3</td>
<td>2.0</td>
<td>2.0</td>
<td>0.0</td>
</tr>
<tr>
<td><strong>Japanese with prompt</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct answers, n (%)</td>
<td>7.7 (26.4)</td>
<td>10.3 (57.4)</td>
<td>3.7 (20.4)</td>
<td>3.0 (27.3)</td>
<td>4.3 (43.3)</td>
<td>6.3 (57.6)</td>
<td>1.3 (44.4)</td>
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<tr>
<td>Incorrect answers, n</td>
<td>13.7</td>
<td>4.0</td>
<td>9.7</td>
<td>6.0</td>
<td>3.7</td>
<td>3.3</td>
<td>1.3</td>
</tr>
<tr>
<td><strong>English</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct answers, n (%)</td>
<td>8.3 (28.7)</td>
<td>9.0 (50)</td>
<td>1.3 (7.4)</td>
<td>4.0 (36.4)</td>
<td>4.7 (46.7)</td>
<td>6.7 (60.6)</td>
<td>0.3 (11.1)</td>
</tr>
<tr>
<td>Incorrect answers, n</td>
<td>14.0</td>
<td>1.7</td>
<td>8.7</td>
<td>4.7</td>
<td>3.7</td>
<td>3.3</td>
<td>2.0</td>
</tr>
<tr>
<td><strong>English with prompt</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct answers, n (%)</td>
<td>9.7 (33.3)</td>
<td>11.3 (63)</td>
<td>7.0 (38.9)</td>
<td>4.7 (42.4)</td>
<td>7.3 (73.3)</td>
<td>6.3 (57.6)</td>
<td>1.0 (33.3)</td>
</tr>
<tr>
<td>Incorrect answers, n</td>
<td>18.3</td>
<td>6.0</td>
<td>11.0</td>
<td>6.3</td>
<td>2.7</td>
<td>3.7</td>
<td>2.0</td>
</tr>
</tbody>
</table>

For the fields of head and neck and nasal allergies, respectively, with text-only input, the rates were 72.7%, 30%, and 33.3%, respectively. With Japanese prompts, they were 57.6%, 43.3%, and 57.4%, respectively. With English translation, they were 60.6%, 46.7%, and 50%, respectively. With English translation and prompts, they were 57.6%, 73.3%, and 63%, respectively. Furthermore, in all fields, the correct answer rate improved with the addition of English translation and prompts.

Correct Answer Rates Based on Question Content

As shown in Table 3, questions related to anatomy had the highest correct answer rates: 44.4% for question text only, 55.6% with Japanese prompts, 51.9% with English translation, and 66.7% with English translation and prompts. The correct answer rates for all question content categories improved with the addition of English translation and prompts.
Table 3. Results based on question content.

<table>
<thead>
<tr>
<th>Results</th>
<th>Treatment</th>
<th>Details of the disease and diagnosis</th>
<th>Examination</th>
<th>Anatomy</th>
<th>Systems</th>
<th>Others</th>
</tr>
</thead>
<tbody>
<tr>
<td>Questions, n</td>
<td>37</td>
<td>32</td>
<td>13</td>
<td>9</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td><strong>Japanese</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct answers, n (%)</td>
<td>6.7 (18)</td>
<td>7.0 (21.9)</td>
<td>3.0 (23.1)</td>
<td>4.0 (44.4)</td>
<td>3.0 (42.9)</td>
<td>2.0 (100)</td>
</tr>
<tr>
<td>Incorrect answers, n</td>
<td>13.7</td>
<td>9.3</td>
<td>7.0</td>
<td>2.0</td>
<td>1.0</td>
<td>0.0</td>
</tr>
<tr>
<td><strong>Japanese with prompt</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct answers, n (%)</td>
<td>12.7 (34.2)</td>
<td>11.0 (34.4)</td>
<td>4.0 (30.8)</td>
<td>5.0 (55.6)</td>
<td>2.0 (28.6)</td>
<td>2.0 (100)</td>
</tr>
<tr>
<td>Incorrect answers, n</td>
<td>14.7</td>
<td>15.7</td>
<td>8.0</td>
<td>1.7</td>
<td>1.7</td>
<td>0.0</td>
</tr>
<tr>
<td><strong>English</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct answers, n (%)</td>
<td>10.0 (27)</td>
<td>10.7 (33.3)</td>
<td>4.0 (30.8)</td>
<td>4.7 (51.9)</td>
<td>3.0 (42.9)</td>
<td>2.0 (100)</td>
</tr>
<tr>
<td>Incorrect answers, n</td>
<td>14.7</td>
<td>13.3</td>
<td>7.0</td>
<td>2.0</td>
<td>1.0</td>
<td>0.0</td>
</tr>
<tr>
<td><strong>English with prompt</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct answers, n (%)</td>
<td>16.7 (45)</td>
<td>14.3 (44.8)</td>
<td>4.7 (35.9)</td>
<td>6.0 (66.7)</td>
<td>3.7 (52.4)</td>
<td>2.0 (100)</td>
</tr>
<tr>
<td>Incorrect answers, n</td>
<td>19.7</td>
<td>17.0</td>
<td>8.3</td>
<td>2.7</td>
<td>2.3</td>
<td>0.0</td>
</tr>
</tbody>
</table>

Correct Answer Rates of Image-Based Questions According to the Type of Image

Table 4 shows the results for each type of figure among the 46 image-based questions. There were 23 questions based on photographs, 11 questions based on radiological images, 8 questions based on graphs, and 4 questions based on histopathological images. While the percentage of correct answers for questions based on radiological images was relatively high, this percentage was low for questions based on graphs, such as physiological tests. In the English translation and prompts, the percentage of correct answers for questions based on radiological images was 51.5%, while that for questions based on graphs was 29.2%.

Table 4. Results for image-based questions discriminated according to the type of image.

<table>
<thead>
<tr>
<th>Results</th>
<th>Photograph</th>
<th>Radiological image</th>
<th>Graph</th>
<th>Histopathological image</th>
</tr>
</thead>
<tbody>
<tr>
<td>Questions, n</td>
<td>23</td>
<td>11</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td><strong>Japanese</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct answers, n (%)</td>
<td>0.7 (2.9)</td>
<td>0.0 (0)</td>
<td>1.0 (12.5)</td>
<td>0.0 (0)</td>
</tr>
<tr>
<td>Incorrect answers, n</td>
<td>0.0</td>
<td>2.0</td>
<td>1.0</td>
<td>0.0</td>
</tr>
<tr>
<td><strong>Japanese with prompt</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct answers, n (%)</td>
<td>5.7 (24.6)</td>
<td>3.3 (30.3)</td>
<td>2.0 (25)</td>
<td>0.7 (16.7)</td>
</tr>
<tr>
<td>Incorrect answers, n</td>
<td>7.7</td>
<td>4.0</td>
<td>1.3</td>
<td>1.7</td>
</tr>
<tr>
<td><strong>English</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct answers, n (%)</td>
<td>2.7 (11.6)</td>
<td>2.7 (24.2)</td>
<td>2.0 (25)</td>
<td>0.3 (8.3)</td>
</tr>
<tr>
<td>Incorrect answers, n</td>
<td>8.3</td>
<td>4.0</td>
<td>1.7</td>
<td>1.0</td>
</tr>
<tr>
<td><strong>English with prompt</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Correct answers, n (%)</td>
<td>9.3 (40.6)</td>
<td>5.7 (51.5)</td>
<td>2.3 (29.2)</td>
<td>1.7 (41.7)</td>
</tr>
<tr>
<td>Incorrect answers, n</td>
<td>12.0</td>
<td>5.0</td>
<td>5.0</td>
<td>2.3</td>
</tr>
</tbody>
</table>

Performance Based on Image-Based Questions Text-Only Input Versus Text-Plus-Image Input

Figure 2 shows the performance of GPT-4V based on imaged-based questions with text-only input and with text-plus image input. On image-based questions with text-only input, the average correct answer rate was 30.4%; and with text-plus-image input, the average correct answer rate was 41.3% (P=.02; Figure 2).
Discussion

Principal Results

In this study, we evaluated the accuracy of GPT-4V in answering 100 questions, including 46 image-based and 54 text-only questions, from the 2023 otolaryngology board certification examination. The results confirmed that the accuracy was higher for text-only questions than for image-based questions. As for the performance of figure recognition, the correct answer rate with text-plus-image input was higher than that with text-only-input. Moreover, we found that the accuracy improved with the addition of English translations and prompts, but responses were often avoided for simple question inputs, suggesting limitations in medical responses. Variability in accuracy was also evident depending on the field and content of the questions.

Our findings showed that the accuracy of GPT-4V for image-based questions was lower than that for text-only questions. This suggests that, although AI excels at analyzing textual information, it still has limitations in analyzing image-based data [10]. Medical images contain complex and diverse information that requires specialized knowledge for interpretation. Therefore, AI remains inferior to human experts. To improve the accuracy of AI for image analysis, further studies on specialized prompts, the development of more advanced image-recognition technologies, and training focused on medical images are necessary.

Comparison With Prior Work

In relation to medical education, the performance of GPT on licensing examinations and specialist-level medical examinations has been verified and reported [1,11-14]. In English-speaking regions, relatively high accuracy rates have been reported [1,14], whereas in non–English-speaking regions, there is variability [11-13,15]. In addition, accuracy rates differ not only by language but also by the type of examination. Generally, there are more favorable reports for national medical licensing examinations, while there are comparatively poorer reports for specialist-level exams [16,17]. Even when looking at Japanese language reports, while national examinations and general practice examinations have shown good results [3-5,18], ophthalmology, pharmacist, nursing, and dentistry examinations have around a 50%-70% accuracy rate [19-22], with the otolaryngology field in this study showing comparable results [6]. In our previous study, the otolaryngology field tended to have a higher frequency of wrong answers for questions about the ear, larynx, and voice, as well as for questions about examination and treatment. This trend has not changed, suggesting that there are strengths and weaknesses within the specialty. Although the percentage of correct answers was lower for image-based questions than for text-only questions, the percentage of correct answers for text-only questions was higher for general and nasal allergy questions compared with those associated with other question areas, which may have affected the difference in the percentage of correct answers according to the specific field. It is believed that there is room for improvement in GPT’s performance, especially in highly specialized fields.

Regarding the effectiveness of prompts for image-based questions, there are reports that the additional input of figures is no different from the input of text only in the Japanese National Medical Practitioners’ Examination [23]. On the other hand, in our study, the percentage of correct answers was approximately 10% higher when figures and text were added compared with text-only input. In addition, among the imaged-based questions, the percentage of correct responses was lower for questions related to physiological tests such as hearing tests and polysomnography than for questions related to radiography and microscopy images.

Although there are likely to be differences in the ability to recognize diagrams depending on the field and specialization, it is thought that the search for dedicated prompts, the development of more advanced image recognition techniques, and training specific to medical images will be necessary to further improve the accuracy of image analysis. Converting the physiological tests so that they can be recognized as numerical
values rather than image recognition could further increase the percentage of correct responses.

The fact that accuracy improved with the addition of English translations and prompts suggests AI is optimized for specific formats and languages. The processing capabilities of GPT-4 for text are specialized in English, and the addition of English prompts was believed to increase the likelihood of generating more accurate answers. Our findings further showed that prompts can enhance the quality of AI answers. This effect was valid for image-based as well as text-only questions, emphasizing the need for effective prompts for medical images.

Limitations

The frequent avoidance of generating answers for simple inputs indicates the limitations of AI in terms of complex medical concepts and specialized knowledge. In the medical field, many problems require specific expertise and contexts, making it challenging for AI to provide adequate answers. Furthermore, the issue of hallucinations, where incorrect answers are presented as if they were correct, has become problematic. This includes instances where AI ignores specific facts, engages in illogical reasoning, or fails to apply concepts to new situations [14,24,25]. There is also concern that such inaccuracies could present barriers to direct comprehension by patients, necessitating careful consideration of how AI is used in practice [26].

In addition, the correlation between the difficulty level for specialists and the difficulty level for GPT-4V is not clear, since neither the percentage of correct answers per question nor the minimum number of correct answers required to pass the examination have been reported. Understanding the difference would allow for further consideration of the situations in which the GPT-4V is used. This highlights the importance of understanding these limitations and appropriately using AI in medical education and clinical diagnoses within the otolaryngology field. Though AI suggestions should be considered when making medical judgments, medical professionals need to make the final decisions.

Conclusions

GPT-4V demonstrated a certain level of accuracy for the 2023 otolaryngology board certification examination, and text-plus-image input increased the accuracy of image-based questions. However, the capabilities of AI for image-based questions were limited. Our findings can form the basis for further research and development of the application of AI in the medical field. Future studies should focus on improving the capabilities of AI in image analysis, designing more effective prompts, and developing multilingual support.

Acknowledgments

The authors would like to thank Ryosei Moto for his technical assistance.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Explanations of this study.

[DOCX File. 261 KB - mededu_v10i1e57054_app1.docx ]

References


https://mededu.jmir.org/2024/1/e57054

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**Abbreviations**

- **AI**: artificial intelligence
- **GPT**: generative pretrained transformer
- **GPT-4V**: ChatGPT-4 Vision
Embracing ChatGPT for Medical Education: Exploring Its Impact on Doctors and Medical Students

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Abstract
ChatGPT (OpenAI), a cutting-edge natural language processing model, holds immense promise for revolutionizing medical education. With its remarkable performance in language-related tasks, ChatGPT offers personalized and efficient learning experiences for medical students and doctors. Through training, it enhances clinical reasoning and decision-making skills, leading to improved case analysis and diagnosis. The model facilitates simulated dialogues, intelligent tutoring, and automated question-answering, enabling the practical application of medical knowledge. However, integrating ChatGPT into medical education raises ethical and legal concerns. Safeguarding patient data and adhering to data protection regulations are critical. Transparent communication with students, physicians, and patients is essential to ensure their understanding of the technology’s purpose and implications, as well as the potential risks and benefits. Maintaining a balance between personalized learning and face-to-face interactions is crucial to avoid hindering critical thinking and communication skills. Despite challenges, ChatGPT offers transformative opportunities. Integrating it with problem-based learning, team-based learning, and case-based learning methodologies can further enhance medical education. With proper regulation and supervision, ChatGPT can contribute to a well-rounded learning environment, nurturing skilled and knowledgeable medical professionals ready to tackle health care challenges. By emphasizing ethical considerations and human-centric approaches, ChatGPT’s potential can be fully harnessed in medical education, benefiting both students and patients alike.

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doi:10.2196/52483

KEYWORDS
artificial intelligence; AI; ChatGPT; medical education; doctors; medical students

Introduction
ChatGPT, whose name is derived from “generative pre-trained transformer,” is a large natural language processing model grounded in artificial intelligence (AI) technology, demonstrating remarkable performance across various language-related tasks [1]. Within the realm of medical education, ChatGPT emerges as a highly promising tool with considerable potential [2]. Through training in the ChatGPT model, medical students and doctors can enhance their clinical reasoning and decision-making capabilities, consequently leading to improved performance in case analysis and diagnosis. Moreover, ChatGPT offers personalized and efficient learning experiences for medical learners by facilitating simulated dialogues, providing intelligent tutoring, and offering automated question-answering, thereby deepening students’ comprehension of medical knowledge [3].

In the realm of transformative technologies in medical education, ChatGPT prominently distinguishes itself, standing out from other large language models by virtue of its unique architecture
and comprehensive training data [4,5]. A pivotal factor setting ChatGPT apart is its monumental scale, boasting an impressive 175 billion parameters. This scale-driven proficiency contrasts starkly with smaller models that may struggle when confronted with complicated queries or tasked with producing coherent replies. With its intricate architectural foundation, ChatGPT possesses the capability to comprehend and generate human-like text across a diverse spectrum of topics, showcasing remarkable coherence and context awareness. What renders the ChatGPT truly distinctive is its specialized focus on fostering dynamic and coherent conversations, thereby excelling in maintaining context over extended interactions. This stands in stark contrast to models primarily designed for single-turn tasks. In educational contexts such as problem-based learning (PBL), team-based learning (TBL), case-based learning (CBL), and precision medical education, ChatGPT takes center stage as a focal point.

Nevertheless, obstacles occur in the implementation of ChatGPT [6]. On the one hand, the effective training and use of the model requires a high level of technical expertise and skill. On the other hand, concerns related to data security and ethical considerations demand careful attention. To fully harness the potential of ChatGPT in medical education, these challenges must be overcome and concerted efforts should be directed toward integrating AI technology with medical education. By leveraging the capabilities of ChatGPT alongside these innovative teaching approaches, medical education can achieve new heights, fostering a generation of skilled and knowledgeable medical professionals ready to tackle the challenges of the healthcare field. This paper aims to illuminate both the benefits and the challenges of ChatGPT in medical education (Figure 1).

Figure 1. Benefits and challenges of ChatGPT in medical education.

**Potential Benefits of ChatGPT in Medical Education**

**Overview**

In the context of medical education, ChatGPT holds immense promise for bolstering the clinical reasoning and decision-making abilities of medical students and physicians [7]. By training the ChatGPT model, medical learners can tap into its powerful natural language generation and understanding capabilities to master the methods and skills of clinical reasoning and decision-making [8,9]. These competencies are critical components of medical education and fundamental skills that medical students and physicians must possess.

**Educational Paradigms: Traditional Vs Enhanced by ChatGPT**

Traditional medical education typically follows a teacher-centric approach, where the content and pace of learning are determined primarily due to its potential to elevate dynamic learning experiences.

By generating learning materials based on each student’s learning status and needs, ChatGPT empowers students to take a more autonomous approach to learning and gain a customized educational experience aligned with their preferences [10,11]. For instance, students can engage in simulated dialogues with ChatGPT, discussing medical cases and diagnostic approaches. Additionally, ChatGPT can adapt based on students’ feedback and performance, providing personalized intelligent tutoring and answering questions. This personalized dialogue approach can be tailored to each student’s unique needs and interests, thereby enhancing their grasp of medical knowledge and skills.
ChatGPT Intelligent Tutoring in PBL Integration

The integration of ChatGPT holds promising implications for PBL in medical education. ChatGPT’s capacity to offer personalized guidance and stimulate critical thinking aligns seamlessly with the core principles of PBL [12]. In this context, ChatGPT functions as an intelligent tutor, adept at steering students through intricate problems by furnishing pertinent information, detailed explanations, and insightful suggestions. The model’s ability to dynamically adjust responses to student queries contributes to creating a vibrant and responsive learning environment. Students can leverage ChatGPT to brainstorm potential solutions, collect relevant research, or validate hypotheses during the problem-solving process [13]. Furthermore, the model can generate patient cases or clinical scenarios based on real-world data, enabling students to apply their knowledge to practical situations. It is essential to design PBL activities that seamlessly incorporate both the advantages offered by ChatGPT and the indispensable experience derived from clinical practice. By maintaining a focus on group discussions and collaborative problem-solving based on actual patient cases, educators ensure that students reap the benefits of ChatGPT’s enhancements while retaining the essential skills cultivated through hands-on clinical interactions and in-depth case analyses. As technology continues to advance, it remains imperative to uphold patient-based learning as the cornerstone of medical education. Recognizing that, at its current stage, ChatGPT cannot entirely replace the critical skills honed through genuine patient interactions and the nuanced analysis of complex cases is vital for preserving the integrity and effectiveness of medical education.

Synergizing ChatGPT With Other Collaborative Teaching Methods

ChatGPT’s application in medical education should be complemented by other teaching methods, such as CBL, TBL, and small-group sessions. The model’s ability to generate diverse perspectives and solutions enhances the overall TBL experience [14]. In CBL scenarios, ChatGPT can function as a case facilitator, generating realistic scenarios, asking probing questions, and providing nuanced feedback. It can simulate authentic patient interactions or complex business dilemmas, allowing learners to apply theoretical knowledge to practical situations. The model’s adaptability ensures that the cases presented are tailored to the evolving needs and understanding of the learners. Within the TBL framework, ChatGPT can facilitate collaboration among team members by offering real-time assistance and promoting knowledge sharing. It can contribute to group discussions, help clarify concepts, and prompt critical thinking among team members. ChatGPT can also facilitate preclass preparation by providing students with foundational knowledge and resources related to the upcoming TBL session. By integrating ChatGPT with these methods, medical educators can create a well-rounded learning experience that maximizes the benefits of both individualized learning and TBL. To enhance team collaboration abilities, medical institutions should prioritize the development of medical students through interprofessional education, where students from different health care disciplines collaborate. Encouraging student-led initiatives and group projects also fosters collaboration, leadership, and effective communication among future medical professionals. This multifaceted approach ensures a well-rounded learning experience, maximizing the benefits of both individualized and collaborative learning while preparing students for the complex challenges of the health care field.

ChatGPT in Precision Medical Education

In the evolving landscape of medical education, the concept of precision medical education has gained prominence [15]. This approach aligns with current trends, notably competency-based medical education (CBME) and pedagogical approaches such as PBL, CBL, and TBL [16]. Precision medical education emphasizes tailoring learning experiences to individual student needs, aligning with the principles of personalized and adaptive learning championed by ChatGPT. CBME focuses on learners progressing at their own pace, demonstrating proficiency in specific competencies. ChatGPT’s intelligent tutoring and adaptability make it a valuable tool in supporting this competency-based model. By providing personalized guidance, generating relevant content, and fostering critical thinking, ChatGPT contributes to a more precise and effective medical education tailored to each learner’s requirements [17]. Furthermore, the integration of ChatGPT with collaborative teaching methods enhances the multifaceted nature of precision education, allowing for a more personalized and effective learning experience.

Table 1. Comparison between traditional medical education and medical education with ChatGPT.

<table>
<thead>
<tr>
<th>Aspect</th>
<th>Traditional medical education</th>
<th>Medical education with ChatGPT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clinical reasoning</td>
<td>Instructor-led lectures and traditional case discussions</td>
<td>Enhanced clinical reasoning, personalized dialogues, and simulated case analyses</td>
</tr>
<tr>
<td>Decision-making</td>
<td>Limited case exposure</td>
<td>Diverse cases and diagnostic approaches</td>
</tr>
<tr>
<td>Personalized learning</td>
<td>One-size-fits-all learning materials and standardized assessments</td>
<td>Tailored learning materials, intelligent tutoring, and automated question-answering based on individual progress</td>
</tr>
<tr>
<td>Interaction with educators</td>
<td>Limited face-to-face interactions</td>
<td>Continuous personalized feedback</td>
</tr>
<tr>
<td>Medical research support</td>
<td>Manual review and analysis</td>
<td>Automated literature review, study design proposals, and statistical analysis</td>
</tr>
<tr>
<td>Team collaboration</td>
<td>Emphasizes group discussions and teamwork</td>
<td>Balancing personalized learning and team-based activities</td>
</tr>
<tr>
<td>Technical expertise and challenges</td>
<td>Less reliance on technology</td>
<td>Skill in using ChatGPT</td>
</tr>
<tr>
<td>Ethical considerations</td>
<td>Data privacy and consent</td>
<td>Addressing ethical implications</td>
</tr>
</tbody>
</table>

https://mededu.jmir.org/2024/1/e52483
Empowering Medical Research With ChatGPT
ChatGPT proves to be a valuable asset in medical research [18]. The intricate relationship between medical research and education, as aligned with the standards and roles outlined by the World Federation for Medical Education (WFME) [19] and Canadian Medical Education Direction System (CanMEDS) [20], not only provides a profound and practical foundation for medical education but also aligns with the comprehensive development requirements for medical professionals. This close connection ensures that medical education remains consistent with the latest advancements in medical science, fostering the cultivation of well-rounded medical practitioners. Medical research relies heavily on extensive literature to support its content and conclusions. However, reading and analyzing vast amounts of literature can be time-consuming and labor-intensive. ChatGPT streamlines research by automating literature review and analysis. Additionally, ChatGPT aids medical researchers in study design and data analysis [21]. By expediting data processing, extracting data features and patterns, generating research design proposals, and offering statistical analysis methods and data visualization tools, ChatGPT facilitates improved experiment design and data analysis.

Challenges of ChatGPT in Medical Education

Overview
While ChatGPT offers substantial benefits to medical education, it faces a spectrum of challenges [22]. The rapid pace of knowledge evolution within the medical field presents a significant hurdle. New research and clinical guidelines continually emerge, demanding constant updates to ChatGPT to ensure that students are provided with the most current and accurate medical information. This necessitates not only the ability to keep up with knowledge updates but also to ensure their accuracy and credibility.

Potential Devaluation of Collaboration
A notable concern emerges regarding the potential devaluation of the collaborative aspect of learning in medical education, particularly in traditional methodologies such as PBL, CBL, and TBL. Collaboration and teamwork are pivotal in these approaches [23], and ChatGPT may inadvertently diminish the importance of human-to-human interaction. Maintaining a balance between technology and interpersonal relationships is vital for effective learning. While ChatGPT enhances PBL through personalized guidance, educators must underscore the enduring importance of patient-based learning and teamwork. Despite its simulation capabilities and theoretical insights, ChatGPT cannot replace practical experiences gained through real-world interactions, especially in medical education. Acknowledging the model’s limitations is crucial to prevent an overreliance on simulated learning. Embedding ChatGPT seamlessly into existing curricula presents a challenge, requiring educators to invest time in designing and integrating AI-driven components aligned with overall learning goals.

Overreliance
Importantly, overreliance on technology may hinder critical thinking and hands-on learning, potentially lowering the quality of education. ChatGPT’s answers can vary or even contradict themselves with each query, further impacting student learning [24]. Learning through ChatGPT might inadvertently reduce face-to-face interactions with educators and peers, impacting effective communication skills in clinical practice. ChatGPT may occasionally disseminate inaccurate medical information, making the prompt recognition and correction of such errors critical [25,26]. The establishment of supervision and feedback mechanisms to enhance ChatGPT’s accuracy is imperative.

Challenge of Personalized Learning
The challenge of personalized learning is a crucial consideration. Every student has distinct needs and academic levels, requiring ChatGPT to offer tailored education that aligns with individual requirements and progress. Achieving this may necessitate the development of more sophisticated algorithms and technologies. Cultural diversity and inclusivity should also be addressed. Medical education needs to accommodate students from different cultural backgrounds. ChatGPT should be capable of delivering information and using teaching methods that ensure effective comprehension and benefits for all students.

Ethical Considerations
The ethical and privacy dimensions of using ChatGPT in medical education are paramount [27,28]. Handling patient data in an educational context and safeguarding patient privacy are complex and vital concerns. This entails strict adherence to regulatory and ethical guidelines. Identifying and rectifying errors is another noteworthy challenge.

Technological Accessibility
Technological accessibility poses a challenge. The effective use of ChatGPT depends on network connectivity and device availability, which can be problematic in various regions and among specific student populations [29]. Strategies must be devised to use ChatGPT in diverse technological environments.
Future Directions of ChatGPT in Medical Education

Overview
To mitigate these issues, appropriate regulation and supervision are essential. Students should receive training in interpersonal interactions to engage effectively with patients and efforts should be made to provide equal access to technology and learning resources, promoting fair and inclusive medical education. Moving forward, research in this field should explore various promising avenues to enhance our comprehension and application of ChatGPT.

Strategies to Tackle Present Challenges
To specifically address the challenges of ChatGPT on PBL, TBL, and CBL, measures should be taken to mitigate potential drawbacks on collective capabilities. Introducing targeted interventions, such as incorporating collaborative exercises and feedback mechanisms, can help balance individual contributions within a team setting. Emphasizing the importance of teamwork in medical education [30], alongside the integration of ChatGPT, can foster a collaborative learning environment.

There is a pressing need to investigate methods that can augment ChatGPT’s capacity to deliver contextually relevant and up-to-date medical information. This involves developing mechanisms for real-time knowledge updates and refining the curation of medical data. Besides, it is crucial to address the ethical and privacy challenges associated with ChatGPT [31]. Future research can focus on devising robust protocols and AI-driven solutions to protect patient data while seamlessly integrating ChatGPT into medical education. Furthermore, exploring innovative approaches for personalizing medical education with ChatGPT presents an exciting opportunity. Research can delve into adaptive learning algorithms and inventive teaching strategies tailored to individual student needs and learning styles. Additionally, there is a need for research on improving ChatGPT’s error identification and correction mechanisms, ensuring the highest level of accuracy and reliability in medical content. Finally, we should examine ways to enhance ChatGPT’s cultural sensitivity and inclusivity in medical education and acknowledge the diversity of student backgrounds and learning requirements. This holistic approach ensures that ChatGPT not only provides accurate medical information but also aligns with the broader goals of medical education in promoting collaboration, ethical considerations, and cultural competence.

Conclusions
In conclusion, ChatGPT enhances medical education by improving clinical reasoning, personalizing learning, promoting precision medical education, and supporting medical research. However, a balanced and responsible integration requires a focus on ethics and human-centered approaches. Medical educators can achieve this balance by customizing learning paths, blending personalization with group activities, assigning team projects, guiding ChatGPT use, and emphasizing ethics and critical thinking training. These steps create a holistic learning environment that prepares students to excel as independent thinkers and team players in health care, optimizing ChatGPT’s role in medical education while maintaining its integrity.

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Authors’ Contributions
AZ provided the idea and designed the study. YW, YZ, BF, YY, and KK contributed to the conceptualization, writing original draft, and writing—review and editing. All authors contributed to the paper and approved the submitted version.

Conflicts of Interest
None declared.

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**Abbreviations**

- **AI**: artificial intelligence
- **CanMEDS**: Canadian Medical Education Direction System
- **CBL**: case-based learning
- **CBME**: competency-based medical education
- **PBL**: problem-based learning
- **TBL**: team-based learning
- **WFME**: World Federation for Medical Education

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Corrigenda and Addenda

Correction: How Does ChatGPT Perform on the United States Medical Licensing Examination (USMLE)? The Implications of Large Language Models for Medical Education and Knowledge Assessment

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Related Article:
Correction of: https://mededu.jmir.org/2023/1/e45312

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In “How Does ChatGPT Perform on the United States Medical Licensing Examination (USMLE)? The Implications of Large Language Models for Medical Education and Knowledge” (JMIR Med Educ 2023;9:e45312) three additions were made to enhance discoverability.

The title originally appeared as:
How Does ChatGPT Perform on the United States Medical Licensing Examination? The Implications of Large Language Models for Medical Education and Knowledge Assessment

And has been changed to:
How Does ChatGPT Perform on the United States Medical Licensing Examination (USMLE)? The Implications of Large Language Models for Medical Education and Knowledge

In the “Objective” section of the Abstract, the following sentence:

This study aimed to evaluate the performance of ChatGPT on questions within the scope of the United States Medical Licensing Examination Step 1 and Step 2 exams, as well as to analyze responses for user interpretability.

Has been changed to read as:

This study aimed to evaluate the performance of ChatGPT on questions within the scope of the United States Medical Licensing Examination (USMLE) Step 1 and Step 2 exams, as well as to analyze responses for user interpretability.

Finally, the abbreviation “USMLE” has been added to the Keywords section.

The correction will appear in the online version of the paper on the JMIR Publications website on February 27, 2024 together with the publication of this correction notice. Because this was made after submission to PubMed, PubMed Central, and other full-text repositories, the corrected article has also been resubmitted to those repositories.
Corrigenda and Addenda

Correction: Telehealth Education in Allied Health Care and Nursing: Web-Based Cross-Sectional Survey of Students’ Perceived Knowledge, Skills, Attitudes, and Experience

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Correction of: https://mededu.jmir.org/2024/1/e51112/

(JMIR Med Educ 2024;10:e59919) doi:10.2196/59919

In “Telehealth Education in Allied Health Care and Nursing: Web-Based Cross-Sectional Survey of Students’ Perceived Knowledge, Skills, Attitudes, and Experience” (JMIR Med Educ 2024;10:e51112) an error was noted.

In the title, the word “student’s” has been revised to “students”.

Therefore, the original title:

Telehealth Education in Allied Health Care and Nursing: Web-Based Cross-Sectional Survey of Student’s Perceived Knowledge, Skills, Attitudes, and Experience

Has been revised to:

Telehealth Education in Allied Health Care and Nursing: Web-Based Cross-Sectional Survey of Students’ Perceived Knowledge, Skills, Attitudes, and Experience

The correction will appear in the online version of the paper on the JMIR Publications website on April 26, 2024 together with the publication of this correction notice. Because this was made after submission to PubMed, PubMed Central, and other full-text repositories, the corrected article has also been resubmitted to those repositories.
ChatGPT in Medical Education: A Precursor for Automation Bias?

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Abstract

Artificial intelligence (AI) in health care has the promise of providing accurate and efficient results. However, AI can also be a black box, where the logic behind its results is nonrational. There are concerns if these questionable results are used in patient care. As physicians have the duty to provide care based on their clinical judgment in addition to their patients’ values and preferences, it is crucial that physicians validate the results from AI. Yet, there are some physicians who exhibit a phenomenon known as automation bias, where there is an assumption from the user that AI is always right. This is a dangerous mindset, as users exhibiting automation bias will not validate the results, given their trust in AI systems. Several factors impact a user’s susceptibility to automation bias, such as inexperience or being born in the digital age. In this editorial, I argue that these factors and a lack of AI education in the medical school curriculum cause automation bias. I also explore the harms of automation bias and why prospective physicians need to be vigilant when using AI. Furthermore, it is important to consider what attitudes are being taught to students when introducing ChatGPT, which could be some students’ first time using AI, prior to their use of AI in the clinical setting. Therefore, in attempts to avoid the problem of automation bias in the long-term, in addition to incorporating AI education into the curriculum, as is necessary, the use of ChatGPT in medical education should be limited to certain tasks. Otherwise, having no constraints on what ChatGPT should be used for could lead to automation bias.

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KEYWORDS
ChatGPT; artificial intelligence; AI; medical students; residents; medical school curriculum; medical education; automation bias; large language models; LLMs; bias

Introduction

With the introduction of artificial intelligence (AI), automated processes for nearly most tasks have become the norm. In the clinical environment, AI has been used for diagnosis, prognosis, and administrative tasks. Given the popularity of other forms of AI—as seen most recently with ChatGPT, a large language model developed by the company OpenAI—there are suggestions for its potential role in medical education. Users of ChatGPT boast its efficiency and relative accuracy, such as in the generation of a patient’s discharge summary or the conduction of literature reviews [1]. As advancements in medicine continue to arise, medical students are burdened with the impossible task of balancing the need to continuously learn and retain competencies and the need to provide compassionate patient care. As a result, some medical students might feel an incentive to use ChatGPT to save them time in their busy schedules. However, despite the novel acclaim, the technical and ethical issues seen with AI, such as biased results or nonsensical outputs, also plague ChatGPT. These problems become exacerbated when medical students inadvertently develop automation bias, where they overrely on AI, and continue to have this mentality when they become residents, at which point they have the potential to harm patients if the AI provides an erroneous outcome. In this editorial, I argue the justification for AI education in the medical school curriculum and how the lack of it leads to the problem of automation bias, as well as the other harms from automation bias. Subsequently, I connect the implications of students using ChatGPT with automation bias. Finally, I provide recommendations for when ChatGPT use is appropriate.
The Need for AI Education in the Medical School Curriculum

As the health care landscape has drastically changed through the years, physicians have had to quickly adapt to the digital age. Given the amount of information physicians are required to retain and the new information they must continue to learn, such as information on emerging diseases and the health data of the patients they track, physicians are expected to interact with computer systems in some capacity, whether it is for charting their patients’ information or consulting clinical decision support systems. However, the lack of content on the technological systems in the health care setting inhibits prospective physicians from understanding the benefits of using these technologies, the ethical issues that can arise with their use, and future innovations, along with the wider implications of AI. In Civaner et al’s [2] survey of medical students’ opinions on AI education, they found that 75.6% of students had either limited or no education on the topic of AI. These participants also noted not feeling well equipped to work with AI in the clinical setting. Additionally, in Yun et al’s [3] proposal for future internal medicine physicians, they suggested that these prospective physicians should be able to appreciate the roles of big data and AI in health care. Clearly, there is a desire from students, as well as residency and fellowship programs, to incorporate AI education into the medical school curriculum and training. AI education and training cannot continue to be delayed, as some forms of AI have already been deployed in the clinical setting.

Although several studies have provided proposals for implementing AI education into the medical school curriculum, they have also noted the difficulties of developing AI education, such as schedule constraints and the challenges of deciding the material that should be covered [4,5]. Additionally, this task should not solely be deferred to the attending physicians, as they themselves might not have the adequate training with AI to teach others [5]. Although these challenges serve as barriers to implementing quality AI education into the curriculum, an attempt to include at least some type of education on or educational resources about AI is needed to prepare students and potentially prevent problems in the clinical setting, as further explored in the following section. Therefore, future physicians, medical students, and residents should be trained on the use of AI in health care and other related topics, such as big data or machine learning, to understand the tools they will be working with. Even though medical students should not be expected to be experts in AI and know every technical aspect of these technologies, they should at least feel comfortable with navigating how and when to use AI.

The Problem of Automation Bias

Although AI is supposed to aid physicians in various processes to decrease their workload and give them more time with their patients, AI can also cause unintended ethical issues. One of the common ethical concerns with AI is that it can essentially be a black box, where the results from the AI are illogical, and the AI developer cannot track how it produced those erroneous results. This problem becomes exacerbated when automation bias arises. Automation bias occurs when a user overrelies on AI systems. Therefore, if a physician exhibits automation bias, then they will not question the results from the AI, potentially leading to bad medical care. In Lyell et al’s [6] study, the error rate associated with a clinical decision support system when it was inaccurate was higher (86.6%) in comparison to the rate it had when it was accurate (58.8%). Although automated processes aid in decision-making and can provide accurate results, there is also the possibility of these systems providing incorrect results and causing irreversible harm on a much larger scale. An example includes the Prescription Drug Monitoring Program (PDMP), a machine learning system that provides risk scores for patients’ likelihood to misuse prescription drugs, which can cause both testimonial injustice and physical harm [7,8]. Testimonial injustice, a form of epistemic injustice, develops when a patient’s account of their health is unfairly dismissed by their physician [8]. Testimonial injustice invalidates the credibility of patients and further implies that their care is dependent on how physicians deem their trustworthy [8]. A patient’s risk scores can be negatively affected if their chart becomes commingled, which is also known as overlay, where a specific person’s electronic health record erroneously pulls in the data of other patients with similar demographic characteristics and compiles these data into 1 chart [7,9]. As such, a patient with chronic pain may not receive the medication they need due to the PDMP providing an incorrect risk score. If a physician uses the risk scores of the PDMP without validating the results or considering their patients’ testimonies, then physical harm, as well as patients’ mistrust toward the physician and the potential deterrence of seeking health care, will ensue. Although AI can aid in the decision-making process, ultimately it is the duty of the physician to ensure that their decisions are based on sound clinical judgment. As such, if a physician with automation bias applies an erroneous outcome to a patient’s care, then the physician becomes accountable for that outcome instead of the AI, as they are the party that used the outcome. To clarify, more sophisticated AI and machine learning systems have been proposed, of which the results would be difficult for users to verify, as these systems use advanced techniques that do not rely on predefined rules. However, the AI systems described in this section are known as expert systems, which use a coded set of rules and rely on predefined rules [10]. Even though the verification process might essentially be beyond the scope of some physicians’ expertise regarding future AI and machine learning, physicians should remain attentive to results from AI.

The Implications for Medical Students and Residents

As seen with the case of the PDMP, automation bias can lead to various harms. Therefore, the systemic issue of automation bias in health care must be addressed. The mentality that AI is always right is often associated with medical students and residents [6,11]. As these groups have grown up in the digital age, they are more comfortable with embracing technology into their practice than older physicians (who either lack digital literacy or are resistant to change). In addition to their openness...
to using AI, medical students and residents might be prone to automation bias, as they lack experience or are not confident in their skills [11]. Multiple studies have found that algorithmic appreciation—a user’s valuing of an algorithm’s outputs—is lower for users who have more experience in a task than for those who are considered nonexperts in that task [12,13]. A combination of factors, such as newer physicians being digital natives, insufficient expertise, and less overall confidence, highlights how the systemic problem of automation bias came to be. Therefore, the deficiency of AI education in medical school and beyond sets up users to become susceptible to automation bias, as they might be unaware of the technical problems with AI. These users will come into the clinical setting with the assumption that AI systems are always accurate, which will cloud their clinical judgment.

In addition to the broader discussion of AI in health care, which students will inevitably have to interact with at some point in their professional careers, I want to focus on an AI that is accessible to students now—ChatGPT. The fact that ChatGPT has passed the US Medical Licensing Examination could entice students to use ChatGPT [14]. Moreover, Tiwari et al [15], who applied the Technology Acceptance Model to ChatGPT, found that students generally had positive views (in terms of perceived usefulness, credibility, social presence, and hedonic motivation) of ChatGPT based on their previous experiences with using the tool. However, just as AI can be a black-box algorithm, so too can ChatGPT, with respect to its hallucinations. ChatGPT’s hallucinations are results that are seemingly feasible but do not actually exist [1,16]. For example, it is commonly known that ChatGPT can make up citations [16,17]. Additionally, in an editorial, ChatGPT had to be prompted several times by the author to finally respond that it cannot generate visual diagrams [18]. Further, ChatGPT’s data sources only cover data from 2021 and prior years, and as its scope is limited to this context, ChatGPT can provide outdated information [19]. Therefore, despite the acclaim, ChatGPT is not as perfect as some claim it to be. Given the push for ChatGPT use, there is a risk that users might develop an AI solutionism mentality, where users assume that AI has the answer to all problems [10]. AI solutionism is closely related to automation bias, as users with the preconceived notion that AI is always right are more willing to turn to AI. As such, if we train medical students to use ChatGPT, will they be more predisposed to automation bias in the future when they become residents? Although there is no direct answer to this question, given what is known about the medical school curriculum, the context of the student population being composed of digital natives, and the AI solutionism mentality, the possibility of this happening seems likely. Some medical students will take their past, positive interactions with ChatGPT, wherein they received the right response, as confirmation that ChatGPT is reliable. The concern here is that students’ perceptions of the reliability of ChatGPT dictate their views on AI, including AI in the clinical setting, making it easier for them to become susceptible to automation bias. Although some suggest using AI suppression, an approach where an AI’s recommendations are not provided if there is “a higher misleading probability,” to mitigate the risk of automation bias, there appears to be no concrete solutions to solving this problem, especially in the context of the “novice” medical student and resident population [20]. It must also be acknowledged that sometimes, AI use cannot be completely avoided in the health care setting. Thus, in controlling the reoccurrence of automation bias, I believe that students must not only be aware of this potential problem but also build the skills required to prevent this mentality. When addressing the risks of AI in the medical school curriculum, automation bias needs to be a discussion topic. Besides teaching about automation bias, when training medical students, it is important to consider the “hidden curriculum” about using AI, that is, the implied lessons, cultures, and views that students learn in lectures or from observations of faculty [21]. If faculty also fall into the trap of AI solutionism, this will lead to a biased perspective on AI and contribute to the “hidden curriculum.” Faculty should serve as an example for students by ensuring that students have the right critical analysis skills and are comfortable with questioning results instead of accepting what is being given to them. This builds students’ confidence in trusting their instincts, which could deter them from automation bias.

When Should ChatGPT Be Used in Medical Schools?

Although this editorial takes a more critical stance on AI and ChatGPT, I want to clarify that this does not mean that these tools should never be used or that their functionalities are ineffective. Notably, in the preclinical phase, the medical school curriculum is not catered to students, as the focus is on ensuring that students have expertise on basic medical concepts, the structure and functions of the body, diseases, diagnoses, and treatment concepts [22,23]. This might be a challenge for some students who prefer different learning methods as opposed to the typical didactic method. ChatGPT can be a beneficial tool for students who prefer student-centered or self-directed learning, as it excels in summarizing information and generating practice questions [18,19,24,25]. Students who struggle with a concept in class or want further explanations could also use ChatGPT as an additional resource. Being able to personalize their learning experiences encourages students toward incorporating ChatGPT into their studies. As such, banning the use of ChatGPT could result in students being even more enticed to seek out the “forbidden” chatbot. Therefore, in addition to integrating AI education into the medical school curriculum and avoiding the “hidden curriculum” about AI, students should feel encouraged to use ChatGPT but only to a certain extent.

Despite the advantages of ChatGPT use, students should not be compelled to turn to ChatGPT for every task. For example, assignments that involve students writing about their firsthand experiences would not be appropriate for ChatGPT. With regard to a hypothetical student who delegated such an assignment to ChatGPT, van de Riddler et al [26] stated that “[r]eflections contribute to a learner’s professional development, but this learner robbed themself of an innate self-reflective opportunity.” Students lose a potential outlet for their emotions and the humanistic aspect of care when they delegate ChatGPT to the task of writing a self-reflection piece [27]. Notably, ChatGPT appears to be popular in the context of scientific writing for the following reasons: “efficiency and versatility in writing with
ChatGPT is an assistive tool but only when used in the right context. To minimize the risk of students developing automation bias, we need to ensure that students receive proper AI education, in which the courses and lessons will teach them about the ethical issues surrounding AI technologies, as well as the problem of automation bias, and encourage the moderate use of AI. ChatGPT should only be used for certain tasks, and it should not be the default resource that students turn to, as this could cause a domino effect, where students develop the automation bias mentality as a result of developing the AI solutionism mentality. Therefore, training medical students to avoid falling into these traps of AI solutionism and automation bias starts in the classroom. Again, the medical school curriculum must reflect the current needs of the students. Furthermore, faculty serve as an example for students; therefore, they should also be proactive in deterring the use of ChatGPT for all tasks and be careful not to contribute to the ‘hidden curriculum’ about AI. Overall, ChatGPT is an assistive tool but only when used in the right context.

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Conflicts of Interest

None declared.

References


**Abbreviations**

AI: artificial intelligence
**PDMP:** Prescription Drug Monitoring Program

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Short Paper

Impact of the COVID-19 Pandemic on Medical Grand Rounds Attendance: Comparison of In-Person and Remote Conferences

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Abstract

Background: Many academic medical centers transitioned from in-person to remote conferences due to the COVID-19 pandemic, but the impact on faculty attendance is unknown.

Objective: This study aims to evaluate changes in attendance at medical grand rounds (MGR) following the transition from an in-person to remote format and as a function of the COVID-19 census at Vanderbilt Medical Center.

Methods: We obtained the faculty attendee characteristics from Department of Medicine records. Attendance was recorded using a SMS text message–based system. The daily COVID-19 census was recorded independently by hospital administration. The main attendance metric was the proportion of eligible faculty that attended each MGR. Comparisons were made for the entire cohort and for individual faculty.

Results: The observation period was from March 2019 to June 2021 and included 101 MGR conferences with more than 600 eligible faculty. Overall attendance was unchanged during the in-person and remote formats (12,536/25,808, 48.6% vs 16,727/32,680, 51.2%; P=.44) and did not change significantly during a surge in the COVID-19 census. Individual faculty members attendance rates varied widely. Absolute differences between formats were less than –20% or greater than 20% for one-third (160/476, 33.6%) of faculty. Pulmonary or critical care faculty attendance increased during the remote format compared to in person (1450/2616, 55.4% vs 1004/2045, 49.1%; P<.001). A cloud-based digital archive of MGR lectures was accessed by <1% of faculty per conference.

Conclusions: Overall faculty attendance at MGR did not change following the transition to a remote format, regardless of the COVID-19 census, but individual attendance habits fluctuated in a bidirectional manner. Incentivizing the use of a digital archive may represent an opportunity to increase faculty consumption of MGR.

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KEYWORDS
continuing medical education; COVID-19; distance education; professional development; virtual learning

Introduction

Medical grand rounds (MGR) has evolved from the bedside [1] to a weekly presentation to the entire department [2]. Due to the COVID-19 pandemic, the format of MGR has undergone another transition, from in person to remote. While MGR attendance patterns for in-person conferences have been reported [3], the impact of remote conferences on faculty attendance at MGR is unknown. The analysis of remote surgical conferences [4,5] has been limited by sample size and aggregate data.

We propose that including more faculty from multiple specialties and individual conference or attendee data will provide more robust analysis that may inform returning to an in-person format, maintaining a remote format, or using a hybrid approach. Therefore, using our institution’s cloud-based attendance recording database, we (1) evaluated MGR attendance over time...
before and after the transition to the remote format and (2) assessed the temporal relationship between our institution’s COVID-19 census and attendance at MGR conferences.

Methods

Study Design, Participants, and Setting
We performed a retrospective cohort study of MGR attendance for all Department of Medicine (DOM) clinical faculty at Vanderbilt Medical Center active between March 2019 and June 2021. All conferences before March 12, 2020, were in person, and all conferences on or following this date were remote.

Attendee Characteristics
For each division within the DOM, the number of faculty eligible to attend each conference as well as the number of faculty that attended each conference were available, as was each faculty member’s academic rank (assistant, associate, or full professor).

Recording of Conference Attendance
Attendance was recorded by a cloud-based continuing medical education (CME) system during the entire observation period. Faculty indicate their attendance by sending an SMS text message containing the unique numeric code for that conference to a specific CME number. Conference attendance is registered as a binary outcome. The number of faculty considered to have attended a conference was obtained directly from this system. The number of faculty considered not to have attended was defined as the difference between the number of faculty eligible to attend and the number for whom attendance was recorded. The proportion of attendance was defined as the ratio of those who attended to those who were eligible over a given time frame (ie, in person or remote).

Individual-Level Attendance Data
For each faculty member, the CME system generates a unique user number that is not related to any other identification mechanism or coupled to any other database. By removing all identifying information from faculty members’ attendance data except this user number, we could track individual attendance over time without the capability of linking these data to a given faculty member’s actual identity.

Archived Conferences
Beginning in November 2019, digital recordings became available shortly after each MGR. Attendance credit was not given for consuming MGR in this manner. The number of faculty members that accessed a given MGR and the date on which each faculty member accessed the conference were available from the archive.

Acquisition of COVID-19–Related Data
Our institution tracked the census of hospital inpatients with positive COVID-19 tests as well as the subset of that group that required intensive care unit (ICU) care or mechanical ventilation. The COVID-19 burden on a given day included the total number of COVID-19 patients (cases) relative to the peak observed during the observation period (calculated as cases or peak), the proportion of patients with COVID-19 requiring ICU care relative to the number of cases (calculated as ICU or cases), and the proportion of patients with COVID-19 requiring mechanical ventilation (calculated as ventilator or cases). We defined the “surge” as the interval between December 2020 and January 2021, when COVID-19 cases were at their maximum.

Statistical Analysis
The main analyses compared the attendance rates during the entire in-person and remote periods as well as during the surge. Additional analyses stratified attendance by academic rank. All comparisons were made using the chi-square test in GraphPad Prism (version 9.2.0; GraphPad Software). For individual attendees, the difference between attendance rates at in-person and remote conferences was calculated, as were the characteristics of the resulting distribution.

Ethical Considerations
This investigation was considered nonresearch activity by the Vanderbilt Medical Center’s institutional review board (number 211362). The need for informed consent was waived because of the retrospective nature of the study.

Results

Cohort Characteristics and Overall Attendance Observations
Characteristics of the MGR conferences, speakers, and faculty attendees are displayed in Table 1.
Table 1. Conference and attendee characteristics.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Value</th>
<th>Value at the end of the observation (range during observation period)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conferences, n</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total during observation period</td>
<td>101</td>
<td>N/A(^a)</td>
</tr>
<tr>
<td>In person (prepandemic)</td>
<td>47</td>
<td>N/A</td>
</tr>
<tr>
<td>Remote (intrapandemic)</td>
<td>54</td>
<td>N/A</td>
</tr>
<tr>
<td>Topic, n</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cardiology</td>
<td>19</td>
<td>N/A</td>
</tr>
<tr>
<td>Endocrine</td>
<td>10</td>
<td>N/A</td>
</tr>
<tr>
<td>Gastroenterology</td>
<td>12</td>
<td>N/A</td>
</tr>
<tr>
<td>General internal medicine</td>
<td>15</td>
<td>N/A</td>
</tr>
<tr>
<td>Geriatric medicine</td>
<td>3</td>
<td>N/A</td>
</tr>
<tr>
<td>Hematology or oncology</td>
<td>10</td>
<td>N/A</td>
</tr>
<tr>
<td>Infectious disease</td>
<td>10</td>
<td>N/A</td>
</tr>
<tr>
<td>Nephrology</td>
<td>7</td>
<td>N/A</td>
</tr>
<tr>
<td>Pulmonary or critical care</td>
<td>7</td>
<td>N/A</td>
</tr>
<tr>
<td>Rheumatology</td>
<td>5</td>
<td>N/A</td>
</tr>
<tr>
<td>Speaker, n</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Internal</td>
<td>41</td>
<td>N/A</td>
</tr>
<tr>
<td>External</td>
<td>60</td>
<td>N/A</td>
</tr>
<tr>
<td>Faculty attendance(^b), mean (SD)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total eligible to attend</td>
<td>579 (22)</td>
<td>611 (544-612)</td>
</tr>
<tr>
<td>Cardiology</td>
<td>100 (2)</td>
<td>103 (95-103)</td>
</tr>
<tr>
<td>Endocrine</td>
<td>25 (2)</td>
<td>28 (23-28)</td>
</tr>
<tr>
<td>Gastroenterology</td>
<td>41 (2)</td>
<td>43 (38-43)</td>
</tr>
<tr>
<td>General internal medicine</td>
<td>175 (8)</td>
<td>187 (161-187)</td>
</tr>
<tr>
<td>Hematology or oncology</td>
<td>65 (2)</td>
<td>69 (60-69)</td>
</tr>
<tr>
<td>Infectious disease</td>
<td>43 (1)</td>
<td>45 (40-45)</td>
</tr>
<tr>
<td>Nephrology</td>
<td>33 (2)</td>
<td>36 (31-36)</td>
</tr>
<tr>
<td>Pulmonary or critical care</td>
<td>46 (2)</td>
<td>46 (42-49)</td>
</tr>
<tr>
<td>Rheumatology</td>
<td>22 (1)</td>
<td>23 (21-23)</td>
</tr>
<tr>
<td>Assistant professor</td>
<td>328 (16)</td>
<td>349 (279-350)</td>
</tr>
<tr>
<td>Associate professor</td>
<td>107 (1)</td>
<td>109 (105-109)</td>
</tr>
<tr>
<td>Full professor</td>
<td>143 (11)</td>
<td>149 (107-151)</td>
</tr>
</tbody>
</table>

\(^a\)N/A: not applicable.

\(^b\)The number of faculty in the subspecialties is fewer than the total due to not listing smaller divisions. Faculty categorized by academic rank may not sum to the total due to a small number of transitions between ranks.

**Figure 1A** shows (1) the time series of MGR attendance over the entire observation period and the number of times a given MGR was accessed from the cloud-based archive within 1 month of the conference, (2) the concurrent time series of COVID-19 cases as a proportion of the peak number recorded during the observation period, and (3) the time series of COVID-19 cases requiring ICU care and ICU cases requiring mechanical ventilation, both as proportions of the number of COVID-19 cases. Despite increases in remote attendance during the beginning of the pandemic (**Figure 1B**) and a brief increase as the surge began to subside (**Figure 1C**), there was no difference in attendance at MGR during the in-person format and the remote format over the entire observation period (12,536/25,808, 48.6% vs 16,727/32,680, 51.2%; \(P=.44\)). The proportion of faculty accessing the MGR digital archive remained low throughout the observation period, never exceeding 5% for any lecture and often not exceeding 1% (mean 0.7%, SD 1.3%).
Figure 1. Time series of medical grand rounds (MGR) attendance and concurrent COVID-19 burden. (A) The entire observation period, (B) focus on the beginning of the remote format, and (C) focus on the surge. At the onset of the remote format, there is a nonsustained increase in attendance. As the COVID-19 census increased rapidly leading up to the peak census, there was no change in attendance. During the peak of the surge, there is a very small transient reduction in attendance followed by an extremely brief increase in attendance during a period of rapid decline in the COVID-19 census. Access to archived MGR lectures remained low during the entire observation period. ICU: intensive care unit.

MGR attendance stratified by academic rank across the in-person and remote formats is shown in Figure 2. Associate (3249/5788, 56.1% vs 2515/4989, 50.4%; \( P < .001 \)) and full professor (3309/7718, 42.9% vs 2433/6757, 36%; \( P < .001 \)) attendance was higher at MGR during the remote format relative to the in-person format.

Figure 2. Attendance at medical grand rounds stratified by academic rank. Assistant professor attendance was the same regardless of conference format, whereas associate and full professor attendance increased during the remote format relative to in person. *\( P < .001 \).

Subinterval and Subgroup Analyses

There was no difference in attendance during the surge compared to the 2 months before (October to November 2020; 2071/4218, 49.1% vs 2194/4229, 51.9%; \( P = .38 \)) or 1 year before (December 2019 to January 2020; 2028/3990, 50.8% vs 2194/4229, 51.9%; \( P = .34 \)).

The attendance trends of DOM subspecialties that were particularly impacted by the pandemic are superimposed on the overall DOM trend in Figure 3 for pulmonary or critical care (CC), infectious diseases (ID), and general internal medicine (GIM).
Selected subspecialty attendance trends. There are distinct qualitative patterns of medical grand rounds (MGR) attendance relative to the entire Department of Medicine (DOM) cohort for faculty in (A) pulmonary or critical care (CC), (B) infectious diseases (ID), and (C) general internal medicine (GIM).

Pulmonary or CC attendance during the remote format was higher than during the in-person format (1450/2616, 55.4% vs 1004/2045, 49.1%; \( P < .001 \)). This attendance pattern persisted while cases were rising and peaking during the surge, when demands on this portion of the faculty were likely greater than prepandemic. ID faculty had higher attendance throughout the entire observation period relative to the whole DOM cohort. The GIM faculty consistently attended MGR less frequently than the rest of the DOM cohort, including a sizable decrease during the peak of the surge.

**Individual-Level Analyses**

Data were available for 476 faculty eligible to attend all the MGR during the observation period. As shown in Figure 4A, attendance rates during in-person conferences did not predict attendance rates for remote conferences. As displayed in Figure 4B, the distribution of the absolute difference between remote and in-person attendance rates is relatively symmetric around the null, but outliers at both tails are noted. Attendance decreased by at least 20% for nearly 15% (64/476; 13.4%) of faculty and increased by at least that amount for 20.2% (96/476) of faculty. The distribution of the differences in individual faculty attendance between remote and in-person conferences is shown in Figure 4C, stratified by in-person attendance rates. The distributions of the 2 lowest categories of in-person attendance exhibit positive skewness, while the remaining categories demonstrate negative skewness, indicating that the direction of the changes in individual attendance patterns observed with the transition in conference format varied based on in-person attendance. Lastly, 4.8% (23/476) of faculty exhibited absolute differences of 50% in attendance between formats.
Discussion

Principal Findings

Overall faculty attendance at MGR remained constant regardless of conference format, suggesting no disadvantage to the remote format. In addition, there may be substantial cost savings [6] and beneficial environmental impacts [7] associated with the remote format as it pertains to external speakers, who comprised the majority (60/101, 59.4%) of this cohort.

The increase in attendance of associate and full professors during the remote format may indicate fewer concurrent clinical obligations for these groups compared to their more junior colleagues. COVID-19–related MGR lectures at the beginning of the remote period may have led to the concurrent initial increase in attendance [8], but attendance quickly regressed to the mean, which was maintained even during a subsequent period of rapid rise and peak in COVID-19 burden.

Paradoxically, pulmonary or CC faculty attendance increased during the pandemic. It is possible that the attendance of the subgroup of non-ICU providers within pulmonary or CC may have increased during the pandemic while the attendance of their ICU-based colleagues declined. We speculate that the decreased attendance of the division of GIM was contributed to by lower attendance within the section of hospital medicine, perhaps because of burnout [9].

Individual faculty attendance habits did not remain static in response to the change in conference format. The pandemic or the remote format may have motivated faculty to attend MGR who did not regularly do so, thus taking the place of faculty that were unable to attend due to increased clinical or administrative responsibilities. The presence of outliers at both extremes of attendance shifts may enrich further investigations of specific drivers of conference attendance, which could inform decisions regarding conference format moving forward.

Archived conferences were infrequently accessed throughout the observation period. Encouraging asynchronous viewing may increase consumption of MGR among faculty who are unable to do so in real time. Offering attendance credit for viewing MGR asynchronously could incentivize otherwise nonattending faculty.

Limitations

This study did not use surveys or other methods of obtaining feedback from faculty regarding their attendance patterns relative to the mode of MGR presentation, as collecting these data was not feasible given the study’s retrospective design.

Attendance does not guarantee the observer has learned from MGR, although mandatory evaluations may not assess this objective either [10].

Conclusions

Overall faculty attendance at MGR was neither durably affected by a pandemic-related transition from in-person to a remote format nor by concurrent COVID-19 burden, although individual attendance behaviors varied considerably. If coupled with archived conference recordings, the remote format may be an equally attended and more cost-effective option for presenting MGR in a postpandemic era.
Acknowledgments
The authors wish to thank Attallah Stout and Joseph Braeuner for assistance with medical grand rounds topic, speaker, and attendance data; Ariel Dunham for assistance with the medical grand rounds digital archive; and Brandi Cherry and Chad Fitzgerald for assistance with COVID-19 census data.

Conflicts of Interest
None declared.

References

Abbreviations
CC: critical care
CME: continuing medical education
DOM: Department of Medicine
GIM: general internal medicine
ICU: intensive care unit
ID: infectious diseases
MGR: medical grand rounds

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Collaborative Development of an Electronic Portfolio to Support the Assessment and Development of Medical Undergraduates

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Abstract

This study outlines the development of an electronic portfolio (e-portfolio) designed to capture and record the overall academic performance of medical undergraduate students throughout their educational journey. Additionally, it facilitates the capture of narratives on lived experiences and sharing of reflections, fostering collaboration between students and their mentors.

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KEYWORDS
e-portfolio; education; health education; learning; medical students; medical school curriculum; medical education; student support; software

Introduction

The Brazilian curriculum guidelines for medical schools incorporate competencies in information technology, emphasizing students’ co-responsibility in acquiring soft skills such as leadership, teamwork, and continuous professional development [1]. The curriculum experience must foster critical and reflective skills [2].

Ribeirão Preto Medical School at University of São Paulo, Brazil (FMRP-USP), is a 72-year-old traditional institution that initiated a curriculum change in January 2023. In this new proposal, we introduced a longitudinal axis and curricular unit called personal and professional development (PPD). The primary objective of PPD is to foster self-reflection on lived experiences, regular self-assessment, and monitoring of the students’ progress in curricular and extracurricular activities, with a mentor’s support.

To support the implementation of the PPD curricular unit, we collaboratively developed a software to serve as the electronic portfolio (e-portfolio) and record the overall academic performance of undergraduate medical students throughout their educational journey. An additional expectation is to encourage and guide teachers to provide and register formative assessments in their disciplines and rotations, and to document their experiences and reflections.

Methods

The collaborative development of the system involved developers, health educators, and students, which was crucial to ensure that the e-portfolio meets the needs and expectations of all stakeholders. Developers contributed technical expertise for functionality and accessibility, while educators shaped content based on educational principles. Students, as primary users, provided valuable feedback.

The main challenge in developing the e-portfolio was to create an initial set of requirements. With various participants bringing different ideas, there was a multitude of perspectives in the initial phase, which brought fundamental enrichment during development but also increased the difficulty of integrating all perspectives.

These challenges were overcome with Scrum [3] integrated with socio-technical research methodology to facilitate the collaborative environment. We implement Scrum practices, such as daily 5-minute meetings and biweekly 30-minute sprint reviews, ensuring incremental and continuous deliveries and communication between the development team and stakeholders, mainly regarding system development. Additionally, we integrated the socio-technical research methodology [4] into SCRUM, aiming to understand the software requirements as well as the various social and technological factors involved.
Regarding software development technologies, we used HTML, CSS, PHP, and the MySQL database management system.

**Ethics Approval**

The study received approval from the research ethics committee of the Clinical Hospital of FMRP-USP (CAAE: 67577523.1.0000.5440).

**Results**

The e-portfolio utilizes a web application architecture (Figure 1). Initially, we developed a structure to manage the registration of all the programs within the medical school, different curricular units, and offerings. We created a registration module for students and faculty members, allowing those to act as mentors, teachers, and discipline coordinators. Additionally, e-portfolio enables the recording of direct observed assessments in clinical settings, using preregistered forms based on methods such as mini-clinical evaluation exercise (Mini-CEx) [5], 360-degree assessment [6], One-Minute Preceptor, direct observation of procedural skills (DOPS), and case-based discussion/chart-stimulated recall (CBD/CSR) [7].

For narratives in medicine [8], there is a specific form to guide students on how to report a lived experience followed by a meaningful reflection, based on the REFLECT rubric for assessing reflective writing [9] (Figure 2).

Students are allowed to fill in data in their private profile (Figure 1), access their disciplines and received assessments, respond to formative assessments, record significant events for their education, check and compare their performance with their cohort, register extracurricular activities, and consult critical incidents recorded.

e-Portfolio enables students, discipline coordinators, and members of the student assessment committee to track assessments and feedback received, providing a longitudinal and progressive view of the student’s cognitive, psychomotor (skills), and attitudinal development (Figures 1 and 2).
Figure 1. Profile and performance report of the medical student in the electronic portfolio (e-portfolio). (A) Profile created by the student in the e-portfolio. (B) Student’s performance in various subjects is presented in relation to the radar chart: the blue line represents a comparison with the cohort mean (depicted by the gray area).
Discussion

This work presents the successful development of an e-portfolio at FMRP-USP. The e-portfolio is continuously enhanced and updated, and it is currently in a state suitable for use in a pilot study. The use of similar tools has been recognized for stimulating personal reflection, fostering collaboration, and strengthening digital literacy among students, encouraging active participation in the learning process [10].

The application of Scrum offered an adaptable framework, promoting efficient collaboration among stakeholders. Additionally, socio-technical research methods, such as qualitative interviews involving in-depth conversations with individuals or groups to explore their experiences related to technology, provided valuable insights into the needs and dynamics of end users in the educational context. The use of Scrum with socio-technical research methods enables a more integrated, collaborative, and reflective approach during development.

Future Steps

We intend to evaluate e-portfolio usability, effectiveness, acceptance, and satisfaction in practical contexts with the objective of consistently enhancing the system and its outcomes.
Acknowledgments

We would like to express our gratitude to the Ribeirão Preto Medical School, University of São Paulo, and the startup Intersection (Ribeirão Preto, Brazil) for their partnership in software development. We would like to thank Prof Francisco S Guimarães for all the support and follow-up with the medical students and mentors. Additionally, we extend our appreciation to the Conselho Nacional de Desenvolvimento Científico e Tecnológico – Brasil (CNPq). This study was financed in part by CNPq (process no.: 001). Furthermore, this study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (CAPES) – Finance Code 001.

Authors’ Contributions

LRAS and VRB contributed to the study concept and design, data acquisition, analysis, interpretation, and manuscript writing. AMO, LMACS, GJA, WDLC, and DCBD contributed to the interpretation, manuscript writing, and critical review of the manuscript for important intellectual content. All authors read and approved the final manuscript.

Conflicts of Interest

None declared.

References


Abbreviations

CAPES: Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (Coordination for the Improvement of Higher Education Personnel)
CBD/CSR: case-based discussion/chart-stimulated recall
CNPq: Conselho Nacional de Desenvolvimento Científico e Tecnológico (National Council for Scientific and Technological Development)
DOPS: direct observation of procedural skills
e-portfolio: electronic portfolio
FMRP-USP: Ribeirão Preto Medical School, University of São Paulo
Mini-CEX: mini-clinical evaluation exercise
PPD: personal and professional development
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The Performance of ChatGPT-4V in Interpreting Images and Tables in the Japanese Medical Licensing Exam

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* all authors contributed equally

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Takashi Watari, MHQS, MD, PhD

Introduction

OpenAI’s ChatGPT, a leading large language model (LLM), has shown promise for medical purposes. The program can pass the United States Medical Licensing Examination (USMLE) and the Japanese Medical Licensing Exam (JMLE) [1-3]. However, previous studies regarding this software have focused on its text-based capabilities. ChatGPT-4 Vision (ChatGPT-4V), announced on September 25, 2023, includes image input features, potentially expanding the medical applications of the program [4]. To assess the multimodal performance of ChatGPT-4V in medicine, its performance on JMLE questions involving clinical images and tables was tested.

Methods

Overview

ChatGPT-4V was used to complete the 117th JMLE in the Japanese language (Figure S1 in Multimedia Appendix 1). Its responses were compared to the passing criteria and mean human examinee score of the JMLE. This study, conducted from October 12 to 14, 2023, used the September 25, 2023, version of the LLM (ChatGPT-4V) with a knowledge cutoff date of January 2022 (Multimedia Appendix 2 [5]). Human examinees’ correct response rates were obtained from statistics based on reports from actual JMLE examinees, calculated by medu4, a preparatory school for the JMLE [5,6].

Statistical Analysis

The mean and 95% CIs of the test scores are provided. A one-sample proportion test was used to compare the correct response rate of the human examinees with that of ChatGPT-4V. Statistical significance was set at $P<.05$ for all 2-tailed tests. All statistical analyses were conducted using Stata statistical software (version 17; StataCor).

Ethical Considerations

This study used previously available web-based data and did not include human participants. Therefore, Shimane University’s Institutional Review Board did not mandate ethics approval.

Results

Evaluation Outcomes

The responses to 386 questions from the 117th JMLE were used in this study. Using the Ministry of Health, Labor, and Welfare criteria, GPT-4V scored 85.1% on the essential knowledge section and 76.5% on the other sections of the JMLE, meeting the passing criteria [6]. For text-only questions, ChatGPT-4V achieved a correct response rate of 84.5%, similar to the mean human examinee score (Table 1). The correct response rate for questions with images was 71.9% for ChatGPT-4V, 13.1 points below the mean human examinee score ($P<.001$). The correct response rate for questions with tables (including figures) was 35.0% for ChatGPT-4V, which was significantly lower than the mean human examinee score (83.9%; $P<.001$).
Table. Correct response rates of ChatGPT Vision (ChatGPT-4V) and human examinees on the Japanese Medical Licensing Examination (JMLE).

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Total, n (%)</th>
<th>Examinees(^a), mean</th>
<th>GPT-4V, mean</th>
<th>95% CI</th>
<th>Difference</th>
<th>(P) value</th>
</tr>
</thead>
<tbody>
<tr>
<td>All questions</td>
<td>386 (100)</td>
<td>84.9</td>
<td>78.2</td>
<td>74.1-82.4</td>
<td>-6.7</td>
<td>.003</td>
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<td>Question category</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Essential knowledge</td>
<td>96 (24.9)</td>
<td>89.6</td>
<td>83.3</td>
<td>75.9-90.8</td>
<td>-6.3</td>
<td>.04</td>
</tr>
<tr>
<td>General clinical knowledge</td>
<td>144 (37.3)</td>
<td>83.1</td>
<td>70.8</td>
<td>63.4-78.3</td>
<td>-12.3</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Specific diseases</td>
<td>146 (37.8)</td>
<td>83.5</td>
<td>82.2</td>
<td>76.0-88.4</td>
<td>-1.3</td>
<td>.67</td>
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<tr>
<td>Type</td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>General</td>
<td>190 (49.2)</td>
<td>84.6</td>
<td>78.9</td>
<td>73.2-84.7</td>
<td>-5.7</td>
<td>.03</td>
</tr>
<tr>
<td>Clinical</td>
<td>149 (38.6)</td>
<td>84.1</td>
<td>77.2</td>
<td>70.4-83.0</td>
<td>-6.9</td>
<td>.02</td>
</tr>
<tr>
<td>Clinical sentence</td>
<td>47 (12.2)</td>
<td>88.5</td>
<td>78.7</td>
<td>67.0-90.4</td>
<td>-9.8</td>
<td>.04</td>
</tr>
<tr>
<td>Imaging and table questions</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Text only</td>
<td>252 (65.3)</td>
<td>84.9</td>
<td>84.5</td>
<td>80.1-89.0</td>
<td>-0.4</td>
<td>.87</td>
</tr>
<tr>
<td>With images</td>
<td>114 (29.5)</td>
<td>85.0</td>
<td>71.9</td>
<td>63.7-80.2</td>
<td>-13.1</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>With tables</td>
<td>20 (5.2)</td>
<td>83.9</td>
<td>35.0</td>
<td>14.1-55.9</td>
<td>-48.9</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

\(^a\)The correct response rates of human examinees are based on a survey of actual human examinees, reported by medu4, a preparatory school for the JMLE [5].

Discussion

Principal Results

Although ChatGPT-4V demonstrated proficiency in text-centric questions, the correct response rates were significantly lower for image and table-oriented questions. ChatGPT-4V may have poorer text comprehension skills compared to ChatGPT-4, even when image processing is not required [7]. Additionally, a language bias may obscure the image context when interpreting images and texts simultaneously, potentially leading to an overreliance on prior text information, even when it contradicts the image context, a phenomenon called “hallucination” [8]. These factors may have led to ChatGPT-4V’s lower rate of correct responses to questions involving images.

Furthermore, responding to questions with tables requires interpreting the Japanese characters within the tables. OpenAI has verified that its GPT-4V model misrecognizes symbols, including image characters [4]. Previous studies have noted that GPT-4V relies on text-based information rather than an analysis of tables when answering questions [8]. In addition, the program’s performance diminishes when interpreting characters in non-Latin languages [9]. These factors may explain the observed decline in performance when interpreting tables containing Japanese characters.

The multimodal LLM GPT-4V is unreliable in interpreting information presented in image or tables, especially for medical purposes [4]. Further development of the program is required for diagnostic applications.

Limitations

This study has several limitations. First, different results may be obtained even when using the same methods owing to the inherent randomness of ChatGPT or version changes in ChatGPT. A report indicates that test results can vary with repeated responses from ChatGPT [10]. Furthermore, when providing images to ChatGPT, we did not remove blank spaces, indicating that the quality of images sent to ChatGPT could also affect the outcomes. Second, the JMLE includes options that, if selected twice or more, will result in failure. However, these options are not publicly disclosed, making them unaccounted for in this study [5]. Finally, although this study focused on ChatGPT, ongoing advancements in other multimodal LLMs should also be considered.

Conclusions

ChatGPT-4V successfully passed the 117th JMLE, demonstrating proficiency in handling including image- and table-based questions. However, more developments are needed to improve its ability to interpret tables. Further research should assess the safety and efficacy of ChatGPT-4V as a multimodal LLM in supporting medical practice, facilitating learning in clinical environments and advancing medical education.
Acknowledgments

We would like to thank Dr Kota Sakaguchi, Shimane University Hospital, for his careful support throughout this study. We would also like to thank Dr Sanjay Saint, a professor at the University of Michigan, for his numerous contributions and support in this work.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Additional statistics.
[DOCX File, 2285 KB - mededu_v10i1e54283_app1.docx ]

Multimedia Appendix 2
Detailed methodology.
[DOCX File, 17 KB - mededu_v10i1e54283_app2.docx ]

References


Abbreviations

ChatGPT-4V: ChatGPT 4 Vision
JMLE: Japanese Medical Licensing Examination
LLM: large language model
USMLE: United States Medical Licensing Examination
Research Letter

Using AI Text-to-Image Generation to Create Novel Illustrations for Medical Education: Current Limitations as Illustrated by Hypothyroidism and Horner Syndrome

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Abstract

Our research letter investigates the potential, as well as the current limitations, of widely available text-to-image tools in generating images for medical education. We focused on illustrations of important physical signs in the face (for which confidentiality issues in conventional patient photograph use may be a particular concern) that medics should know about, and we used facial images of hypothyroidism and Horner syndrome as examples.

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KEYWORDS
artificial intelligence; AI; medical illustration; medical images; medical education; image; images; illustration; illustrations; photo; photos; photographs; face; facial; paralysis; photograph; photography; Horner's syndrome; Horner syndrome; Bernard syndrome; Bernard's syndrome; miosis; oculosympathetic; ptosis; ophthalmoplegia; nervous system; autonomic; eye; eyes; pupil; pupils; neurologic; neurological

Introduction

Artificial intelligence (AI) has become integral in medicine, outperforming skilled radiologists in certain domains [1]. However, there is limited exploration of AI's potential in producing illustrations for medical education [2,3]. Confidentiality concerns can limit traditional patient photo use, especially when facial features are essential [4]. Using widely available AI text-to-image tools, we aimed to create images portraying distinct facial signs important for medical trainees—hypothyroidism (myxedema) and Horner syndrome [5,6]. These tools generate unique, high-quality images based on text prompts, utilizing learned probability distributions rather than pre-existing images [7].

Methods

ChatGPT was used to generate prompts for the two AI text-to-image tools used in this study—DALL·E 2 and Midjourney (Multimedia Appendix 1) [8-10], with which the prompts were used to generate images for hypothyroidism and Horner syndrome. The images were assessed and selected, using the following suitability criteria:

1. Images were excluded if any of the following features were present: insufficient coverage of the face, blurred images, a lack of realistic or humanoid features, a lack of continuity of edges, background noise, cloning errors, and geometrical and shadow inconsistencies.

2. Remaining images were accepted if they adequately represented the facial features of hypothyroidism or Horner syndrome, as judged by the coauthors (all were experienced physicians).

If adequate images could not be generated via the above methods, additional prompts, which were not generated with ChatGPT, were used. If adequate images were still not generated, then secondary editing via Microsoft Paint and GNU
Image Manipulation Program (GIMP) was performed on the best image to try and meet the criteria listed above.

**Results**

**Facial Features of Hypothyroidism**

Using ChatGPT, the following text prompt was generated (restricted to the DALL·E 2 prompt word limit):

*Generate an image depicting a middle-aged Caucasian woman with hypothyroidism presenting with facial myxedema. The woman should be shown in a frontal view, focusing on her face, scalp, and neck, without any makeup. The face must be very rounded and extreme scalp balding with coarse hair. Skin looks dry and pale. Outer eyebrows have a paucity of hairs, eyelids look very puffy. She looks tired.*

The prompt was used to generate 120 images. Of these, 53 were removed, using our preset exclusion criteria. Of the remaining 67, only 17 met some of the criteria for adequately representing facial features of hypothyroidism. The best image was selected as Figure 1 [9], with no additional editing needed.

**Figure 1.** Artificial intelligence text-to-image production of facial features typical of hypothyroidism (myxedema) showing classical clinical features, including a rounded face with dry, pale skin; puffy eyelids; a general appearance of tiredness; and partial balding with coarse hair and loss of hair in the eyebrows (especially in the outer third). This image was produced by using DALL·E 2 [9] alone and without additional editing.

**Horner Syndrome**

The following prompt was obtained from ChatGPT:

*Create an illustrative depiction of a patient displaying Horner’s syndrome, emphasizing the key clinical features, such as ptosis (drooping of the upper eyelid), miosis (constricted pupil), and anhidrosis (lack of sweating) on one side of the face. Ensure the image is clear and medically accurate, aiding in the understanding of this neurological condition.*

Of the 120 images, 85 met our exclusion criteria, but none met our inclusion criteria, even after alternative prompts and DALL·E 2 were used. We therefore selected the best image (produced by Midjourney) and then performed secondary editing with Microsoft Paint and GIMP (Figure 2 [10]). This produced an image of Horner syndrome that was judged as adequate.

**Figure 2.** Generated illustration of Horner syndrome. Image 1 was produced by using Midjourney [10]. Image 2 shows the result after minor image editing (as described in our Methods section) to attenuate the key teaching features, which are labeled in image 3 (A: ptosis; B: miosis; C: apparent enophthalmos; D: upside-down ptosis).
Discussion

We aimed to explore the potential, as well as the current limits, of AI text-to-image generation in producing illustrations of medical conditions affecting the face. Without the use of high-quality medical images, it can be more challenging to teach others about these important conditions [11]. We showed that AI text-to-image generation is readily possible for hypothyroidism—a condition with symmetrical features. However, for Horner syndrome—a condition with asymmetrical features—adequate images could only be produced after some additional slight editing, reflecting a possible limiting factor of these tools. Ours are the first AI-generated images of classical facial features of hypothyroidism and Horner syndrome that we are aware of.

Confidentiality has become an increasing concern in the use of medical images over the last few decades. Text-to-image tools have ethical issues, including issues of consent for the original photos used to train these tools. Additionally, issues of accuracy are key. Nonmedics might be misled on medical signs by using such tools. Targets for future research are the potential for biases with these tools and the danger of stereotypes being perpetuated. Despite these limitations, AI-generated images may enhance case-based learning, allowing students to study and analyze a diverse range of medical cases. Text-to-image tools show exciting potential and may allow easier access to high-quality images in medical education [12,13].

Conflicts of Interest
None declared.

Multimedia Appendix 1
Tools used in this article (all prompts entered in English).
[DOCX File, 13 KB - mededu_v10i1e52155_app1.docx ]

References

Abbreviations
AI: artificial intelligence
GIMP: GNU Image Manipulation Program
Kumar A, Burr P, Young TM
Using AI Text-to-Image Generation to Create Novel Illustrations for Medical Education: Current Limitations as Illustrated by Hypothyroidism and Horner Syndrome
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A Proposed Decision-Making Framework for the Translation of In-Person Clinical Care to Digital Care: Tutorial

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Abstract

The continued demand for digital health requires that providers adapt thought processes to enable sound clinical decision-making in digital settings. Providers report that lack of training is a barrier to providing digital health care. Physical examination techniques and hands-on interventions must be adjusted in safe, reliable, and feasible ways to provide digital care, and decision-making may be impacted by modifications made to these techniques. We have proposed a framework to determine whether a procedure can be modified to obtain a comparable result in a digital environment or whether a referral to in-person care is required. The decision-making framework was developed using program outcomes of a digital physical therapy platform and aims to alleviate barriers to delivering digital care that providers may experience. This paper describes the unique considerations a provider must make when collecting background information, selecting and executing procedures, assessing results, and determining whether they can proceed with clinical care in digital settings.

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KEYWORDS
clinical decision-making; digital health; telehealth; telerehab; framework; digital medicine; cognitive process; telemedicine; clinical training

Introduction

Background

Digital health is revolutionizing health care, and the COVID-19 pandemic has led to rapid acceleration of the use of digital health technologies, particularly the adoption of telehealth. Digital health, including the use of telehealth or telemedicine, allows health care practitioners to provide services without being in the same physical location as the patient. Telehealth can include synchronous or asynchronous messaging with providers, video calls, audio-only calls, and the secure transmission of information over the internet between patients and their providers [1]. Digital health can also include information gathered by medical devices, wearable sensors, apps, or other software [2]. The application of technology in health care has a vast potential to increase access to care and improve quality.

Research indicates that telehealth outcomes are equivalent to in-person care in rehabilitation [3-5] and can be an effective intervention for addressing pain and function limitations in a variety of musculoskeletal conditions [6]. Clinical outcomes from telehealth episodes of care are comparable with in-person rehabilitation for conditions such as osteoarthritis, low-back pain, hip and knee replacement, multiple sclerosis, and cardiac and pulmonary rehabilitation [3]. Increasing evidence supports that telehealth physical therapy delivered by a mobile app provides clinical outcomes comparable with those of in-person care [3,4,7]. Research also reveals that telehealth decreases travel time and costs [8]. It is well documented that patients recognize the benefits of telehealth as well, demonstrating high engagement [9-11] and high levels of satisfaction across multiple metrics, including quality of care, convenient access to multiple specialists, improved care and coordination with digital care, and outcomes similar to in-person care [12-17].

Despite evidence of the benefits of telehealth, there are barriers to the integration of telehealth into traditional health care models. For example, physical therapists (PTs) report apprehension toward utilizing telehealth in their practice, reporting insufficient preparation and inadequate knowledge about how to implement telehealth visits, influencing providers’ acceptance, preferences, and outcomes [12,18,19]. Further, less than half (42%) of health care providers surveyed believed telehealth was as effective as face-to-face care, and 21% reported insufficient training [18,19]. Another significant barrier to digital health adoption is the belief that lack of physical contact hampers accurate diagnosis and management [12,18,19]. Successful integration of telehealth into traditional health care models will only be achieved through addressing provider beliefs about the efficacy of telehealth and instruction in providing equivalent care through a new model.

Telehealth requires the translation of traditional clinical skills to a new medium [20,21]. Remote patient care is characterized by dynamic patient environments, unique safety concerns, and
a lack of traditional patient care tools, forcing the provider to act in new and dynamic ways to provide effective care. When encountering new clinical scenarios, many providers look for guidance through decision-making frameworks. Frameworks outline a structured and systematic approach to problem-solving that incorporates evidence and specific context, and promotes informed decisions [22]. When used in health care, decision-making frameworks can ensure consistency, reduce bias, and enhance the quality of decisions and quality of care [22-24]. A standardized process assists health care professionals in assessing risks and benefits, improves outcomes, and provides patient-centered evidence-based care [24].

Delivering effective care in a digital health setting requires that health care providers adapt their thought processes to account for the nuances of the interactions between technology and the patient to enable sound clinical decision-making in the digital health setting. This paper introduces a decision-making framework to determine whether a clinical procedure is feasible in a telehealth setting with similar quality, accuracy, and reliability as in-person encounters, or when the use of an equivalent but alternative procedure is most appropriate. We propose that utilizing a clinical decision-making framework can alleviate clinicians’ concerns about the efficacy of digital health and assist the implementation of clinical best practices in a digital setting. The purpose of this paper is threefold: (1) to propose a decision-making framework to train and inform health care providers that increases provider efficacy with the translation of skills to this new medium; (2) to propose a thought model that allows quantitative testing through implementation research; and (3) to realize the potential for telehealth for patients and providers to improve access to care independent of geography.

Development of the Framework

This framework was the result of a review of the current literature and the authors’ combined expertise in providing telehealth physical therapy. The authors have a combined 18 years of experience in telehealth, including providing patient care, designing and implementing training for providers, as well as managing a nationwide network of telehealth PTs. This framework has been applied to clinical practice and refined based on the outcomes of over 10,000 patient cases.

Analysis of program outcomes and the identification of PT behaviors that lead to positive clinical outcomes influenced the development of this framework. Program data confirmed that provider behavior during telehealth episodes directly impacts clinical outcomes in an app-based telehealth physical therapy program [4] and that when interventions provide high value, patients will be highly engaged [11] resulting in cost savings [25]. Prior literature describes how to translate specific evidence-based evaluation techniques for the application of telehealth and how to utilize established clinical practice guidelines for telehealth episodes [26-32]. However, procedure-specific training cannot prepare providers for the dynamic nature of telehealth encounters that include variations in the patient’s environment, health status, caregiver support, digital literacy, equipment availability, and other factors. In response to the ever-changing context of telehealth visits and to fully equip health care providers working in a digital environment, a decision-making framework was developed. This framework was designed to help providers identify the relevant factors in the clinical picture, assess possible actions, and make decisions that lead to positive clinical outcomes. The process of defining this framework was iterative, data-driven, and emphasized patient-centered design. We incorporated an understanding of the users on our platform, the tasks they completed, and the digital environment; development was driven and refined by patient surveys, feedback, and outcomes. We believe this framework will assist clinicians in translating their clinical skills to digital practice to enable optimal clinical outcomes, convenience, and satisfaction. Initially, learning to leverage the steps of the framework may increase time in decision-making but as the clinician becomes experienced the process will become efficient and give more options for the telehealth environment.

Utilizing the Framework

Appropriate application of a decision-making framework in a clinical setting requires that certain conditions are met. First, the clinical problem must be within the scope of the clinician’s practice. This ensures the clinician is appropriately trained and licensed to provide care and make clinical decisions. In the case of digital health, appropriate training includes proficiency with digital tools, technology, and website manner in addition to medical or clinical training [33,34]. Second, the patient must be appropriate for digital care. Appropriateness for care requires that the patient’s cognition level, medical status, digital literacy, communication abilities, technology access, physical environment, and preference all support safe digital care interactions. Finally, providers must consider the security and regulatory implications of digital care, including ensuring compliance with HIPAA (Health Insurance Portability and Accountability Act), local and federal privacy regulations, and data security requirements. If the provider, patient, and technology all meet these conditions, the application of this framework is appropriate.

At each step of the process, the provider must determine whether telehealth is the most appropriate method of providing care. When a provider determines that telehealth is not appropriate for the patient, they should inform the patient of the next steps, which may include activation of emergency services, coordination of care to facilitate referral to a specialist, in-person visit, or obtaining labs or imaging. Figure 1 provides a visual representation of the steps included in this decision making framework.
Figure 1. The decision-making path. At every step of the patient encounter, providers must determine whether telehealth is the best option for the clinical scenario. The determination process should be the same whether the provider is using a traditional procedure or a procedure that has been modified for the patient’s environment. At each step, the provider must determine whether they can continue down the decision-making path, or if they need to return to the start of the decision-making process using an alternative procedure. If no acceptable digital option exists at any step, they must refer to in-person care.

Description of the Decision-Making Framework

Step 1: Collect Background Information
Clinicians may collect relevant clinical information using data from chart review and review of a digital intake form. The subjective interview of a telehealth visit should proceed as it does in an in-person visit, with emphasis on the chief complaint, relevant health history, current and past medical conditions, and social history. The subjective portion of the examination may also include a visual assessment of the patient’s environment, inquiry about equipment availability, and availability of caregiver support, which are factors unique to telehealth but enhance the clinical picture. If at the conclusion of the subjective interview, the provider has identified an urgent medical need, or that telehealth is not appropriate then the patient may be referred to in-person care at this time. If the provider is confident that they have collected the information needed to inform the objective examination and that it is safe and appropriate to continue with a telehealth objective examination, they will move to the next step.
Step 2: Select an Examination Procedure

Providers will select the examination procedures based on the information gathered in the subjective examination. Procedures should be evidence-based and relevant to the differential diagnosis process. Once a procedure has been selected, the provider must consider the feasibility, reliability, and validity of the procedure when performed in a digital setting.

To evaluate feasibility, we consider whether the patient has the resources, space, ability, and knowledge necessary to complete the procedure safely. The provider will consider information gathered in the subjective portion regarding the patient’s cognitive status, physical ability, social support, environment and technological resources, and time available to determine if the procedure can be accurately performed. If the setup for a test is complicated or the instructions are lengthy, the time constraints of a patient visit may make a test not feasible.

Reliability is the quality of a measure that produces reproducible scores on repeat administrations of a test. Reliability is thus a prerequisite for test validity [35]. Validity is the measure of how accurately a test measures the underlying trait of interest [35,36]. When assessing patients in-person, reliability is supported by a clinical environment standardized for all sessions. In digital health settings, tests are performed in the patient’s environment and providers must look for alternative ways to ensure results are reliable and valid. If a traditional procedure cannot be performed with acceptable feasibility and reliability, then providers should consider if an alternative procedure can provide the same clinical information. Alternative methods will be unique to the patient’s resources, abilities, and environment, but alternatives should be assessed for feasibility and reliability. Functional testing is often an acceptable alternative for traditional tests when the equipment or environment is standardized.

The reliability of functional tests can be increased if the same equipment in the home is used for subsequent testing. For example, a 30-second sit-to-stand test [37] using the same chair in the patient’s home will give a clinician reliable data for each assessment. Further, measurements such as joint range of motion, can be tracked by having the patient reach to low, medium, or high shelves in their home and reassessed using the same shelves. This technique allows the provider to monitor and document progress in an easily accessible, functional and standardized way within the patient’s environment.

Selecting a procedure means that the provider will make dynamic decisions unique to the patient they are seeing. For example, during an in-person visit, manual muscle testing of internal rotation of the shoulder is often used to indicate subscapularis muscle rupture or dysfunction. In digital settings, the provider cannot provide manual resistance, but the same information can be obtained using the Gerber test [38]. If the patient is unable to achieve the testing position for a Gerber test, a provider could consider functional strength testing such as lifting canned goods. In this scenario, the provider will ensure reliability by using the same number of cans at each assessment. To ensure validity, the provider must ensure that the patient is performing the test correctly; in this example, a patient lifting the canned goods with a straight arm would provide an invalid result but lifting with a bent elbow would appropriately stress the biceps and give a valid result.

If there is no procedure that can be performed that is feasible and reliable in the digital setting, and this information is required for clinical decision-making, then a referral to in-person care would be indicated. For example, if a clinician suspects rupture of the anterior cruciate ligament and determines that a Lachman test is necessary, but is not feasible via telehealth, then a referral for in-person assessment is required.

Step 3: Execute the Clinical Procedure

Performing the clinical procedures in digital settings requires different skills than in in-person settings. Digital settings require the provider to assist the patient in managing their environment and any relevant equipment needed during the visit. Therefore, it is incumbent on the provider to communicate with the patient explicitly about the procedure prior to execution and ensure they have the relevant equipment and can use it appropriately.

The provider should communicate what equipment is needed (eg, a sturdy chair with arms). Providers should give clear directions to the patient on how to set up any equipment and where the patient should be positioned. Additionally, the provider must describe how to utilize technology during the procedure. Appropriate audio, video, and lighting setup ensures the provider can see and hear the patient adequately while they perform the tasks. The provider should review each step of the procedure with the patient prior to performing it and allow the patient to ask questions or clarify instructions. The patient should have a good understanding of what information the procedure is gathering so that the patient can monitor and report the appropriate variable during the procedure. For example, during a balance assessment, the patient should understand if they are balancing for as long as they can without toe touches, or if they should count the number of toe touches within the given time frame. The provider should document the method used for the procedure, equipment, setup, and outcome to ensure subsequent tests can be performed in a standard way. If the patient is unable to perform the procedure as directed by the provider, then the provider should consider alternative procedures or referral to in-person care.

Step 4: Assess Results

Once the procedure has been performed, the provider determines whether the result answers the original clinical question and their confidence level in the result. Confidence will be affected by how accurately the patient was able to follow the provider’s instructions, and if technology worked as expected. If the patient performed the test incorrectly or if there was video or audio lag or poor clarity available, the provider may have low confidence in the result. A procedure that was performed as instructed in an environment that was reliably standardized using the same equipment and set up with technology that worked without disruption will provide high confidence.

Step 5: Proceed With Clinical Care, Repeat, or Refer

High confidence in the outcome allows the provider to continue care in the digital setting. If the provider has low confidence in the result, they can repeat steps 1 through 4 again using an
alternative procedure to achieve a result that provides high confidence. If the provider is seeking information that is essential to the care of the patient and no procedure can be performed in a manner that provides a result that is reliable, reproducible, and yields high confidence, then a referral to in-person care is needed. Table 1 provides a list of the factors that should be considered when making clinical decisions in digital settings.

Table. The relevant factors the provider should consider as they progress through the decision-making process. At each stage, the provider must determine whether telehealth is appropriate for this clinical scenario.

<table>
<thead>
<tr>
<th>Factors</th>
<th>Key points</th>
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<tbody>
<tr>
<td>Collect background information</td>
<td>- Subjective history may include chief complaint and health history as well as:</td>
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<tr>
<td></td>
<td>- Cognition level</td>
</tr>
<tr>
<td></td>
<td>- Digital literacy</td>
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<tr>
<td></td>
<td>- Communication abilities</td>
</tr>
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<td></td>
<td>- Technology access</td>
</tr>
<tr>
<td></td>
<td>- Features of physical environment</td>
</tr>
<tr>
<td></td>
<td>- Patient preference for digital health tools</td>
</tr>
<tr>
<td></td>
<td>- If each criterion is not met, then the patient must be referred to in-person care</td>
</tr>
<tr>
<td>Select procedures</td>
<td>- Traditional procedures, digital alternatives, or functional tests may be used if they are:</td>
</tr>
<tr>
<td></td>
<td>- Necessary for clinical reasoning</td>
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<tr>
<td></td>
<td>- Evidence-based</td>
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<td></td>
<td>- Feasible</td>
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<td></td>
<td>- Reliable</td>
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<tr>
<td></td>
<td>- If no procedure meets these criteria, then the patient must be referred to in-person care</td>
</tr>
<tr>
<td>Execute procedures</td>
<td>- Instruct the patient about:</td>
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<td></td>
<td>- Equipment required</td>
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<td></td>
<td>- Technology settings</td>
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<td></td>
<td>- Environment set up</td>
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<td></td>
<td>- Performance of the procedure</td>
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<td></td>
<td>- Outcome reporting</td>
</tr>
<tr>
<td></td>
<td>- If execution of the procedure is impeded by any of these factors, the provider will consider alternative procedures or refer to in-person care</td>
</tr>
<tr>
<td>Assess results</td>
<td>- Determine if the reliability of the result was affected by:</td>
</tr>
<tr>
<td></td>
<td>- Procedure performance</td>
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<tr>
<td></td>
<td>- Technology</td>
</tr>
<tr>
<td></td>
<td>- Reporting accuracy</td>
</tr>
<tr>
<td></td>
<td>- Does the provider have confidence in the result of the procedure?</td>
</tr>
<tr>
<td>Proceed with clinical care, repeat, or refer</td>
<td>- Do you need more clinical information?</td>
</tr>
<tr>
<td></td>
<td>- If no:</td>
</tr>
<tr>
<td></td>
<td>- Proceed with clinical care</td>
</tr>
<tr>
<td></td>
<td>- If yes:</td>
</tr>
<tr>
<td></td>
<td>- Repeat decision-making steps</td>
</tr>
<tr>
<td></td>
<td>- Refer if no alternative exists</td>
</tr>
</tbody>
</table>

Clinical Application

Overview

The application of this decision-making framework can be illustrated through clinical examples. This example provides descriptions of how procedures can be modified but provides high-value clinical information when feasibility, reliability, and reproducibility are considered. Assessment of confidence allows providers to determine the value of the result prior to proceeding with clinical care or referring to in-person care. Figure 2 provides a visual representation of the decision-making process used in the patient scenario.

https://mededu.jmir.org/2024/1/e52993
**Figure 2.** Description of clinical application of proposed decision-making framework using the timed up and go test and modified test. The provider proceeded through the first process but had low confidence in performance. They then repeated the decision-making process with modifications made to the test environment and procedure. The modified test produced a high-confidence result and allowed clinical care to proceed.

**Patient Scenario**
Consider a hypothetical case of a 79-year-old woman living in a rural community who scheduled a telehealth visit with her primary care provider (PCP) to discuss concerns regarding mobility. Mobility assessment is within the scope of the provider in this example, who has the appropriate training and expertise to perform telehealth visits. The visit will take place on the platform provided by the health system and meet applicable HIPAA and data security requirements. The provider has access to the patient’s medical history as a part of the software platform.

**Step 1: Collect Background Information**
The patient’s chief complaint is frequent stumbling, often the result of catching her toe while walking, which has resulted in loss of balance, frequently holding onto furniture or walls while walking, and avoiding walking in the community due to fear of falling. She reports no falls to the ground and no other health status changes but is concerned that her balance will continue to decline. The provider assesses the patient’s cognitive status, communication ability, and preference for digital health during the subjective assessment. As part of the telehealth visit, the provider completes red flag screening and review of systems and finds no neurological deficits, no indication of cardiac
impairment, and no history to suggest that the mobility concerns are the result of sinister pathology. Her PCP would like to quantify the mobility impairments in a standardized way during the telehealth visit and the patient agrees to this. The patient reports that her husband is available during the telehealth visit to assist if needed. As the patient has no current history of falls, health history is clear, and the patient has a caregiver present, the PCP feels confident that they can complete a mobility assessment safely via telehealth.

**Step 2: Select Procedure**

The PCP chooses the Timed Up and Go (TUG) test [39] as it is evidenced-based and recommended by the Center for Disease Control STEADI protocol [40]. TUG is a timed mobility test in which patients rise from a standard chair, walk to a line on the floor 10 feet away, turn, return to the chair, and sit. Patients are instructed to wear their regular footwear and can use a walking aid during the test if needed.

The PCP assesses feasibility by asking if the patient has access to the equipment needed: a sturdy chair such as a dining chair, stopwatch, tape measure, and tape. The PCP describes the test to the patient and husband and asks if they feel able to achieve the setup and execute the test. The PCP will be able to gather qualitative information about gait during the test by having the patient face their device’s camera toward the test area. The outcome of the TUG is time-based, which the PCP determines to be reliable through digital means. The PCP decides that the caregiver will manage the stopwatch to mitigate any lag in the internet connection during the test. Using a tape measure to define distance and using the same chair in the same location will ensure that the test setup is reproducible for subsequent testing. The provider educates the patient’s caregiver on the start or stop timing procedure of the TUG, further ensuring reliability. The PCP will assess qualitative mobility by visually assessing movement during the test using the camera of the mobile device. The PCP determines that the TUG is feasible and reliable in a digital setting and provides the clinical information required to make clinical decisions about treatments for this patient, so no alternative is necessary.

**Step 3: Execute Procedure**

The PCP instructs the patient’s husband to gather a sturdy chair and stopwatch, measure 10 feet on the floor, and mark it with a line of tape. The provider instructs the patient and caregiver to arrange the camera of their mobile device in a manner that allows the PCP to observe the test. The caregiver is instructed on starting or stopping the stopwatch. The patient is instructed on the test procedure according to the standard TUG instructions. The caregiver is instructed to report the time to completion of the procedure to the PCP. The provider answers clarifying questions for the patient and caregiver, and they perform the test. During the test the provider can hear that the caregiver fumbles with the stopwatch, and the patient leaves the video frame.

**Step 4: Assess Results**

While the environment setup was standardized supporting reliability, the caregiver reported difficulty with starting or stopping the timer, impacting the accuracy of the timed result. The patient left the visual frame during the test, impacting the ability to assess qualitative aspects of gait such as stopping and changing directions. The provider determines they have low confidence in the result and is unable to determine if the patient exceeded the recommended time of <12 seconds for test completion, or if there are mobility deficits that prompt recommendations for assistive device use.

**Step 5: Proceed With Clinical Care, Repeat or Refer**

The provider has low confidence in the result of the test and does not feel they can proceed with clinical care based on the results. The need for mobility assessment remains, and the provider feels that modifications of the testing scenario may allow them to gain the clinical information they need, so a referral to in-person care is not necessary. The home environment had only one area where a 10-foot space was available to complete the TUG, however, the family was unable to position the camera in a manner that allowed the whole area to be seen by the provider. Additionally, the caregiver had difficulty starting and stopping the timer, decreasing the accuracy of the result. The provider determines that the variables measured by the TUG test appropriately provide the clinical information they need, but he will need to utilize an alternative testing method to enable him to address the limitations. He will repeat decision-making steps using a digital alternative to gain the information he needs from the mobility assessment.

Background information remains the same, so the provider can proceed to select an alternative procedure. They decide to address the limitations of the first attempt by choosing a new testing location where they can standardize the test using landmarks in the patient’s home. The caregiver is instructed to position the front legs of the chair even with a door frame and will have the patient walk to the end of the hallway, touch the wall, and return to the chair. The distance walked is less than the 10 feet required of the TUG, but the patient is visible to the provider the whole distance. Additionally, the provider will give audio cues to start and stop the test while he manages the timer remotely. The provider and patient determine together that this setup is feasible and easily reproducible for subsequent testing. The modifications will allow the provider to assess movement quality as well as ensure timed results are accurate, which addresses the limitations of the prior test.

Execution of the modified procedure requires instruction regarding chair location and placement of the mobile device so the camera captures the whole testing area. The patient is instructed on how to perform the modified test procedure. The performance of the modified test proceeds without audio or video lag or distortion. After the second test provider feels confident that the timed result was successful. The provider was able to assess the quality of mobility throughout the whole test. Because the provider has high confidence in the clinical information they obtained through the alternative test, they can proceed with clinical care. The provider determines that the patient would benefit from using a single-point cane to improve balance with changing directions when walking. The PCP also prescribes physical therapy to address balance, gait, and lower extremity strength. The patient will schedule a follow-up telehealth visit with the PCP in 4 weeks and they will repeat...
the modified mobility test at that time using the same setup to assess the effect of these interventions.

Discussion

Principal Findings

Providing a decision-making framework for clinicians to utilize in digital care can alleviate clinicians’ concerns about implementing digital care in their practice. To our knowledge, a framework that assists providers in translating in-person clinical skills to digital care does not exist. This framework enables clinicians to practice effectively in the most accessible environment for the patient while prioritizing evidence-based practice, assessing risks, and providing patient-centered care. As digital care is increasingly desired by patients [19,23,41,42], it is imperative that providers are confident in decision-making in digital settings so telehealth remains safe, efficient, and equivalent to in-person care.

The value of a clinical procedure is reliant upon the feasibility, reliability, and clinician confidence, as well as the interaction of those variables with digital technology. A procedure that is feasible, reliable, and reproducible, but is performed poorly and provides low confidence has less value in clinical decision-making than an alternative digital procedure that deviates from standard performance but instills high confidence in clinical decision-making. This improves patient safety by determining whether a patient can remain in a digital care environment or should be referred to in-person care. Additionally, the framework encourages clinicians to use evidence-based practice guidelines as the basis for care, modifying procedures in a feasible and reliable manner to improve outcomes. This will ensure consistency, reduce bias, and enhance the quality of decisions in digital care [22-24]. The application example demonstrated that modifications made based on the patient’s environment and technology limitations enabled the provider to proceed with digital care in a manner consistent with clinical best practices and supported the provision of safe, effective, and quality care.

Time is a valuable resource in medical care, and providers must be confident in decisions made during clinical encounters. In situations where decisions must be made quickly, utilizing a framework can assist with decision-making efficiency [22-24]. Novice clinicians or providers who are transitioning to digital care may benefit from a framework to help them determine the best course of action in a timely manner. With increased provider experience and repetition, the decision-making process will be more efficient and timely. For example, experienced telehealth clinicians become proficient in scanning the patient environment, determining feasibility based on available resources, as well as becoming efficient at modifying traditional procedures based on the patient’s environment, and instructing patients on camera setup and how to utilize technology efficiently. In scenarios like the clinical application described above, an experienced provider may identify potential barriers prior to execution and decide to utilize a modified procedure from the start to save time.

This framework builds on the existing literature that shows similar diagnostic accuracy between in-person and digital examination techniques [26,29-31]. Lack of physical contact when working through telehealth was perceived to hamper accurate and effective diagnosis and management [18]. However, many commonly performed physical examination techniques have poor sensitivity and interrater reliability. This is evident in the poor interrater reliability scores of techniques such as palpation of lumbar structures [43] and assessment of breath sounds [44]. Decision-making tools that enable providers to evaluate alternative methods for gathering clinical information help to overcome these barriers and increase confidence that practitioners are providing effective, safe care. Additionally, adapting procedures allows patients the full benefit of telehealth, including convenience, cost-savings, better adherence, higher engagement, and improved access to care in rural or underserved areas [20].

Future Research

Avenues for further research should include randomized control trials comparing trained versus untrained providers to determine whether the utilization of this framework leads to improved clinical outcomes, provider self-efficacy, and patient satisfaction scores, and would provide insight to overcoming the barriers to digital health that providers may experience. Research is needed in implementation science to determine if training clinicians in using a framework will increase treatment fidelity. Similarly, this framework can be considered in future studies to provide further evidence of the efficacy of digital care and enable the full potential of telehealth for all stakeholders.

Further understanding of how providers make decisions to include digital tools in patient care is needed. Understanding provider confidence in modifying in-person techniques and clinical problem-solving in digital settings may improve providers’ willingness to utilize digital care with their patients. Provider training about how to modify traditional procedures, evaluating the efficacy of modified procedures, and assessing confidence in results may increase provider self-efficacy in digital settings. Best practices and standardized education for health care providers on how to effectively use digital tools should be established.

Limitations

There are limitations of this framework as it is broad in scope and cannot address every situation. Independent tests should be performed to evaluate the usability of the framework and its effectiveness in improving guideline implementation. We recognize that no single framework can be used for all guidelines or contexts. Provider behavior will be influenced by environment, resources, technology, and other factors despite training in using a decision-making framework.

Conclusion

We created a framework for clinicians to determine whether a particular procedure can be performed feasibly in a digital health setting with the same quality, accuracy, and reliability as in a traditional setting. Utilizing a framework to assist in clinical decision-making is important to alleviate clinicians’ concerns
about using digital tools and help guide the translation of the best available evidence from traditional care to digital care. The increased demand by patients for digital care requires a new set of clinical skills, and this framework enables providers to comply with clinical best practices and offer high-quality care for patients who want to receive their care via telehealth.

Conflicts of Interest

JM and TN are employed shareholders in Omada Health Inc.

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A Call for a Health Data–Informed Workforce Among Clinicians

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Abstract

A momentous amount of health data has been and is being collected. Across all levels of health care, data are driving decision-making and impacting patient care. A new field of knowledge and role for those in health care is emerging—the need for a health data–informed workforce. In this viewpoint, we describe the approaches needed to build a health data–informed workforce, a new and critical skill for the health care ecosystem.

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KEYWORDS

health data–informed workforce; health data; health informaticist; data literacy; workforce development

Background

Health care has become a data-driven business. It is no longer acceptable that both incoming and current health care professionals and business leaders lack an understanding of the influence data has on health care delivery. The clinician coauthors listed here represent this sphere and are still learning every day. We represent the diverse background of professionals that exist in the health data space, with a wide variety of journeys into this arena [1]. "Health data" is a broad term, often referring to data collected and exchanged in electronic systems. Everyday health data are entered, exchanged, and used to make important decisions from the patient level to the systems level. Health care professionals today need an understanding of the utilization and impact of health data to optimize care delivery and interact with the many systems they encounter daily.

When we entered the health care industry over 20 years ago, we were hopeful clinicians excited to impact patients’ lives. For many of us, we quickly became disillusioned by a system that was driven not by patient outcomes but by reimbursement. Yet, we regained hope with pivotal moments, including when Don Berwick challenged health care organizations to promote quality and evidence-based medicine with the Institute for Healthcare Improvement; the proliferation of electronic health record (EHR) usage leading to the potential to share patient information across systems [2-4]; and the opportunity to move from fee-for-service to value-based payment [5]. We continue to grow in hope, as many openly discuss health equity and social determinants and drivers of health. In addition, the conversations and investments in workforce related to health data knowledge and expertise are ongoing and receiving national attention. Opportunities abound with the expansive growth of artificial intelligence and machine learning.

However, none of these impending innovations can grow and disseminate without understanding data. Gaining an understanding about health data and their use by clinicians is critical to promote the key structural aspects necessary to improve health care delivery, including interoperability, data standards, quality measures, and reimbursement for health outcomes. When we started in health care, the understanding of the impact of health data did not truly and widely exist. In our experience, we find that many clinicians are unconsciously incompetent—lacking a basic understanding of how data are used, what health data consist of, and where data flow [6]. Unconscious incompetence occurs when the decision makers lack the true information and expertise needed to make an informed decision [6]. This lack of competence causes uninformed decision-making in the health care ecosystem, which causes more challenge. Technology and data become a burden and not a solution.

In health care, a health data–informed workforce is needed to remedy the gaps and make the important connections for positive change. In our experiences and those of our peers, we interact with clinicians who learned about informatics and health data on the job [1]. Many stories start with an interest in data and technology or some savviness with technology. These are individuals willing to lean into innovation and learn through failure. Yet, their learning curve is steep and lacks the efficiency.
that a health data–informed workforce could address. The understanding of health data has become a shared team value critical to growing and expanding the evidence to support interprofessional practice. Now is the time to move beyond the early adopters and explore how we can expand the health data–informed workforce. We acknowledge previous authors that have called for this momentum to grow and call for ongoing and widespread engagement. In this viewpoint, we attempt to define the health data–informed workforce at the micro-, meso-, and macrolevels. We then offer suggestions for clinicians wanting to level up their competence in health data.

What Is a Health Data–Informed Workforce?

A health data–informed workforce includes clinicians with a basic understanding of data along with their exchange and influence on decision-making. The ideal would be to move clinicians from being unconsciously incompetent to consciously competent. However, the amount of knowledge expected is overwhelming. The complexity of health data has evolved into the field of health informatics. Multiple studies have indicated that the field of health informatics is diverse, with a wide variety of education and workplace requirements [1,7,8]. Health informatics is a field that explores the use of health data for “scientific inquiry, problem-solving, decision making” with the intent to improve health care delivery and impact [9]. Yet, health data impact every level of health care, from the micro- to macrolevel, calling upon all clinicians to hold a basic understanding.

For the purposes of this viewpoint, we consider the microlevel to be interactions with patients and clinicians; the mesolevel focuses on the infrastructure and systems in place for health data sharing; and the macrolevel addresses the impact of policy on health data. Clinicians who are data informed at each of these levels will improve the impact of health data utility and ensure that decisions made around health data and technology will facilitate positive change.

At the clinician and patient level (ie, the microlevel), data are used to make clinical decisions. The widespread adoption of EHR systems supported by the 21st Century Cures Act and provisions against information blocking in the Office of the National Coordinator of Health Information Technology’s Final Rule place a premium on data, and data literacy, in health care delivery [10]. The availability of data and the ability for patients to access their health data through patient portals and other digital applications can advance shared decision-making, promoting improved health outcomes while empowering patient’s involvement in their care. Yet, EHRs have introduced burden, and many clinicians are under information overload, which can result in health care errors [9,11]. A recent piece in the *Journal of the American Medical Association* titled “Death by Patient Portal” illustrates the love-hate relationship that occurs with much of health technology and data [12]. Data are flowing and being shared, but questions remain on how much and how to make information usable for patients and clinicians. Despite these challenges, data and technology are reported to only continue to grow in health care. This calls on clinicians to know how to access patient data in their EHRs, understand where patients track and record data, and feel comfortable translating health information to multiple levels of digital and health literacy. A health data–informed clinician knows to use tools such as health information exchanges (HIEs) to ensure that they are making clinical decisions with comprehensive patient data beyond the EHR [13]. An HIE extracts data from multiple EHRs and matches that data into a comprehensive patient record. In some health care organizations, HIEs are integrated into the EHR. They can provide quick and comprehensive patient data for clinical decision-making [14]. Due to HIEs, health care becomes more proactive and less reactive when clinicians are aware of a recent emergency department visit, for example. At the same time, HIEs can lead to information overload for providers. In addition, clinicians improve their patient experience when they have information about the patient journey and history, which an HIE can provide [15]. Patients also report a better patient experience when they are not forced to “repeat their story” or re-enter information they have already reported.

Many health care organizations use data for various reasons, including use by health care delivery systems, payers, and academic researchers. When it comes to the mesolevel, the health data–informed workforce needs to understand data governance, including understanding how, why, and when data are shared and recognizing the importance of privacy and security. Patient consent remains important to ensure patients know when and where their data are being shared and how they are being used. In addition, health technology selection and vetting, along with vendor management, is critical. Vendors can offer solutions, yet at the same time, these tools can have unintended consequences from data being entered into multiple systems, causing burden on clinicians and a lack of data completeness in a patient’s record. Clinicians need to recognize the importance of interoperability as it impacts data access and use between systems. Interoperability refers to the ability to exchange data in a useful manner. An interoperable approach reduces double documentation and siloed health data [16]. At the same time, health data have extensive protections under the Health Insurance Portability and Accountability Act (HIPAA), which requires thoughtfulness to the exchange and use of data across systems. We have witnessed too many clinicians enamored with a piece of technology without vetting its ability to further health care. Great technology that further silos data into multiple systems and lacks expanded adoption can cause more burden and potential patient harm. We need a workforce that questions the benefits and challenges how additional technology and data can actually improve health care delivery along with their interoperability.

Health data–informed clinicians also recognize the importance and value of data standards [17]. Data standards provide a critical foundation for data exchange. Decisions are being made daily in health care organizations without the recognition or use of data standards. One example is choosing to create a health-related social need screener without considerations of existing tools or data standards work, such as that led by the Gravity Project [18]. These approaches further denigrate the system and cause a myriad of challenges to interoperability.
For the macrolevel, understanding and advocating for local and federal policies that support the proliferation of growing workforce expertise is critical for the health data-informed clinician. Clinicians need a basic recognition and understanding of how policy drives health data utility [19]. The gaps in the workforce around health informatics have been identified and acknowledged [7,20,21]. Efforts in this area have been made by the American Medical Informatics Association’s 10×10 program and the federal funding to support the Public Health Informatics and Technology Workforce Program by the Office of National Coordinator of Health Information Technology. These policies and investments provide opportunities to support both current professionals and those entering the workforce, representing examples of the impact of policy on health data.

How Do Clinicians Level Up?

Overview

If this sparks something inside you, the next step is to be curious about how to develop into a health data-informed clinician. All clinicians should be on a journey as lifelong learners. Health and health care constantly change, not to mention technology and data use. Becoming more data informed does not mean getting a new degree, even though that is an option. In this next section, we share some basic aspects for those desiring to become a health data-informed clinician. Certainly, we cannot go into extensive depth, but we hope this plants seeds to grow. Some strategies to level up are as follows.

Get to Know a Health Informaticist

No one can or is expected to know everything, which is why health care is a team sport. One strategy to help build a health data-informed workforce is for clinicians to learn the role of health informaticists. Health informatics “is the interprofessional field that studies and pursues the effective uses of biomedical data, information, and knowledge for scientific inquiry, problem-solving, decision making, motivated by efforts to improve human health” [9]. In other words, health informatics is a wide field focused on health data and their utility to impact health care outcomes. Health informaticists hold expertise in data management, security, privacy, and governance requirements to support safe handling of protected health information [1]. They are also challenged to ensure that health data are interpreted and presented meaningfully to stakeholders, including clinicians; health care leaders; and most importantly, patients [22]. Health informaticists go by different names in different organizations, including clinical informaticist, data analyst, business analyst, etc [23,24]. Their roles and demands may vary based on where they work. However, many organizations have informatics expertise in their organization. The next step would be to include an informaticist as part of the team. They can be invaluable in selecting health technology, vendor management, training and implementation, and project implementation, not to mention data handling! They offer a wide variety of skills to a team interacting with health technology and data, including data extraction, quality metrics, data analysis, dashboard builds, etc [1].

Use an HIE

HIEs are state-based or regional infrastructures that match data across multiple EHRs to provide a comprehensive patient record [25]. The sophistication of HIEs vary, yet they are a tool available to clinicians in multiple health systems that often go underutilized. In some cases, HIEs can be queried for information on the patient. They can also be used to send and receive information on a patient to allow for more comprehensive decision-making [14,15]. Clinicians can find out if their health care organization is part of their local HIE to gain access and training on how to use an HIE to improve clinical decision-making.

Recognize the Importance of Data Standards

Clinicians have an important role in entering health data, which impacts the ability to analyze data from health data utilities. Recognizing the importance of the use of appropriate data standards is important for clinicians. In the informatics field, you often hear the term “garbage in, garbage out,” and much effort has been made to extract and clean data to show the impact of quality payment programs, which have induced new health care system burden. Clinicians can work with their informatics team to ensure documentation is structured in a meaningful way. The United States Core Data for Interoperability offers guidance around common ways to document that can promote data sharing [26].

Get Some Training

There is a variety of professional organizations that can support the learning and growing of professionals targeted at clinicians. These organizations offer conferences, web-based trainings, and certifications. Some federal resources also exist, including the Office of the National Coordinator for Health Information Technology, who offers webinars and other valuable resources. Table 1 calls out some of these resources. Each organization offers a variety of training opportunities. Another option is to seek a mentor in health informatics, partnering with someone with experience to learn from.

Table 1. Organizations and resources.

<table>
<thead>
<tr>
<th>Resource</th>
<th>Website</th>
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<tr>
<td>American Health Information Management Association (AHIMA)</td>
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<tr>
<td>American Medical Informatics Association (AMIA)</td>
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<tr>
<td>Civitas Networks for Health</td>
<td>[29]</td>
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<tr>
<td>Healthcare Information and Management Systems Society (HIMSS)</td>
<td>[30]</td>
</tr>
<tr>
<td>Office of the National Coordinator for Health Information Technology</td>
<td>[31]</td>
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</table>
For some, upskilling may be entering the field of health informatics. Academic programs exist in health information management and health informatics across the country. Many professional organizations offer discipline-tailored programming in health informatics specifically in medicine and nursing. Many programs offer web-based options and teach core skills.

It is normal to feel intimidated by the terminology and concepts. However, it is important to remember that health data are being used to drive lots of decisions. Garnering a basic understanding will improve clinical skills and help with patient advocacy to improve care delivery. Everyone can take some simple steps to become more health data informed.

**What Can Educators Do?**

**Overview**

It is impossible to know everything about the field of informatics and health data. Instead, the intent should not be about teaching all the skills but instead the critical thinking skills necessary to consider how and why technology and data can be used in health care. As a society, we need to cultivate minds that can think and problem solve for a future we do not yet exist in. As educators, we need to encourage the ability to embrace ambiguity and innovation while recognizing that human beings approach these elements in different ways that can cultivate adoption at different rates of speed. Educating a health data–informed workforce requires educators to recognize that technical and technology skills are important but not enough. The focus should include the following.

**Promotion of Data Literacy**

Basic data literacy involves understanding how data can be used to effect positive change in patient outcomes, cost reduction, and mitigation of caregiver burnout, among other applications. Data literacy is the ability to read and understand data. For those advanced in this area, data literacy includes communicating and sharing data in ways appropriate to the audience. Health data literacy in an informed health care workforce includes training on effective data management throughout the health data life cycle and how to traverse the knowledge discovery process, from data to information to knowledge and, ultimately, wisdom and actionable insights. The Data, Information, Knowledge and Wisdom Model provides a theoretical framework that spans from reviewing data to applying data in impactful ways [32].

A significant amount of health data is collected, and deciding what to do with it requires a deeper understanding. Educators should push learners to move beyond reviewing data to deeply engaging with them in meaningful ways to improve health care.

**Ethical Use of Health Data**

Data, especially health data, require a high level of care and stewardship. Educators need to focus on the ethics of data use; data governance, including privacy and security along with appropriate data-sharing strategies; and the importance of recognizing data literacy for key stakeholders, including patients, policy makers, payers, clinicians, and health care executives. Data brokering and its impact on health care continue to evolve. The infusion of artificial intelligence will continue to generate new ethical questions, opportunities, and concerns [33]. In addition, gaps in data and new data areas such as social determinants and drivers of health offer new and interesting challenges to consider [18]. Furthermore, innovation should always be grounded in asking the “what if” questions to ensure that ethical considerations are always an aspect of data use.

**Focus on Data Utility**

Health data are being collected at a momentous rate. Educators must focus on preparing a health data–informed workforce to recognize the utility of data for the audience. This must also be considered in implementing health information technology mechanisms focused on user experience and human-centered design to ensure that health data are used thoughtfully and ethically. Data standards are also critical to utility, such as the United States Core Data for Interoperability [26]. We have witnessed many implementations without the consideration of data standards, causing barriers to interoperability that can produce harm in patient care. We can name multiple examples where technology is purchased without even considering how systems will share or integrate data, causing myriad other challenges in health care.

**Recognize the Impact of the System**

Health care is a large system within systems. Health technology and data are driven by systems, whether they be legal, policy, or reimbursement. Implementing data and technology without a strong understanding of the mechanisms and systems thinking is problematic. A health data–informed workforce recognizes the many layered systems impacting health information technology and data use implementation. Ensuring that the workforce engages in systems thinking and searching for “the why” in implementation and data use is a critical skill. In addition, clinicians should not feel disempowered and instead recognize the role they can play at the microlevel in patient interactions to improve the use of health data for improved outcomes.

**Conclusion**

Our hope is to promote a conversation and spark innovation around the need to expand and grow the health data–informed workforce. We certainly cannot provide every piece of advice or suggestion here. Yet, we hope to spark a revolution to grow the cadre of passionate advocates for the proliferation of health data and technology in ways that truly support equity, reduce burden, and improve health care delivery. Additionally, we are not saying that data skills are not critical—they are. We recognize that we need more than that. We need a workforce that asks questions about where data go and how they are used and that becomes more informed on the data tools of their patients. We need a health data–informed workforce now and into the future.
References


Abbreviations

EHR: electronic health record

HIE: health information exchange

HIPAA: Health Insurance Portability and Accountability Act

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Knowledge Transfer and Networking Upon Implementation of a Transdisciplinary Digital Health Curriculum in a Unique Digital Health Training Culture: Prospective Analysis

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Abstract

Background: Digital health has been taught at medical faculties for a few years. However, in general, the teaching of digital competencies in medical education and training is still underrepresented.

Objective: This study aims to analyze the objective acquisition of digital competencies through the implementation of a transdisciplinary digital health curriculum as a compulsory elective subject at a German university. The main subject areas of digital leadership and management, digital learning and didactics, digital communication, robotics, and generative artificial intelligence were developed and taught in a transdisciplinary manner over a period of 1 semester.

Methods: The participants evaluated the relevant content of the curriculum regarding the competencies already taught in advance during the study, using a Likert scale. The participants’ increase in digital competencies were examined with a pre-post test consisting of 12 questions. Statistical analysis was performed using an unpaired 2-tailed Student t test. A P value of <.05 was considered statistically significant. Furthermore, an analysis of the acceptance of the transdisciplinary approach as well as the application of an alternative examination method (term paper instead of a test with closed and open questions) was carried out.

Results: In the first year after the introduction of the compulsory elective subject, students of human medicine (n=15), dentistry (n=3), and medical biotechnology (n=2) participated in the curriculum. In total, 13 participants were women (7 men), and 61.1% (n=11) of the participants in human medicine and dentistry were in the preclinical study stage (clinical: n=7, 38.9%). All the aforementioned learning objectives were largely absent in all study sections (preclinical: mean 4.2; clinical: mean 4.4; P=.02). The pre-post test comparison revealed a significant increase of 106% in knowledge (P<.001) among the participants.

Conclusions: The transdisciplinary teaching of a digital health curriculum, including digital teaching methods, considers perspectives and skills from different disciplines. Our new curriculum facilitates an objective increase in knowledge regarding the complex challenges of the digital transformation of our health care system. Of the 16 student term papers arising from the course, robotics and artificial intelligence attracted the most interest, accounting for 9 of the submissions.

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KEYWORDS
big data; digital didactics; digital health applications; digital leadership; digital literacy; generative artificial intelligence; mobile working; robotics; telemedicine; wearables

Introduction

Background

With the Digital Healthcare Act (German: Digitale-Versorgung-Gesetz), the spectrum of digitalization in the health care system was expanded in Germany in 2019. It includes, among others, the promotion of telemedicine and the expansion of the telematics infrastructure. In addition, a legal framework was created, which, for the first time, entitles insured persons to digital health applications. Digital health applications belong to low-risk medical devices and are primarily intended to support the detection, monitoring, treatment, or alleviation of diseases, injuries, or disabilities. Since January 2021, patients have also been entitled to have access to their data, which have generated during hospital treatment and stored in their electronic patient record. This facilitates electronic provision of medical information, in particular findings, diagnoses, treatment measures carried out and planned, as well as treatment reports for use across facilities, disciplines, and sectors [1,2].

These and further developments show that digital health is creating a new form of health care and is changing the way medicine is delivered and managed [3].
For medical educators, this evolution presents a 2-fold challenge: first, to understand and keep up with the rapidly evolving digital health landscape; and second, to effectively integrate this knowledge into medical curricula to prepare the next generation of health care professionals. Recognizing this gap and the opportunity it presents, the implementation of a comprehensive digital health curriculum is paramount.

Previous studies have suggested that digital health education should be integrated into medical school curricula, with a special emphasis on topics related to knowledge, skills, and attitudes [4]. Several other studies have emphasized the need for medical schools to prepare students for a future in digital health by incorporating digital health competencies into their curricula [4-7].

However, the transdisciplinary approach within university (digital) teaching is still not widespread. The need for such an approach arises from the potential for innovation [8] and is based on professional policy framework conditions such as the new dental licencing regulations [9]. Elective classes seem to be suitable formats for timely introduction, but a longitudinal implementation in mandatory curricula should be the goal [5].

The Implementation of a Transdisciplinary “Digital Health” Curriculum at Our University

The curriculum “Digital Health - Digitalisation and Digital Transformation of Medicine” was offered for the first time at our university in the winter semester of 2022-2023. Students from all faculties and all semesters of the university were eligible to participate.

The learning objectives were developed on the basis of existing literature [4-6,10] and interviews with transdisciplinary experts in the areas of human medicine, dental medicine, medical didactics, computer science, business administration, theology, and ethics. The curriculum is divided into the 4 subareas of digital didactics, namely digital communication, management and digital leadership, and robotics and generative artificial intelligence (AI), each with 14 weekly lessons as well as an introductory event and a final examination and evaluation event. The lessons particularly encompassed the following topics: augmented or virtual reality, big data or generative AI, data protection or information security, digital leadership, digital didactics, ethical aspects of digital health, new work, robotics, social media, open educational resources, digital health applications, wearables, simulation training, and telemedicine (Table 1).

Table 1. Digital health curriculum.

<table>
<thead>
<tr>
<th>Topics</th>
<th>Goals, subareas, and time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Digital communication</td>
<td>• Goal: knowledge transfer regarding modern communication systems, consideration of legal framework conditions, and ethical aspects during transdisciplinary implementation and application</td>
</tr>
<tr>
<td></td>
<td>• Subareas: telemedicine, digital patient files, ethics, messenger apps, digital health applications</td>
</tr>
<tr>
<td></td>
<td>• Time: 3 lessons, each lasting 90 minutes</td>
</tr>
<tr>
<td>Digital didactics</td>
<td>• Goal: application of modern teaching and learning methods and creating a nondiscriminatory framework for studies</td>
</tr>
<tr>
<td></td>
<td>• Subareas: open educational resources, virtual or augmented reality, simulation training</td>
</tr>
<tr>
<td></td>
<td>• Time: 3 lessons, each lasting 90 minutes</td>
</tr>
<tr>
<td>Management and digital leadership</td>
<td>• Goal: knowledge transfer regarding digital transformation including economic aspects as well as the importance of innovative leadership styles</td>
</tr>
<tr>
<td></td>
<td>• Subareas: leadership, information security, data protection, economy, social media, and mobile working</td>
</tr>
<tr>
<td></td>
<td>• Time: 3 lessons, each lasting 90 minutes</td>
</tr>
<tr>
<td>Robotics and artificial intelligence</td>
<td>• Goal: knowledge transfer about possible applications of surgical robots, individualized medicine, and possible uses of generative artificial intelligence in teaching, research, and patient treatment</td>
</tr>
<tr>
<td></td>
<td>• Subareas: robotics, generative artificial intelligence, wearables, and big data</td>
</tr>
<tr>
<td></td>
<td>• Time: 3 lessons, each lasting 90 minutes</td>
</tr>
</tbody>
</table>

The aims of this digital health curriculum are as follows: (1) integrating basic digital health content into the curriculum of a university in northern Germany; in a transdisciplinary approach, students will be taught the necessary competencies to be able to apply digital health technologies in their later work; (2) considering the new licencing regulations for dentists; dental students, in particular, should be encouraged to use the newly implemented compulsory elective subject to gain knowledge in the field of digital health; and (3) to encourage students to critically engage with the topic of digital health within the framework of a scientific thesis; this also intended to reflect currently relevant digital health topics from the students’ perspective as a basis for further curriculum development.
The curriculum contents were taught over a period of 1 semester within the framework of a compulsory elective subject.

Furthermore, this study aims to analyze the objective acquisition of digital competencies through the implementation of a transdisciplinary digital health curriculum at a German university.

Methods

Ethical Considerations

The study has been reviewed by the ethics committee of the Faculty of Medicine of the University of Rostock, Germany, and has been approved (A 2022-0137).

Demographics and Previous Teaching of Digital Health

Student-related data about educational level, gender distribution, and career goals were analyzed. At the beginning of the semester, students were asked whether digital health learning objectives had already been taught in previous courses, using a Likert scale (1=very well taught to 5=not taught at all).

Students’ Assessment and a New Examination Approach for Further Development

To measure the allocation of knowledge of the participants, the participants’ prior knowledge was assessed during the introductory lesson through a theoretical test (pretest) consisting of 12 questions. Ten questions were multiple-choice and 2 were open questions. The test was specifically related to the topics covered in the curriculum. Multiple-choice questions assessed knowledge on the topics of digital transformation, ethics, change management, data protection, robot-assisted surgery, digital patient files, video consultation, and simulation training. The didactics section was covered by 2 open questions and 1 multiple-choice question. At the final seminar, the theoretical test was repeated with similar questions (posttest).

In addition to the standardized questions, students were asked to write a scientific paper. The topic could be chosen independently. However, a prerequisite was a content-related reference to the overarching topic of digital health. The objectives of the examination are to (1) encourage students to critically engage with a digital health topic of their choice, (2) promote scientific work, and (3) obtain an insight into the topics of digital health perceived as relevant by the students as a basis for further curriculum development.

For further structuring of the curriculum, the scientific papers were assigned to one of the main topic areas based on the selected headings and abstract contents.

Statistical Analysis

The data were analyzed using SPSS (version 27; IBM Corp) software. The gender distribution, career goals, intended subject area, and scientific papers were analyzed descriptively. Statistical analysis of pre-post test results and previous teaching of learning objectives was performed using an unpaired (learning objectives) and paired (pre-post test results) 2-tailed Student t test. A P value of <.05 was considered statistically significant.

Results

Educational Level of the Participants

Within the first year, a total of 20 students (5 in the winter term and 15 in the summer term) participated in the digital health curriculum. The average age of the participants was 22.3 (range 19-30) years. At the time of participation, 15 participants studied human medicine, 3 participants were studying dentistry, and 2 participants were studying medical biotechnology. In total, 11 (61.1%) students in human and dental medicine were in the preclinical phase and 7 (38.9%) were in the clinical phase.

Gender Distribution

Figure 1 shows the gender ratio according to the subjects of study among the participants. In total, 13 participants were female and 7 were male. Among human medicine students, 10 were female and 5 were male. Two dentistry students were male and 1 was female. Both biotechnology students were female.
Career Goals

Two questions were aligned with the focus on future professional activities. The first question asked whether the respondents wanted to work in an inpatient or outpatient setting. The options “other” and “don’t know yet” could also be selected. Furthermore, the students were asked about their desired goal of becoming a specialist doctor. As shown in Multimedia Appendix 1, the majority of participants are still undecided on whether they want to work in the outpatient or inpatient sector in future. Multimedia Appendix 2 shows the answers to the question about the goal of becoming a medical specialist, which was answered by the participating human medicine students. According to this, most of the participants who already know their career goal intended to become a specialist in surgery (n=4).

Previous Teaching of Digital Health

During the first lesson, students were asked whether digital health learning objectives have already been taught in previous courses, using a Likert scale (1=very well taught to 5=not taught at all). Table 2 shows the corresponding evaluations.
Among clinical students, significantly better overall coverage of the digital health learning objectives is evident.

Pre-Post Test Results and Term Paper Evaluation

In the pretest, the participants scored an average of 4 points compared to 8.3 points in the posttest. Consequently, there was a significant increase of 106% in knowledge (P<.001; Table 3).

As shown in Table 4, the most frequently selected main topic was robotics and AI.
Table. Digital health topics selected by students for their term papers.

<table>
<thead>
<tr>
<th>Titles of the students’ term papers</th>
<th>Digital health main topic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Progress of computer-assisted procedures and robotics in implantology</td>
<td>Robotics and AI&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>Mind reading with functional magnetic resonance imaging and AI</td>
<td>Robotics and AI</td>
</tr>
<tr>
<td>To what extent can the Da Vinci Robot help reduce postoperative complications?</td>
<td>Robotics and AI</td>
</tr>
<tr>
<td>Algorithms against prejudice? The role of AI in combating gender discrimination in the health sector</td>
<td>Robotics and AI</td>
</tr>
<tr>
<td>What opportunities arise from the use of AI in medicine and what are the associated problems?</td>
<td>Robotics and AI</td>
</tr>
<tr>
<td>Applications of AI in Radiology</td>
<td>Robotics and AI</td>
</tr>
<tr>
<td>AI and robotics in Orthopaedics and Trauma Surgery</td>
<td>Robotics and AI</td>
</tr>
<tr>
<td>Opportunities and limits of AI in the health sector</td>
<td>Robotics and AI</td>
</tr>
<tr>
<td>Use of AI for early detection of dementia</td>
<td>Robotics and AI</td>
</tr>
<tr>
<td>Data ethics in the digital world</td>
<td>Management and leadership</td>
</tr>
<tr>
<td>Does digitalisation in medicine lead to a loss of skills and knowledge among medical staff?</td>
<td>Digital didactics</td>
</tr>
<tr>
<td>“Flipped Classroom”: Possibilities of redesigning of an accompanying seminar on the study of human medicine.</td>
<td>Digital didactics</td>
</tr>
<tr>
<td>Implementation of an interdisciplinary elective subject “Digital Health”</td>
<td>Digital didactics</td>
</tr>
<tr>
<td>Aspects of discrimination against older people in digital medicine</td>
<td>Digital communication</td>
</tr>
<tr>
<td>What role do chatbots play in medical studies</td>
<td>Digital communication</td>
</tr>
</tbody>
</table>

<sup>a</sup>AI: artificial intelligence.

Discussion

Overview

Current social, political, and economic developments in Germany require a reorientation of university teaching, considering digital learning and teaching strategies. The necessity is also reflected in the restructuring of established framework conditions, such as the amendment of dental and medical licencing regulations [9,11].

This study aimed to analyze the objective acquisition of digital competencies through the implementation of a transdisciplinary digital health curriculum at a German university.

The learning objectives were imparted on the main topics of management and digital leadership, robotics and AI, digital communication, and digital didactics within the framework of a 1-semester curriculum. Objective knowledge gain was determined using a pre-post test design. In addition, the extent to which the approach of transdisciplinary networking could be implemented was analyzed. This was quantified by the disciplines and the number of clinical and preclinical participants. Overall, the results were analysed over 1 year (2 cohorts). In the second run, the number of participants has already tripled.

Characterization of the Participants

According to the Federal Statistical Office, 64.8% of students in human medicine in 2021 were female [12]. This corresponds to the distribution of participants in our curriculum, even when considering the isolated subject group of human medicine being the most frequently represented. Consequently, it can be assumed that the topic is not gender-specific and is of equal interest to male and female students. This cannot be confirmed for participants from the fields of dentistry and medical biotechnology. However, the small number of participants must be considered here.

Previous Teaching of Digital Health

Evaluation of the students at the beginning of the semester revealed that all the content of the curriculum has not been taught at all or only to a very limited extent. Even though there was a significant difference in knowledge between the clinical and preclinical sections, this concerns all participants. Consequently, it can be assumed that this deficit will not be sufficiently compensated for in higher semesters with regard to the clinical phase.

The results also indicate that most participants are still open about their career goals. This applies both to the future field of work (outpatient vs inpatient) and to the intended specialization. Therefore, the general approach to teaching content can be considered suitable.

Assessment of the Increase in Knowledge

As reported by studies with a similar study design, a significant objective increase in knowledge could be achieved among participants through the curricular dissemination of knowledge on relevant digital health topics. It should be noted that some students participated in the curriculum out of interest in the content but without aiming to achieve a good grade.
Consequently, it can be assumed that some students did not prepare for the posttest. The fact that summative assessment of the intended learning objectives at the beginning of the curriculum increases learning success has previously been described [13].

Regarding the current evidence in the development of digital literacy, the focus is increasingly on social interaction and lifelong learning skills in an innovative teaching and learning culture, in addition to subject knowledge [5].

**Term Paper Evaluation**

When analyzing the selected term papers, it quickly became clear that the topic of AI is of outstanding importance among digital health topics. This seems to be explained, in particular, by the strong media presence of the topic. The rapid development of generative AI has received special media attention with the launch of ChatGPT in 2022 [14-16]. Two challenges arise, in particular, for the curriculum. Although the special importance of flexible and adaptive teaching formats to be able to integrate innovations into teaching without delay is becoming apparent, the establishment of framework conditions for the application of generative AI in teaching, research, and clinical practice is coming into focus. Both focal points and associated challenges were already considered and will be further developed for our future digital health curriculum.

**The Role of Leadership in a Digital Health Training Culture**

Digital transformation is a continuous process that is better accepted by those who perceive digitalization as relevant to their own work. Digital leadership describes the special role of managers in the implementation of digital transformation. It is up to managers in the health care sector to align the strategic orientation to digital transformation with the company’s goals and needs and to create an appropriate digital culture. Regarding the provision of early access to the necessary knowledge on topics related to digital health, managers in the field of education have a special responsibility [17].

The transdisciplinary approach of the digital health curriculum acknowledges the current evidence for the success of digital transformation. In particular, evidence from economic evaluations has shown that in a networked environment, the opening of boundaries is necessary to create innovation and exploit synergies [8].

With an average value of 5 on the Likert scale, the results of the initial evaluation show that this knowledge has not yet been imparted in the participants’ previous curricula. Consideration of the transdisciplinary digital health curriculum is, therefore, of particular importance.

**Digitalization Connects: the Necessity of a Transdisciplinary Digital Health Curriculum**

The goal of opening the curriculum to all faculties is to expand the transdisciplinary network to promote an innovation-driven teaching and learning environment. This basic idea represents a unique selling point for previously established digital health curricula. Our results indicate that this opportunity was already realized in the first year by students from 3 different disciplines, such as human medicine, dentistry, and medical biotechnology. The distribution of clinical and preclinical students also shows cross-semester interest.

In the future, an increase in the participation of dental medicine students is expected. This is due to the new orientation of the dental licencing regulations, which mandate participating in curricula by choosing from among the elective subject areas (to which the compulsory digital health elective subject is assigned), both for the preclinical and clinical study phases [9].

It should be noted, however, that only 5 out of 20 students did not belong to the field of human medicine. These results suggest that the transdisciplinary approach needs to be further promoted, addressed, and implemented to achieve an even better transdisciplinary exchange.

Social media use may present an opportunity for increasing the visibility of our transdisciplinary curriculum and its learning objectives. The curriculum is currently already accompanied by a social media channel. The importance of social media in teaching and research is currently the focus of social debates and scientific studies [18,19]. For better assessment of the importance of social media in a modern academic teaching and learning culture, the authors believe that further studies are needed.

**Emerging Technologies in a Transforming Health Care System**

The use of modern technologies has enormous potential for optimizing patient treatment [20,21]. In surgery, in particular, there is a wide range of applications in the operating theater and perioperative management.

A recent editorial describes current emerging innovations with particular potential, which are also included in the digital health curriculum [20]. In particular, this involves the contents of machine learning–enabled clinical decision-making support, computer vision and augmented reality, as well as wearable devices and remote patient monitoring. The dynamic nature of these developments, among others, shows the particular importance of a flexible and adaptive curriculum to be able to integrate emerging technologies into teaching without delay.

Robot-assisted surgery, including approaches to telesurgery, is of particular importance, especially in surgery. The special importance of robotics for patient care has already been described several times and is now an integral part of numerous hospitals [22,23].

The special importance of robotics is also reflected in the selection of homework topics. Three of the 16 papers submitted focus on robotics in medicine.

However, the increasing use of robotics in the operating theater also requires special skills that can and must be practised extensively in a simulation-based setting [24]. This requires time and financial resources, as well as training in a supervised setting [25]. In teaching and further education, these prerequisites represent a hurdle. In particular, cost-intensive virtual and augmented reality simulators are often only rarely available.
available; their use in teaching is generally yet not structured [26]. User acceptance is indisputably high and can increase satisfaction in addition to learning success [27]. However, the topic requires economic reflection and a basic understanding of project management—an aspect that was addressed in the curriculum section of Management and Digital Leadership.

In addition to the implementation and continuous further development of technical innovations in clinical applications, achievements with disruptive innovation power also play a special role in future teaching and research. The disruptive potential of digital transformation is currently manifesting itself in particular in the launch of generative AI, such as ChatGPT [14].

**Generative AI, Web-Based Meetings, and the Challenge of Flexible Adaptive Training**

The examination of digital teaching methods has experienced a surge in innovation, particularly in the context of the COVID-19 pandemic [28]. Experience in the field of telemedicine has provided a blueprint for web-based teaching with simultaneous integration of knowledge content in telemedicine. Thus, knowledge transfer could be extended by the achievement of local flexibility [28].

But approaches that account for time flexibility are also described: the “flipped classroom” model, for example, is an approach to active self-directed learning in which students acquire the basic concepts themselves before class—for example, through recorded lectures or instructional learning modules provided by a learning management system—so that class time can be used for active learning activities such as exercises, projects, or discussions. Valuable time spent in person is used for the application, rather than acquisition, of knowledge. This can increase both student performance and student satisfaction [29,30].

In addition to the flexibility of location and time, there are often limits to accessing real-world working environments. To be able to train practical and theoretical skills in a realistic setting, such as an operating theater, teaching using virtual and augmented reality offers promising potential.

Virtual reality refers to complete visual immersion in an artificial, computer-generated environment. In augmented reality, holograms, which often also enable interaction, appear projected into the room through semitransparent glasses. Mixed reality is the combination of digital screens with projected interactional holograms. The user sees the real world while simultaneously manipulating the digital content generated by the device [31].

Both technologies are increasingly being integrated in the clinical setting, but also in teaching, such as the visualization of organs. In clinical applications, augmented reality enables the simulation of patient encounters to train communication skills or intraoperative decision-making to increase safety during surgery [32].

**Limitations**

This study’s limitations particularly include its single-center design and the small number of participants at the time of analysis. In addition, the final test only examined excerpts from topics that cannot represent the full scope of the curriculum. The choice of term paper is also subject to numerous influencing factors, so the motivation for choosing the topic cannot be clearly identified.

**Conclusions**

This study aims to analyze the objective acquisition of digital competencies through the implementation of a transdisciplinary digital health curriculum at a German university. The results show that relevant content on digital health topics has not been taught sufficiently at the university outside our new digital health curriculum. The objective increase in the knowledge on these topics within the framework of the digital health curriculum could be verified as significant via a pre-post test design.

The approach of transdisciplinary development of a digital health curriculum seems especially promising. We provided dentistry students a platform to complete their recently compulsory elective subject. We observed that dentistry students could complete their recently compulsory elective subject when using an appropriate digital platform.

The integration of written assignments as a special examination element can promote critical engagement with digital health content. This also facilitates gaining insight into digital health topics and issues that are relevant to students. We can harness these insights in further developing our curriculum.

Together with the current literature, our data indicate that the content of digital health curricula must be transferred into standard teaching for all health science students.

**Acknowledgments**

We would like to thank all the speakers who supported the digital health curriculum with their presentations and expert knowledge.

**Conflicts of Interest**

None declared.

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**Multimedia Appendix 1**

Career goals.

[ PNG File, 37 KB - mededu_v10i1e51389_app1.png ]
Multimedia Appendix 2
Aspired specialist of the human medicine participants.

References


Abbreviations

AI: artificial intelligence
Hospital Use of a Web-Based Clinical Knowledge Support System and In-Training Examination Performance Among Postgraduate Resident Physicians in Japan: Nationwide Observational Study

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Abstract

Background: The relationship between educational outcomes and the use of web-based clinical knowledge support systems in teaching hospitals remains unknown in Japan. A previous study on this topic could have been affected by recall bias because of the use of a self-reported questionnaire.

Objective: We aimed to explore the relationship between the use of the Wolters Kluwer UpToDate clinical knowledge support system in teaching hospitals and residents’ General Medicine In-Training Examination (GM-ITE) scores. In this study, we objectively evaluated the relationship between the total number of UpToDate hospital use logs and the GM-ITE scores.

Methods: This nationwide cross-sectional study included postgraduate year–1 and –2 residents who had taken the examination in the 2020 academic year. Hospital-level information was obtained from published web pages, and UpToDate hospital use logs were provided by Wolters Kluwer. We evaluated the relationship between the total number of UpToDate hospital use logs and residents’ GM-ITE scores. We analyzed 215 teaching hospitals with at least 5 GM-ITE examinees and hospital use logs from 2017 to 2019.

Results: The study population consisted of 3013 residents from 215 teaching hospitals with at least 5 GM-ITE examinees and web-based resource use log data from 2017 to 2019. High-use hospital residents had significantly higher GM-ITE scores than low-use hospital residents (mean 26.9, SD 2.0 vs mean 26.2, SD 2.3; P=.009; Cohen d=0.35, 95% CI 0.08-0.62). The GM-ITE scores were significantly correlated with the total number of hospital use logs (Pearson r=0.28; P<.001). The multilevel analysis revealed a positive association between the total number of logs divided by the number of hospital physicians and the GM-ITE scores (estimated coefficient=0.36, 95% CI 0.14-0.59; P=.001).

Conclusions: The findings suggest that the development of residents’ clinical reasoning abilities through UpToDate is associated with high GM-ITE scores. Thus, higher use of UpToDate may lead physicians and residents in high-use hospitals to increase the implementation of evidence-based medicine, leading to high educational outcomes.

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Introduction

Sir William Osler [1] stated that “to study the phenomena of disease without books is to sail in an uncharted sea, while to study books without patients is not to go to sea at all.” Self-learning is known to develop basic clinical skills [2-4], and several studies have demonstrated the effectiveness of web-based clinical knowledge support systems. For example, a study examining the US Residency Internal Medicine In-Training Examination (IM-ITE) score reports a 3.7% increase in the IM-ITE score per 100 hours of UpToDate use [5]. In addition, UpToDate users are more satisfied with their answer accuracy, interaction, and overall satisfaction than PubMed Clinical Queries users [6]. Thus, UpToDate may be effective at the hospital level because hospitals using UpToDate have been reported to show a significantly shorter length of stay for patients [7-9]. UpToDate is already the most widely used web-based clinical knowledge support system among residents (65.5%) and the third most used system among physicians (40.4%) [9].

The General Medicine In-Training Examination (GM-ITE) is an in-training examination developed to provide residents and training program directors with an objective, reliable, and valid assessment of clinical knowledge during training. It uses the same methodology as the IM-ITE [10-12] and comprises the following 4 domains: medical interview/professionalism, symptomatology/clinical reasoning, clinical procedures, and disease knowledge. The examinations consist of 60 questions (6 on medical interview/professionalism, 15 on symptomatology/clinical reasoning, 15 on clinical procedure, and 24 on disease knowledge) and include video- and audio-format questions. The GM-ITE was first introduced in 2011 by the Japan Institute for Advancement of the Medical Education Program (JAMEP), a nonprofit organization, and is administered annually. The questions are prepared annually by a committee of experienced physicians, and peers are reviewed by an independent committee. The examinations are open to the residents of teaching hospitals that have applied to offer the GM-ITE and comprise the following 4 domains: medical interview/professionalism, symptomatology/clinical reasoning, clinical procedures, and disease knowledge. The examinations consist of 60 questions (6 on medical interview/professionalism, 15 on symptomatology/clinical reasoning, 15 on clinical procedure, and 24 on disease knowledge) and include video- and audio-format questions. The GM-ITE was first introduced in 2011 by the Japan Institute for Advancement of the Medical Education Program (JAMEP), a nonprofit organization, and is administered annually. The questions are prepared annually by a committee of experienced physicians, and peers are reviewed by an independent committee. The examinations are open to the residents of teaching hospitals that have applied to offer the examinations [13,14].

We previously reported that self-study time and use of UpToDate had positive relationships with GM-ITE scores [4]. However, those findings could have been affected by recall bias because of the use of a self-reported questionnaire, which meant that objectivity could not be guaranteed. In this study, therefore, we objectively evaluated the relationship between the total number of hospital use logs in UpToDate and the GM-ITE scores of hospital residents. Hospital use logs were used because residents have several opportunities to acquire second-hand knowledge from their supervisors, reflecting the evidence-based medicine (EBM) culture of teaching hospitals. The introduction of clinical knowledge support systems has recently increased among resident and senior doctors, although the frequency of use is low because of language barriers and is far from the global standard [9]. The postgraduate 2-year residency system was established in 2004 in Japan. The use of the Yanegawara (“tilted roof” in Japanese) style of education, in which senior doctors teach resident physicians and postgraduate year (PGY)-2 residents teach PGY-1 residents based on EBM using web-based medical resources, such as UpToDate, has also become widespread [15]. The merit of the Yanegawara-style education is the aspect of teaching among residents with close grade levels. Internationally, peer teaching or peer tutor systems have been shown to be effective in medical education [16,17].

The aim of this study was to evaluate the correlation between the total number of UpToDate hospital use logs and the GM-ITE scores of resident physicians objectively.

Methods

Study Design and Population

We conducted a nationwide observational study of postgraduate residents in Japan using both mean GM-ITE scores and the total number of UpToDate hospital use logs to examine their relationship. The 2020 GM-ITE and self-reported questionnaire were conducted between January 13 and 31, 2021, and the data were collected during the same period. We accessed the data set for research purposes on June 16, 2021.

In Japan, postgraduate resident physicians are required to undergo at minimum a 2-year postgraduate residency program after 6 years of undergraduate medical school. In the program, the resident physicians rotate around 7 clinical departments: internal medicine, surgery, emergency medicine, pediatrics, obstetrics and gynecology, psychiatry, and community-based medicine. The Ministry of Health, Labour and Welfare has established guidelines for postgraduate clinical training programs to teach communication skills, professionalism, and ethics, in addition to basic clinical knowledge and skills, to resident physicians. Medical students in their final year of an undergraduate medical program can apply for the postgraduate residency program at more than approximately 1000 clinical teaching hospitals in Japan using a web-based matching system [18].

Measurements

We collected hospital-level information (number of physicians, monthly salary, number of ambulances, number of permitted beds, type of tertiary emergency care, location, and type of hospital) from published web pages. The hospital use logs of the web-based clinical knowledge support system (UpToDate) in the 3 years from 2017 to 2019 were provided by Wolters
Kluwer. UpToDate log data were defined as the number of topic review page views. We also collected GM-ITE scores. We hypothesized that supervisors’ use of UpToDate reflects the culture of EBM resident education at each teaching hospital. Furthermore, we decided to use UpToDate hospital use logs from 2017 to 2019 to examine their association with the 2020 GM-ITE scores because educational effects are not immediately reflected after an intervention. Resident-level information (sex, grade, number of monthly emergency department duties, average number of patients in charge, general medicine department rotation, self-study time, and weekly duty hours) were obtained using a self-reported questionnaire administered immediately after the GM-ITE. These variables were selected based on previous studies [19-21].

Statistical Analyses
Hospitals were classified as low or high use according to their UpToDate hospital use logs. The total number of use logs was divided by the number of physicians and was log-transformed into base 2. The monthly salary, number of ambulances, and number of permitted beds were also log-transformed into base 2. Low-use hospitals were defined as those with fewer than the median log-transformed number of hospital use logs, whereas high-use hospitals were defined as those with greater than or equal to the median log-transformed number of hospital use logs. Differences between low- and high-use hospitals were examined for statistical significance using the Student 2-tailed t test. Categorical variables were compared using the \( \chi^2 \) test and presented as frequencies with percentages. The effect size (Cohen \( d \)) was estimated using the median difference between low- and high-use hospitals divided by the pooled SD—a value of 0.2 was considered a small effect, 0.5 was considered a medium effect, and 0.8 was considered a large effect [22].

Hospital-level analysis was performed using scatter plots to examine the association between the mean GM-ITE score and the number of UpToDate hospital use logs aggregated at the hospital level. We analyzed the association between the GM-ITE scores and the total number of UpToDate hospital use logs in each hospital over 3 years, using a linear multilevel regression model. The multilevel analysis was adjusted for sex, location, and type of hospital in addition to statistically significant factors in the univariate analysis. In those analyses, the domain of medical interview/professionalism in the GM-ITE was excluded from the analysis because we believed that it was not a clinical skill that could be improved using UpToDate. All analyses were performed using SAS software (version 9.4; SAS Institute Inc).

Ethical Considerations
This study was performed in accordance with the principles of the Declaration of Helsinki and STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines. All the methods followed the Ethical Guidelines for Medical and Health Research Involving Human Subjects. Informed consent was obtained from each participant after clarifying the explanatory research document, including data anonymization and voluntary participation. Only participants who provided consent were included in this study, and they were also provided an opportunity to opt out. The study was approved by the Ethics Review Board of JAMEP (approval 21-1).

Results
The 2020 GM-ITE was offered at 593 teaching hospitals nationwide, and 7669 residents took the exams. A total of 6816 residents from 588 teaching hospitals participated in the survey on the training environment. The study population consisted of 3013 residents from 215 teaching hospitals with at least 5 GM-ITE examinees and web-based resource use log data from 2017 to 2019. Hospitals in all regions of Japan, namely Hokkaido, Tohoku, Kanto, Chubu, Kinki, Chugoku, Shikoku, Kyushu, and Okinawa, were included. The mean number of GM-ITE examinees per hospital was 14.1 (SD 8.6).

The hospital-level information is presented in Table 1. The mean GM-ITE score of all the hospitals was 26.5 (SD 2.2); of the 215 hospitals, 115 (53.5%) were secondary care hospitals, 159 (74%) were located in rural areas, and 204 (94.9%) were community-based hospitals. Residents of high-use hospitals achieved significantly higher GM-ITE scores than those of low-use hospitals (mean 26.9, SD 2.0 vs mean 26.2, SD 2.3; \( P=0.009; \) Cohen \( d=0.35, 95\% \) CI 0.08-0.62). Monthly salary (in JPY ¥100,000; JPY ¥100=US $0.64) was significantly higher in low-use hospitals than high-use hospitals (mean 3.7, SD 0.8 vs mean 3.3, SD 0.7; \( P<0.001 \)). The resident-level information is presented in Multimedia Appendix 1; 68.5% (2076/3031) were male and 50.5% (1531/3031) were PGY-2 residents.

Correlations between total use in 3 years divided by the number of physicians and GM-ITE scores were analyzed (Figure 1). The mean GM-ITE hospital score was significantly correlated with the total number of UpToDate hospital use logs (Pearson \( r=0.28, P<0.001 \); Spearman \( r_s=0.27, P<0.001 \)). The linear regression function was \( y = 24.13 + 0.66 \times \log\text{(total use/number of physicians)} \); therefore, the difference in the mean GM-ITE score between the total use divided by the number of physicians at values of 8 and 128 was 2.64 (Figure 1). Multimedia Appendix 2 shows the relationship between GM-ITE scores and hospital- and resident-level information using an univariate analysis. The statistically significant factors were log-transformed total number of hospital use logs in 3 years divided by the number of physicians (\( P<0.001 \)), log-transformed number of ambulances (\( P<0.001 \)), log-transformed number of permitted beds (\( P=0.005 \)), type of tertiary emergency care (\( P=0.01 \)), grade (\( P<0.001 \)), number of monthly emergency department duty (\( P=0.004-0.046 \)), average number of patients in charge (from \( P<0.001 \) to \( P=0.01 \)), general medicine department rotation (\( P=0.004 \)), self-study time (\( P=0.02-0.04 \)), and weekly duty hours (\( P<0.001 \)). The multilevel analysis was adjusted for all these factors in addition to sex, location, and type of hospital. Table 2 shows the relationship between GM-ITE scores and hospital- and resident-level information using a multilevel analysis. The multilevel analysis revealed a positive association between 3-year total hospital use logs and GM-ITE scores (estimated coefficient=0.36, 95% CI 0.14-0.59; \( P<0.001 \)). Multimedia Appendix 3 shows the results of the analysis of all 4 domains (medical interview/professionalism, symptomatology/clinical reasoning, clinical procedures, and disease knowledge). The result also revealed a positive association between the use of UpToDate and GM-ITE scores (estimated coefficient=0.41, 95% CI 0.18-0.65; \( P<0.001 \)).
<table>
<thead>
<tr>
<th>Hospital-level information</th>
<th>Total (N=215)</th>
<th>Low-use hospitals (n=107)</th>
<th>High-use hospitals (n=108)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total number of use logs of UpToDate, mean (SD)</td>
<td>10,485.1 (20,231.4)</td>
<td>2578.7 (2,278.2)</td>
<td>18,318.2 (26,249.5)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Number of physicians, mean (SD)</td>
<td>144.2 (91.4)</td>
<td>116.3 (61.9)</td>
<td>171.8 (106.6)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Total use in 3 years/number of physicians, mean (SD)</td>
<td>56.5 (62.2)</td>
<td>20.2 (8.7)</td>
<td>92.4 (71.1)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Log-transformed total use in 3 years/number of physicians, mean (SD)</td>
<td>5.2 (1.3)</td>
<td>4.1 (0.9)</td>
<td>6.3 (0.8)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Monthly salary (in JPY ¥100,000)a, mean (SD)</td>
<td>3.5 (0.8)</td>
<td>3.7 (0.8)</td>
<td>3.3 (0.7)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Log-transformed monthly salary (in JPY ¥100,000)</td>
<td>1.8 (0.3)</td>
<td>1.9 (0.3)</td>
<td>1.7 (0.3)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>Number of ambulances, mean (SD)</td>
<td>4882.6 (2399.2)</td>
<td>4462.0 (2183.9)</td>
<td>5299.4 (2536.8)</td>
<td>.01</td>
</tr>
<tr>
<td>Log-transformed number of ambulances, mean (SD)</td>
<td>12.1 (0.8)</td>
<td>11.9 (0.7)</td>
<td>12.2 (0.8)</td>
<td>.02</td>
</tr>
<tr>
<td>Number of permitted beds, mean (SD)</td>
<td>497.8 (166.8)</td>
<td>461.2 (158.9)</td>
<td>534.0 (167.3)</td>
<td>.001</td>
</tr>
<tr>
<td>Log-transformed number of permitted beds, mean (SD)</td>
<td>8.9 (0.5)</td>
<td>8.8 (0.5)</td>
<td>9.0 (0.4)</td>
<td>&lt;.001</td>
</tr>
</tbody>
</table>

**Type of tertiary emergency care, n (%)**

- Tertiary medical care: 100 (46.5), 41 (38.3), 59 (54.6)
- Secondary care: 115 (53.5), 66 (61.7), 49 (45.4)

**Location, n (%)**

- Urban area: 56 (26), 23 (21.5), 33 (30.6)
- Rural area: 159 (74), 84 (78.5), 75 (69.4)

**Type of hospital, n (%)**

- University hospital: 11 (5.1), 2 (1.9), 9 (8.3)
- Community-based hospital: 204 (94.9), 105 (98.1), 99 (91.7)

**GM-ITEb score, mean (SD)**

- 26.5 (2.2), 26.2 (2.3), 26.9 (2.0), .009

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*a* JPY ¥100=US $0.64.  
*b* GM-ITE: General Medicine In-Training Examination.
Figure 1. Correlation between total use of UpToDate and mean General Medicine In-Training Examination (GM-ITE) scores.
Table. Factors related to General Medicine In-Training Examination (GM-ITE) scores (multilevel analysis).

<table>
<thead>
<tr>
<th>Factors</th>
<th>Estimated coefficient (95% CI)</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Hospital-level information</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-transformed total use of UpToDate in 3 years/number of physicians</td>
<td>0.36 (0.14 to 0.29)</td>
<td>.001</td>
</tr>
<tr>
<td>Log-transformed number of ambulances</td>
<td>0.34 (−0.08 to 0.77)</td>
<td>.11</td>
</tr>
<tr>
<td>Log-transformed number of permitted beds</td>
<td>0.36 (−0.39 to 1.12)</td>
<td>.35</td>
</tr>
<tr>
<td><strong>Type of tertiary emergency care</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tertiary medical care</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>Secondary care</td>
<td>−0.20 (−0.80 to 0.40)</td>
<td>.51</td>
</tr>
<tr>
<td><strong>Location</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban area</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>Rural area</td>
<td>0.72 (0.09 to 1.35)</td>
<td>.02</td>
</tr>
<tr>
<td><strong>Type of hospital</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>University hospital</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>Community-based hospital</td>
<td>0.52 (−0.82 to 1.88)</td>
<td>.44</td>
</tr>
<tr>
<td><strong>Resident-level information</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Sex</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>Female</td>
<td>0.08 (−0.28 to 0.45)</td>
<td>.66</td>
</tr>
<tr>
<td><strong>Grade</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PGY-1</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>PGY-2</td>
<td>0.81 (0.45 to 1.17)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td><strong>Number of monthly emergency department duties</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>1-2</td>
<td>0.46 (−0.64 to 1.58)</td>
<td>.41</td>
</tr>
<tr>
<td>3-5</td>
<td>0.81 (−0.28 to 1.92)</td>
<td>.15</td>
</tr>
<tr>
<td>&gt;6</td>
<td>0.48 (−0.75 to 1.72)</td>
<td>.45</td>
</tr>
<tr>
<td>Unknown</td>
<td>−0.42 (−3.38 to 2.54)</td>
<td>.78</td>
</tr>
<tr>
<td><strong>Average number of patients in charge</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-4</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>5-9</td>
<td>0.76 (0.30 to 1.21)</td>
<td>.001</td>
</tr>
<tr>
<td>10-14</td>
<td>0.62 (−0.10 to 1.35)</td>
<td>.09</td>
</tr>
<tr>
<td>&gt;15</td>
<td>1.20 (−0.07 to 2.47)</td>
<td>.06</td>
</tr>
<tr>
<td>Unknown</td>
<td>−1.03 (−2.27 to 0.20)</td>
<td>.10</td>
</tr>
<tr>
<td><strong>General medicine department rotation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>No</td>
<td>−0.12 (−0.54 to 0.29)</td>
<td>.56</td>
</tr>
<tr>
<td><strong>Self-study time (min/d)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>None</td>
<td>Reference</td>
<td>Reference</td>
</tr>
<tr>
<td>0-30</td>
<td>−0.10 (−1.13 to 0.92)</td>
<td>.84</td>
</tr>
<tr>
<td>31-60</td>
<td>0.31 (−0.70 to 1.33)</td>
<td>.54</td>
</tr>
</tbody>
</table>
Factors & Estimated coefficient (95% CI) & P value & \\
61-90 & 0.94 (−0.12 to 2.01) & .08 \\
>91 & 1.03 (−0.25 to 2.32) & .12 \\
Weekly duty hours (h/wk) & & & \\
0-59 & Reference & Reference & \\
60-79 & 0.67 (0.27 to 1.07) & <.001 \\
>80 & −0.10 (−0.60 to 0.38) & .67 \\

*PGY: postgraduate year.

Discussion

We objectively evaluated the relationship between hospital use logs of the web-based clinical knowledge support system, UpToDate, at teaching hospitals and residents’ GM-ITE scores. Residents of high-use hospitals achieved significantly higher GM-ITE scores, an objective index of the basic clinical ability of residents, than those of low-use hospitals. There are 2 main situations in which residents use web-based clinical knowledge support systems such as UpToDate: “actual clinical settings such as bedside and outpatient care” and “self-improvement.” UpToDate is useful in situations where immediate evidence-based care must be provided to the patient in front of a resident [23]. In terms of self-improvement, among both residents and senior doctors, web-based clinical knowledge support systems could lead to the development of basic clinical abilities because they can collect the latest information more efficiently than from textbooks [9].

The use of a web-based clinical knowledge support system is associated with high GM-ITE scores owing to the residents’ knowledge of clinical reasoning. The clinical training guidelines of the Ministry of Health, Labour and Welfare highlight the importance of studying clinical reasoning and problem-solving abilities, and residents are required to have the ability to (1) make a differential diagnosis and initial response to high-frequency symptoms through an appropriate clinical reasoning process and (2) collect patient information and make clinical decisions in consideration of the patient’s intentions and quality of life based on the latest medical knowledge. Residents constantly acquire the latest medical knowledge and use evidence-based and their own experiences to solve clinical problems. The questions in the GM-ITE include clinical reasoning questions in accordance with the guidelines of the Ministry of Health, Labour and Welfare. As UpToDate contains a series of flows that “list differential diagnoses from symptoms and link them to accurate diagnoses,” we believe the use of UpToDate would help residents develop their clinical reasoning abilities. Therefore, we speculate that the development of residents’ clinical reasoning abilities through UpToDate is associated with high GM-ITE scores.

Japanese residents are required to gain greater outpatient clinical experience to acquire basic clinical skills, including communication and clinical reasoning, during this 2-year training period. The postgraduate clinical residency system has been revised regularly, and the latest revision in 2020 requires a 1-month general outpatient training rotation for residents. Therefore, outpatient training is becoming increasingly important in Japanese clinical resident education programs.

Previous studies have demonstrated the usefulness of web-based clinical knowledge support systems in outpatient care. A comparison of outpatient diagnostic errors made by physicians with and without the use of UpToDate shows that diagnostic errors were significantly reduced in the case of physicians who used UpToDate [24]. Internal medicine residents’ responses to patient-specific questions encountered in outpatient settings have been known to improve their clinical skills and patient care decisions. UpToDate has been reported to be the second most commonly used tool for gathering information after MEDLINE and is an extremely helpful information source [25]. We speculate that the GM-ITE includes questions regarding outpatient care that are associated with the development of clinical residents’ outpatient care abilities and high GM-ITE scores.

Factors significantly and positively associated with GM-ITE scores in the multilevel analysis results, besides the use of UpToDate, were location, PGY-2 grade, average number of patients in charge, and weekly duty hours. Residents of rural teaching hospitals may have the opportunity to examine more patients, because the number of physicians affiliated with rural teaching hospitals is lower than that with urban teaching hospitals. Consequently, they may acquire greater clinical experience and knowledge [26]. Regarding the difference in grades, we believe that the difference in clinical experience is directly reflected in GM-ITE scores. This finding is consistent with the results of our previous study [4]. We recommend that residents develop a proactive attitude toward patient care because basic clinical skills tend to develop with daily patient management. The results of the multilevel analysis showed that 60-79 weekly duty hours were significantly and positively associated with GM-ITE scores. This finding supports our previous results [20]; we believe there are optimal working hours for improving clinical competency.

The development of residents’ basic clinical skills does not require many supervisors; however, high-quality and highly productive education is necessary. A previous Japanese study showed that education delivered by a limited number of supervisors was more likely to develop residents’ basic clinical skills [27]. Furthermore, residents who rotated in general medicine achieved higher GM-ITE scores [4]. We believe the following factors are required for future residency education: generalist residency education by general medicine specialists; use of productive web-based clinical knowledge support

Factors significantly and positively associated with GM-ITE scores, above factors, were location, PGY-2 grade, average number of patients in charge, and weekly duty hours. Residents of rural teaching hospitals may have the opportunity to examine more patients, because the number of physicians affiliated with rural teaching hospitals is lower than that with urban teaching hospitals. Consequently, they may acquire greater clinical experience and knowledge [26]. Regarding the difference in grades, we believe that the difference in clinical experience is directly reflected in GM-ITE scores. This finding is consistent with the results of our previous study [4]. We recommend that residents develop a proactive attitude toward patient care because basic clinical skills tend to develop with daily patient management. The results of the multilevel analysis showed that 60-79 weekly duty hours were significantly and positively associated with GM-ITE scores. This finding supports our previous results [20]; we believe there are optimal working hours for improving clinical competency.

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systems, such as UpToDate; EBM culture; and the Yanegawara-style educational system.

This study has a few limitations. First, the scores were examined among a limited number of GM-ITE examinees. Although there are approximately 18,000 PGY-1 and -2 residents in Japan, only 3013 residents were analyzed in this study, accounting for approximately one-sixth (16.7%) of the total population. In addition, as the GM-ITE is a voluntary examination, a bias toward highly motivated residents taking the exam may exist. Therefore, the generalizability of this study is not ensured. Second, causal relationships could not be guaranteed because the study design was cross-sectional. To control for selection bias and to assess causality, we believe that planning a randomized controlled trial targeting nationwide resident physicians is necessary. In this randomized controlled trial, the GM-ITE scores would be the primary end point, and the intervention would control for the presence or absence of web-based clinical knowledge support systems. Third, we did not assess the baseline clinical skills of the GM-ITE examinees in this study, and differences in undergraduate medical school education could have impacted the study results. Fourth, the hospital use logs did not include detailed information, such as user information and access time. It was not possible to identify user-specific information, such as residents, physicians, and co-medical professionals (e.g., nurses), from the log data. Fifth, the results came from a single web-based clinical knowledge support system. Although there are other web-based clinical knowledge support systems that aid residents, physicians, and paramedical workers, we did not compare UpToDate with them. Some resident physicians in Japan may use web-based clinical knowledge support systems other than UpToDate. Although we could not obtain data on systems other than UpToDate for this study, we aim to include them in our next research project to validate the current results.

In conclusion, residents in high-use hospitals had significantly higher GM-ITE scores than those in low-use hospitals, indicating that GM-ITE scores are associated with web-based resource use logs. A previous study showed an association between web-based resource use and resident GM-ITE scores using data from a self-reported survey of clinical residents [4]. Our findings are consistent with those of previous studies and include data that ensure objectivity. Frequent use of web-based clinical knowledge support systems will increase the likelihood of physicians, including faculty, senior, and junior residents, implementing EBM and senior physicians teaching juniors using the Yanegawara-style education, which may lead to higher educational outcomes.

Acknowledgments

We thank the members of Japan Institute for Advancement of Medical Education Program (JAMEP) for their assistance. We would like to thank Editage for English language editing and Wolters Kluwer for providing log data on web-based resource use. This work was supported by the Health, Labour and Welfare Policy Grants from the Ministry of Health, Labour and Welfare’s Research on Region Medical (21IA2004).

Data Availability

The data are not available for sharing because we did not obtain relevant consent from the participants to publish them. The corresponding author will respond to inquiries on data analyses.

Authors’ Contributions

K Kataoka and MN had full access to all data in the study and take responsibility for the integrity of the data and accuracy of the data analysis. YN and YT contributed to study concept and design. K Kataoka, YN, TS, YY, KS, MN, KN, SF, SN, K Katayama, MK, RU, HK, and YT contributed to the acquisition, analysis, and interpretation of data. K Kataoka and YN contributed to manuscript drafting. YN, HK, and YT contributed to critical revision of the manuscript for important intellectual content. K Kataoka and MN contribute to statistical analysis. RU and YN contributed to administrative, technical, or material support. YN, HK, and YT contributed to supervision.

Conflicts of Interest

YN received an honorarium from the Japan Institute for Advancement of Medical Education Program (JAMEP) as a General Medicine In-Training Examination (GM-ITE) project manager. YT is a director of JAMEP. YT, HK, and KS received honoraria for delivering lectures for JAMEP. TS, YY, KS, and SF received honoraria from JAMEP as exam preparers for the GM-ITE. YN and YT received honoraria from Wolters Kluwer for delivering the Wolters Kluwer lecture. K Kataoka, MN, KN, SN, K Katayama, MK, and RU declare no competing interests.

Multimedia Appendix 1

Background characteristics of the residents.

[DOCX File, 29 KB - mededu_v10i1e52207_app1.docx ]
Factors related to General Medicine In-Training Examination scores, including the 4 domains (multilevel analysis).

References


Abbreviations
- EBM: evidence-based medicine
- GM-ITE: General Medicine In-Training Examination
- IM-ITE: Internal Medicine In-Training Examination
- JAMEP: Japan Institute for Advancement of the Medical Education Program
- PGY: postgraduate year
- STROBE: Strengthening the Reporting of Observational Studies in Epidemiology
Digital Health Education for the Future: The SaNuRN (Santé Numérique Rouen-Nice) Consortium’s Journey

Julien Grosjean¹,²*, PhD; Frank Dufour³*, PhD; Arriel Benis⁴*, PhD; Jean-Marie Januet¹, RN, PhD; Pascal Staccini³, MD, PhD; Stéfan Jacques Darmoni¹,², MD, PhD

Corresponding Author:
Arriel Benis, PhD

Abstract

Santé Numérique Rouen-Nice (SaNuRN; “Digital Health Rouen-Nice” in English) is a 5-year project by the University of Rouen Normandy (URN) and Côte d’Azur University (CAU) consortium to optimize digital health education for medical and paramedical students, professionals, and administrators. The project includes a skills framework, training modules, and teaching resources. In 2027, SaNuRN is expected to train a significant portion of the 400,000 health and paramedical students at the French national level. Our purpose is to give a synopsis of the SaNuRN initiative, emphasizing its novel educational methods and how they will enhance the delivery of digital health education. Our goals include showcasing SaNuRN as a comprehensive program consisting of a proficiency framework, instructional modules, and educational materials and explaining how SaNuRN is implemented in the participating academic institutions. SaNuRN is aimed at educating and training health and paramedical students in digital health. The project is a cooperative effort between URN and CAU, covering 4 French departments. It is based on the French National Referential on Digital Health (FNRDH), which defines the skills and competencies to be acquired and validated by every student in the health, paramedical, and social professions curricula. The SaNuRN team is currently adapting the existing URN and CAU syllabi to FNRDH and developing short-duration video capsules of 20-30 minutes to teach all the relevant material. The project aims to ensure that the largest student population earns the necessary skills, and it has developed a 2-tier system involving facilitators who will enable the efficient expansion of the project’s educational outreach and support the students in learning the needed material efficiently. With a focus on real-world scenarios and innovative teaching activities integrating telemedicine devices and virtual professionals, SaNuRN is committed to enabling continuous learning for health care professionals in clinical practice. The SaNuRN team introduced new ways of evaluating health care professionals by shifting from a knowledge-based to a competencies-based evaluation, aligning with the Miller teaching pyramid and using the Objective Structured Clinical Examination and Script Concordance Test in digital health education. Drawing on the expertise of URN, CAU, and their public health and digital research laboratories and partners, SaNuRN represents a platform for continuous innovation, including telemedicine training and living labs with virtual and interactive professional activities. SaNuRN is committed to enabling continuous learning for health care professionals in clinical practice. The SaNuRN team introduced new ways of evaluating health care professionals by shifting from a knowledge-based to a competencies-based evaluation, aligning with the Miller teaching pyramid and using the Objective Structured Clinical Examination and Script Concordance Test in digital health education. Drawing on the expertise of URN, CAU, and their public health and digital research laboratories and partners, SaNuRN represents a platform for continuous innovation, including telemedicine training and living labs with virtual and interactive professional activities. SaNuRN provides a comprehensive, personalized, 30-hour training package for health and paramedical students, addressing all 70 FNRDH competencies. The project is enhanced using artificial intelligence and natural language processing to create virtual patients and professionals for digital health care simulation. SaNuRN teaching materials are open access. It collaborates with academic institutions worldwide to develop educational material on digital health in English and multilingual formats. SaNuRN offers a practical and persuasive training approach to meet the current digital health education requirements.

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KEYWORDS
digital health; medical informatics; education; health education; curriculum; students; teaching materials; hybrid learning; program development; capacity building; access to information; e-learning; open access; open data; skills framework; competency-based learning; telemedicine training; medical simulation; objective structured clinical examination; OSCE; script concordance test; SCT; virtual patient
Introduction and Background

Digital health and health informatics are at the crossroads of medicine and health sciences, computer science and engineering, information and communication sciences, mathematics, statistics, technology, and innovation management [1]. Digital health has been a component of regular training in medical schools for 40 years [2-4] under different labels, such as medical informatics [5], medical computing (in the United States) [6], and e-health [7], with high heterogeneity in content at the national level. In France, digital health is a subdomain of public health, which is also part of the training in medical and paramedical schools [8].

In 2022, the French Ministry of Health, and in particular its Delegation of Digital Health, published an open call for project proposals to support innovative approaches to develop initial academic and continuing professional education in digital health to health-related students, professionals and administrators; law specialists; computer scientists; and data protection officers. “Health-related students and professionals” was mainly referring to students enrolled in health-related programs, including medicine; odontology; pharmacy; midwifery; and paramedical fields such as nursing, physiotherapy, speech therapy, and hearing-aid technician, as well as training programs for social workers [9]. A budget of €71 million (US $75.73 million) has been secured to achieve this specific call to deal with the expected need to train over 400,000 health and paramedical professions students in 2027 at the national level.

The University of Rouen Normandy (URN) and the Côte d’Azur University (CAU), as a consortium, have successfully answered this call by getting a 5-year grant for their joint project, Santé Numérique Rouen-Nice (SaNuRN; “Digital Health Rouen-Nice” in English) [10]. SaNuRN began on September 1, 2022, with a cost estimate of €6,891,923 (US $7,351,441) and a grant contribution of €3,951,200 (US $4,214,646), with the goal of training around 30,000 students by 2027.

Before the initiation of this national project in France, there was a notable deficiency in digital health training for health students and practically none in paramedical schools. The primary focus was on health students pursuing master’s degrees, such as medicine, pharmacy, dentistry, and midwifery. For instance, a national master’s program in medical informatics has been established at Sorbonne University for the past 25 years. However, up until 2020, there was no existing digital health training curriculum for health students at the bachelor’s degree level. Consequently, a comprehensive curriculum in digital health had to be developed from scratch for both health and paramedical students at the bachelor’s degree level.

Before the SaNuRN project, a 10-hour module was introduced for all first-year medical students in CAU in 2020, and in URN, a 20-hour module was implemented for some first-year medical students in 2021. The open call from the Delegation of Digital Health at the French Ministry of Health emphasized allocating 80% of the training effort to the bachelor’s degree level. One of the challenges of the SaNuRN project was assembling a team of digital health specialists to train all health-related students. The initial 2 years of the SaNuRN project (2022-2024) were dedicated to implementing a digital health teaching module for all health-related students, including both health and paramedical programs, at the bachelor’s degree level.

This paper aims to provide an overview of the SaNuRN project, highlighting its pedagogical innovations and how its implementation will optimize digital health education. Our objectives are to present SaNuRN as a whole, comprising a skills framework, training modules, and teaching resources, and to describe how SaNuRN is and will be deployed in the consortium institutions. Below, we describe the SaNuRN project and its objectives. Next, we detail the skills framework and training modules, explaining the teaching resources and how they are deployed. Finally, we discuss the pedagogical innovations and expected impact of the SaNuRN project on digital health education and the quality of care and patient outcomes.

Building a Digital Health Education Lifelong Platform (SaNuRN) as a Cooperation Achievement

Overview

The SaNuRN project emerged in the context of a long-lasting cooperation between URN and CAU in digital health (SJD and PS), medical simulation (Professors Louis Sibert and Jean-Paul Fournier), and general practice (Professors Matthieu Schuers and David Darmon), as a primary use case for teaching digital health during postgraduate studies and residency. From our perspective, this extensive cooperation was a decisive factor in the grant application’s success. URN is located in the northwest of France and CAU is located in the southeast. The distance between them is around 1000 km, and this points out the challenges related to the SaNuRN consortium, which is well managed by using as much dematerialized infrastructure as possible to deliver digital health teaching and learning content. Thus, the first-stage objective of SaNuRN is to educate and train all students in health-related fields in digital health at 4 French departments (Seine-Maritime and Eure in Normandy for URN, and Alpes-Maritimes and Var in Provence-Alpes-Côte d’Azur for CAU), to cover a population of 4 million inhabitants; the target of SaNuRN is to train about 2800 health-related students each year.

Targeted Skills and Competencies

To support this effort, the SaNuRN team activities are based on the French National Referential on Digital Health (FNRDH) [11]. Created and published in 2021, this referential gives a framework and defines the skills and competencies to be acquired and validated by every student in the health, paramedical, and social professions curricula [8]. The exhaustive list of skills and competencies of the FNRDH is detailed in Multimedia Appendix 1. The skills defined in the FNRDH are organized into five competency categories: (1) security, (2) health data, (3) communication in health, (4) digital tools in health, and (5) telehealth and teleactivities. FNRDH is built around a three-level hierarchy: (1) the 5 competencies as introduced above, (2) a total of 25 subcompetencies (eg, to identify an end user or a health professional and to characterize...
and manage nominative data, applying the European rules such as the General Data Protection Regulation (GDPR), and (3) a total of 70 different abilities (eg, to understand the life cycle of the digital health data and to take actions against virus and malware). In June 2023, FNRDH was integrated into the HeTOP terminology server to create a Catalog and Index of Health Digital Teaching Resources (CIDHR) to be usable by all French health and paramedical students.

**Adapting Existing Resources to the FNRDH Framework**

Since the beginning of the project in October 2022, the primary need has consisted of adapting the existing URN and CAU syllabi to FNRDH. The SaNuRN project builds in a matrix format to adapt FNRDH for each degree (bachelor’s, master’s, doctorate, or residency) and each field of study (eg, medicine, nursing, or physiotherapy). Furthermore, the course focuses on digital health in each field of study and, at each degree level, is limited to 30 hours of lectures and practices to address the 70 competencies of the FNRDH skills framework. To manage this challenge, the SaNuRN team is developing short-duration video capsules of 20-30 minutes to teach all the relevant material adapted to the degree levels and fields of study by taking into account the expectations within each degree, discipline, and potential learning sites (URN, CAU, and their partners).

It is essential to notice that the pedagogical components of the SaNuRN project are derived from existing teaching resources previously developed by the 2 Departments of Digital Health at URN and CAU. For example, West Normandy has 7 nursing schools (partners of URN), and the SaNuRN project has adapted its training to each of them specifically.

Since the inception of the SaNuRN project, additional teaching modules have been introduced to address the list of FNRDH skills and competencies. Among these modules, one is dedicated to cybersecurity and another to health data. This supplementary course emphasizes practical applications, featuring instructional videos on the use of specific tools aligned with the skills and competencies of the FNRDH. These tools include (1) a secure email tool, (2) guidance on accessing Mon Espace Santé—a digital platform designed for citizens and patients to manage their digital documents actively, (3) Health French National Identification, and (4) ethics in health (refer to Figure 1). The SaNuRN consortium used existing videos from the French National Digital Health Agency to develop these new teaching resources.

As of January 2024, the personalized 30-hour module is accessible in 2 modes: as freely available teaching resources for any health-related student through an open data website and as specific video capsules within the URN and CAU private teaching environments. A total of 24 hours of preexisting resources, predating the SaNuRN project, were adapted to cater to various audiences, focusing on nurses and pharmacists. Overall, 80% (56/70) of the FNRDH competencies are covered by at least 1 SaNuRN teaching resource.

In line with the strategic decision made by the SaNuRN consortium in response to the French Delegation of Digital Health, all teaching materials generated during the project will be openly accessible on a website (“teaching open data”). Furthermore, from these teaching materials (eg, cybersecurity), several short-duration capsules were developed to suit the specific needs of students in various specialties, including medicine, pharmacy, and nursing.

A significant advantage of SaNuRN is that all these resources are freely accessible to everyone, aiming to benefit health and paramedical students and professionals.
Facilitating Digital Health Education Adoption and Improvement

To ensure that the largest student population earns the necessary skills, the SaNuRN project has developed a 2-tier system. The first tier involves selecting teaching staff in each professional specialty field involved in the project that will act as facilitators. They will enable the efficient expansion of the project’s educational outreach and facilitate periodic updating of the skills framework within each professional specialty. Additionally, these facilitators will support the students in learning the needed material efficiently. The training of these facilitators began in May 2023 for a year.

Based on the outcomes of the first tier, the second tier will consist of adjusting the educational resources that were initially only based on the FNRDH. This will facilitate the deployment, student and teaching staff engagement, and adoption of the digital health teaching modules in all health and paramedical specialties.

The SaNuRN Approach to Digital Health Education Innovation

Overview

As a part of the requirements of the SaNuRN’s grant, 80% of the funding is dedicated to first-degree students (bachelor’s), corresponding to most of the health and paramedical students.
that are enrolled. The SaNuRN consortium has already largely fulfilled this objective by massively educating and training in traditional classroom settings or through self-training.

In the next 3 and half years (see Figure 1), the SaNuRN consortium will focus on pedagogical digital health innovations for the second and third degrees of all health-related fields of study. For example, the consortium has already planned pluriprofessional training sessions for the first semester of 2024 (eg, medicine residents with nursing students, both involved in specific teleconsultations). The first scheduled training session is about clinical data warehouses from various health and paramedical perspectives.

New paradigms are already present in the SaNuRN digital health syllabus and have been introduced to public health residents, particularly the paradigm of “One Digital Health” [18], defined as the intersection of one health and digital health. The SaNuRN team has developed two other innovations: (1) modification of the evaluation process with a shift from a knowledge-based to a competencies-based evaluation, as proposed by the Miller teaching pyramid [19], such as the Objective Structured Clinical Examination, and (2) Script Concordance Test in digital health, using a Health Professional Connected Office (see Figure 1).

Furthermore, several aspects will be mainly at the heart of the innovation of the SaNuRN project, as presented below.

**Interactive and Innovative Components of Courses**

The characteristics of the SaNuRN project are primarily the combination of knowledge and expertise from URN, CAU, and their public health and digital research laboratories and partners.

**Integrated Telemedicine Devices**

Two medical simulation centers, at URN [20] and at CAU [21], have already established living labs. These labs include simulated professional offices and patient apartments, providing a platform to test various software in different health situations, especially in general practice. Soon, 2 integrated telemedicine units will be available for health and paramedical students to test different health situations using scenarios of simulated patients.

By 2027, the SaNuRN project aims to implement several teaching modules that will be financially self-sustainable (ie, that will run in the future without the financial support available for the grant period). These modules will offer digital health training for continuous learning in general practice and private companies, including big pharma and health technology (or “medtech”) companies. For instance, a full-day teaching module has been developed to help private companies handle clinical data warehouses. The medical simulation centers in Rouen (URN) and Nice (CAU) will be used to conduct most of these training sessions.

**Living Labs With Virtual and Interactive Professional Activities**

The SaNuRN program includes a conversational virtual clinical simulator using artificial intelligence techniques combined with natural language processing, with the modeling of clinical situations defined for the training of all health care professionals (eg, physicians, pharmacists, nurses, and physiotherapists).

Analogous to expert systems, this tool, on the one hand, will be able to play the role of a professional (ie, backward chaining), asking questions to a patient while adjusting to the patient’s responses (similarly to a computer-assisted diagnostic aid). On the other hand, the system will play the role of the patient (ie, forward chaining), answering a professional’s questions (simulated clinical examination of the virtual patient).

### A Comprehensive Overview of SaNuRN’s First Achievements

#### Digital Health Education Before SaNuRN (September 2022)

Before SaNuRN (September 2022), digital health was already taught in URN and CAU. Indeed, for example, first-year students at the health schools at URN and CAU received an initial and primary education on digital health. Specifically, since 2021, a total of 15% (150/1000) of the students at URN took a 20-hour course as a part of a minor in health digital science, and since 2020, a total of 100% (1000/1000) at CAU received a 10-hour mandatory course. These digital health courses are performed in a traditional large classroom setting at URN and CAU.

#### Adaptations in Nursing Schools

In West Normandy, a teaching self-learning module was provided to the 7 nursing schools, representing 600 nursing students. In the first semester of 2022, the teaching module was directly derived from the one provided for health students, with an identical duration of 20 hours. Very quickly, in response to the feedback from nursing students, the SaNuRN consortium analyzed the teaching discrepancies between the real needs of these nursing students and the content of the digital health teaching module. Therefore, a 6-hour training was reorganized for the second semester. Furthermore, for each teaching module, all the examples provided were modified and adapted to the nursing student’s needs (eg, to demonstrate the need for health smart cards in their specific practice).

#### Implementation and Expansion During SaNuRN’s First Year

During the first academic year of the SaNuRN project (2022-2023), around 2000 students specializing in health care and paramedical specialties were trained. According to our knowledge and the various national agencies involved in the program, this number is significantly higher than those at other French universities. The West Normandy nursing schools provided only 20 hours of digital health training. These schools have requested an additional 10-hour course in the third year of the curriculum to fulfill the 30-hour teaching requirement.

#### Expansion and Hybrid Learning

In the ongoing academic year (2023-2024), the SaNuRN consortium has engaged several new student cohorts. At URN, 200 second-year medical students (ie, students who passed the first highly selective year at the school of health and chose to...
Study medicine) have participated in hybrid training, including 4 hours of face-to-face organized courses and 25 hours of self-training (see Figure 1). Additionally, around 100 second-year pharmacy students (ie, similar to students who chose to study medicine, except they chose to study pharmacy instead) may opt for this digital health teaching module. A total of 100 physiotherapy and ergotheraphy students are also involved in the project, dedicating 24 hours to self-training. For all these new URN students, the SaNuRN team proposes the following module: a 2-hour introduction teaching (see Figure 1).

At CAU, 400 nursing students from 4 nursing schools will participate in the SaNuRN project in 2024. Lastly, 20 public health residents from URN and CAU will have access to advanced teaching resources. Thus, 100% of medical and paramedical students will be trained in digital health at both universities in 2025.

The Delegation of Digital Health of the French Ministry of Health aims to educate and train 400,000 students in digital health by 2027 using a 30-hour module based on the FNRDH guideline. The SaNuRN project plans to teach 13,200 students over 5 years.

The overall SaNuRN project during the 5 years is summarized in Figure 1; most of the effort is made for students in the first degree of their studies to attain the 100% rate of trained students in digital health. The SaNuRN consortium will fit this goal in June 2025. Then, specific contents are available for second and third degrees to improve the knowledge and competencies in specific situations and medical and paramedical disciplines (eg, videos and live demonstrations of teleconsulting with nurses, physicians, or physiotherapists).

Training Trainers

Goals and Framework

Since May 2023, specific training sessions have been performed for digital health trainers. The “Training the Trainers” component of the SaNuRN project is instrumental to attaining the project’s primary goal, that is, providing education on digital health for undergraduate students of all medical, paramedical, and social disciplines in the academic year 2024-2025. The goals of this component are to obtain from the trainees—who all are faculty members actively teaching in the various academic programs and institutions responsible for undergraduate education in medicine, paramedicine, and social work—the most accurate information about their students such as their profiles, schedules and course works, and preparation for the discipline of digital health.

Program Structure and Implementation

This information is further used to:

- Design the most appropriate pedagogical resources in terms of format, depth of knowledge, types of learning activities, and modes of assessment.
- Evaluate and train the faculty members in the discipline of digital health.
- Train them in the design of e-learning curricula and the use of digital pedagogical resources.
- Prepare them for the integration of the 30 hours of education to digital health in their respective programs.

Core Activities and Learning Objectives

The “Training the Trainers” program has been organized as a yearlong, ongoing, asynchronous, and remote training activity primarily to respond to the significant disparity regarding the trainees’ availability, who, for the most part, could not commit to a fixed time slot, and to allow for an extensive immersion within the discipline itself and consistent exposure to digital technologies. All the collaborative and remote tools used in the development and course of this program were unknown to the trainees, and it took time and practice for all of them to attain a good level of proficiency and confidence.

This model allowed the program to admit new trainees at different stages and moments of its development.

Development of Pedagogical Resources

The program started in May 2023 with 15 faculty members enrolled. It is scheduled to last until the end of May 2024, with, as of today, 34 members representing all the disciplines concerned with the integration of new courses in digital health.

The core activity of the program consists of the complete understanding of the reference framework (FNRDH: Multimedia Appendix 1) and the planning and design of its integration within existing courses and academic programs. Through a collective explication of all capacities included in the FNRDH, the group of trainees has identified 5 learning topics forming the core common foundation shared by all health-related disciplines: “cybersecurity,” the “digital health system,” “digital communication,” “digital professional communication,” and “further developments of digital health.” In order to accommodate the various specificities of the existing academic programs, each of these topics has been divided into teaching modules of roughly 20 minutes, allowing easy customization and integration into existing curricula.

All program trainees contribute to designing and producing these 30 modules, representing the first 10 hours of education in digital health for first-year undergraduate students in health-related disciplines. These modules are designed to be delivered as autonomous self-teaching, asynchronous modules, thus allowing all faculty members to monitor students’ activity and progress with their own methods and tools.

Together with these modules, the trainees are producing web-based interactive resources with the help of a partner of the SaNuRN program, IKIGAI, a nonprofit game design company. Two types of such interactive resources are currently being produced: a gamified quiz and a set of flashcards for practice and memorization.

Innovative Pedagogical Tools: Introduction of Learning and Assessment Scenario

The “Training the Trainers” program provides trainees with a fully immersive experience in digital communication and education and an in-depth analysis of the FNRDH, allowing them to clearly envision the multiple ramifications of the new discipline of e-health.
With the “Training the Trainers” program (see Figure 1), the SaNuRN project has introduced, at the undergraduate level, one major innovative pedagogical tool, the Learning and Assessment Scenario. This tool consists of a detailed outline of a complex professional situation involving digital tools and technologies and the collaboration of professionals from other disciplines. The students presented with this situation must engage in collaborative activities to assess the situation’s multiple dimensions and propose a coordinated plan of action to solve the issue. This teaching tool preforges tools used at the graduate and postgraduate levels, such as the Objective Structured Clinical Examination and Script Concordance Test. The Learning and Assessment Scenario also serves as an efficient tool to teach the much-needed interprofessional collaboration skills that are brought to higher levels of complexity and depth by digital technologies. With this progressive strategy, the educational program created by SaNuRN, covering the 3 cycles of medical, paramedical, and social work studies, creates a consistent continuum of educational engagement for faculty members and students in meaningful interactions with digital technologies.

Evaluation Plans
Currently, no formal (qualitative or quantitative) evaluation has been performed in the SaNuRN project; 2 qualitative evaluations have already been planned: in URN and CAU, 1 for medical students and 1 for nurse students. One indirect positive measure is the presence of health-related students in URN and CAU during the first year’s training sessions. However, the presence was not mandatory, and over 90% of health-related students were present in the 20-hour training module in URN and 10-hour training module in CAU.

Discussion
Overview
During the first academic year of the SaNuRN project (2022-2023), around 2000 students specializing in health care and paramedical specialties received training, a significantly higher number than other French universities. In the ongoing academic year (2023-2024), various new student cohorts are participating in the project, including medical, pharmacy, physiotherapy, and ergotherapy students and public health residents. The SaNuRN project aims to educate 13,200 students over 5 years, contributing to the Delegation of Digital Health’s goal of training 400,000 students by 2027. The project primarily focuses on first-degree students in the initial years (bachelor’s), with specific content for second- and third-degree students (master’s and PhD or residency) to enhance knowledge and competencies in various medical and paramedical disciplines.

The SaNuRN consortium plans to introduce innovative teaching methods, including interprofessional training sessions, competency-based evaluations, and the use of telemedicine devices. Interactive and innovative course components, combined with living labs and virtual clinical simulators, form the core of the project’s innovations.

The key strengths and limitations of the SaNuRN project rely on (1) the fulfillment of the French Ministry of Health’s aim to make digital health learning mandatory and (2) compliance with professional international recommendations, even when the specificities for the French higher education system make it challenging.

Strengths

Fulfilling National Commitments With the SaNuRN Project
By September 2024, learning digital health will be mandatory for all health and paramedical students in France. At that time, the SaNuRN project will be able to fulfill the national commitment to teaching digital health by addressing the 70 FNRDH competencies in a 30-hour training package.

Fitting Global Trends in Digital Health Education
In addition to France, several countries are proposing digital health training at the national level. However, only a handful of countries have established such competencies for clinical practice in their core medical school curriculum [22]. In England, the National Health Service has launched the Digital Readiness Education program [23]. It aims to improve digital skills, understanding, knowledge, and awareness across the multidisciplinary health and care workforce to support new working methods. This program focuses on continuous training. A qualitative study evaluated digital competencies in Singapore for its national medical school curriculum (which included 4 medical schools) [22]. One of the main conclusions was the need to enhance the sharing of educational resources and expertise. This point is also crucial in the French program, so the SaNuRN project has decided to create “open access” and “open data” teaching resources that are shareable with all French health and paramedical schools. An experiment was also conducted in Italy, using Petri-Nets to improve digital health literacy [24].

Looking at Internationalizing the SaNuRN’s Concept
An essential advantage of SaNuRN is that all teaching materials created during the project are freely available to anyone, even explicitly targeting all health and paramedical students and professionals [17]. Most of the teaching material is created in French. However, thanks to international collaborations with institutions such as the Holon Institute of Technology (HIT) in Israel, a large part of the SaNuRN material is coproduced and available in English. This approach allows these partners, URN and CAU, to use the relevant SaNuRN resources in their curricula. For example, some SaNuRN resources (lessons) have been cocreated or coenhanced with lecturers in charge of health data science courses of the Department of Digital Medical Technologies at the HIT in Israel [25].

Complying With the International Medical Informatics Association Recommendations
The International Medical Informatics Association has published 2 versions of its international recommendations in biomedical and health informatics education, initially in 2000 and revised in 2010 and 2023 [26]. The International Medical Informatics Association recommendations are a framework for national
initiatives in biomedical and health informatics education and for constituting international programs and exchange of students and teachers in this digital health field. Zainal et al [27] have proposed a scoping review on clinical informatics training in medical school education curricula; these authors proposed 4 main recommendations that are very similar to those used in the SaNuRN project: situating digital health curriculum within specific contexts, developing evidence-based guidelines for robust digital health education, developing validated assessment techniques to evaluate curriculum effectiveness, and equipping educators with relevant digital health training.

Limitations

**Needing to Align With Other International Standards**

The teaching model may not be entirely compatible with other international approaches; drawing inspiration from experiences in other countries and attempting to fit within a shared framework would be advisable.

**Temporarily Focusing on Undergraduate Students**

Because the project was principally focusing its efforts on undergraduate degrees for its first 2 years, no international collaboration was initiated, apart from a cooperation with the HIT in Israel, as such collaboration usually targets graduate and postgraduate levels. At the national level, for the master’s and PhD degrees, the SaNuRN consortium is planning to cooperate in 2024 with several French universities (Sorbonne Université, Paris Cité, Besançon Université, and Rennes Université), as well as European universities, in particular University for Health Sciences, Medical Informatics and Technology in Austria and continuing its cooperation with the HIT in Israel.

**Conclusion**

The SaNuRN project addresses France’s national commitment to teaching digital health. SaNuRN addresses all 70 FNRDH skills and competencies (Multimedia Appendix 1) with a comprehensive, personalized, 30-hour training package for each health or paramedical student according to their degree level, field of study, and university curriculum. This innovative approach is enhanced by using artificial intelligence and natural language processing to create virtual patients and professionals for digital health care simulation, allowing each student to replay and practice various clinical situations. SaNuRN teaching materials are openly accessible. Moreover, SaNuRN, aiming to answer new needs of the French health schools and paramedical professions, is collaborating with academic institutions worldwide to develop educational material in digital health in English and multilingual formats. SaNuRN offers an enhanced training approach that is both effective and persuasive, making it a challenging solution to the current digital health education requirements in France and potentially Europe and worldwide.

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**Data Availability**

Data sharing does not apply to this paper, as no data sets were generated or analyzed during this study.

**Authors' Contributions**

JG contributed to conceptualization, funding acquisition, investigation, methodology, project administration, supervision, visualization, and writing (original draft, review, and editing). FD contributed to methodology, supervision, and writing (review and editing). AB contributed to conceptualization, investigation, visualization, and writing (original draft, review, and editing). J-MI contributed to methodology, supervision, and writing (review and editing). PS contributed to conceptualization, funding acquisition, investigation, methodology, project administration, supervision, visualization, and writing (original draft, review, and editing). SJD contributed to conceptualization, formal analysis, funding acquisition, investigation, methodology, project administration, supervision, validation, visualization, and writing (original draft, review, and editing).

**Conflicts of Interest**

None declared.

**Multimedia Appendix 1**

List of skills and competencies of the French National Referential on Digital Health (FNRDH).

[PDF File, 145 KB - mededu_v10i1e53997_app1.pdf ]

**References**


Abbreviations

CAU: Côte d’Azur University  
CIDHR: Catalog and Index of Health Digital Teaching Resources  
FNRDH: French National Referential on Digital Health  
GPDR: General Data Protection Regulation  
HIT: Holon Institute of Technology  
SaNuRN: Santé Numérique Rouen-Nice (Digital Health Rouen-Nice)  
URN: University of Rouen Normandy

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