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Contents

Letter to the Editor

Original Paper

Exploring the Cost of eLearning in Health Professions Education: Scoping Review

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Abstract

Background: Existing research on the costs associated with the design and deployment of eLearning in health professions education is limited. The relative costs of these learning platforms to those of face-to-face learning are also not well understood. The lack of predefined costing models used for eLearning cost data capture has made it difficult to complete cost evaluation.

Objective: The key aim of this scoping review was to explore the state of evidence concerning cost capture within eLearning in health professions education. The review explores the available data to define cost calculations related to eLearning.

Methods: The scoping review was performed using a search strategy with Medical Subject Heading terms and related keywords centered on eLearning and cost calculation with a population scope of health professionals in all countries. The search was limited to articles published in English. No restriction was placed on literature publication date.

Results: In total, 7344 articles were returned from the original search of the literature. Of these, 232 were relevant to associated keywords or abstract references following screening. Full-text review resulted in 168 studies being excluded. Of these, 61 studies were excluded because they were unrelated to eLearning and focused on general education. In addition, 103 studies were excluded because of lack of detailed information regarding costs; these studies referred to cost in ways either indicating cost favorability or unfavorability, but without data to support findings. Finally, 4 studies were excluded because of limited cost data that were insufficient for analysis. In total, 42 studies provided data and analysis of the impact of cost and value in health professions education. The most common data source was total cost of training (n=29). Other sources included cost per learner, referring to the cost for individual students (n=13). The population most frequently cited was medical students (n=15), although 12 articles focused on multiple populations. A further 22 studies provide details of costing approaches for the production and delivery of eLearning. These studies offer insight into the ways eLearning has been budgeted and project-managed through implementation.

Conclusions: Although cost is a recognized factor in studies detailing eLearning design and implementation, the way cost is captured is inconsistent. Despite a perception that eLearning is more cost-effective than face-to-face instruction, there is not yet sufficient evidence to assert this conclusively. A rigorous, repeatable data capture method is needed, in addition to a means to leverage existing economic evaluation methods that can then test eLearning cost-effectiveness and how to implement eLearning with cost benefits and advantages over traditional instruction.

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KEYWORDS

education; distance education; professional education; online education; online learning; costs and cost analysis; economics

Introduction

Significant investment is necessary to adapt and expand global health care staff to transition to the medical challenges of the 21st century. The demands on the workforce range from an aging population and emphasis on chronic disease management [1] to access to primary care, where there is a direct link to the cost of training medical personnel. Primary care depends more heavily on public sector investment than other medical specialties, and scarce resources limit the number of personnel who can be trained [2]. As one example, with the increasing cost of delivery of care within the United Kingdom, the National Health Service has recognized that medical providers must take a greater role in education and training [3]. Creating production efficiencies in education and training may assist with the supply of medical personnel to support clinical skills and applied health-related skills. eLearning, defined as "an approach to teaching and learning, representing all or part of the educational model applied, that is based on the use of electronic media and devices as tools for improving access to training, communication and interaction and that facilitates the adoption of new ways of understanding and developing learning" [4], presents a possible opportunity to change and optimize training by providing a scalable means for instruction, thus reducing the costs necessary in delivery and implementation.

A potential critical opportunity of eLearning is the long-term efficiency gain in its delivery model in contrast to other forms of instruction; however, the costs to develop eLearning are significant when executed to a high standard [5]. To achieve better cost management of eLearning and ensure scale-up and adoption, data are required to identify the factors that influence eLearning design and production. Research on the use of eLearning in medicine suggests that measurement of costs in studies is often inconsistent [6]. Therefore, the aim of this scoping review was to provide a broad overview of the state of evidence concerning measurement of costs in eLearning. Understanding these costs will enable better planning in the design and production of eLearning.

Methods

Design

Scoping reviews are a form of rapid knowledge synthesis that identify the sources and evidence available to address research questions in a systematic manner. The established scoping review methodology by Levac et al [7] was chosen for this review, as the research question aims to provide a broad understanding of the literature available in this field to ultimately inform subsequent reviews or research agendas.

Identifying the Relevant Research Question

To establish a comprehensive understanding of the costs [8] associated with eLearning, we conducted a scoping review [7,9] to assess the available literature that quantifies the cost to deliver eLearning in health professions education. For the purpose of this review, cost is defined as the total costs (direct and indirect) from inception to deployment, including the design, development, and delivery (or implementation). Within the study analysis, we attempt to analyze how these costs have been reported by studies, with an understanding that separate factors and sources of these total costs may or may not be reported. Factors influencing these costs could, for example, include the level of experience of the teams producing content. This aggregate grouping of studies will impact the way studies are compared to each other and should be taken into account when reading this review, as other study themes or classifications could impact interpretation of results. The research question under investigation is: What is known in the literature about cost calculations related to eLearning in health professions education in regard to (a) practical cost analysis, with respect to cost per learner and comparison to face-to-face instruction; and (b) the choices in practice of costing methods and models? A secondary question is: How has the publication frequency of this field developed over time?

These questions were derived using the PICO (Population, Intervention, Comparison, Outcome) framework [10]. In this review, the *population* is defined as learners in health professions in all countries; this decision was made to ensure comprehensive coverage of all health professionals to best understand the state of evidence internationally. The *intervention* instrument being evaluated is eLearning in health professions education (inclusive of various forms of training, including basic and advanced continuing professional development, university-level training, patient education, and various other training forms provided by an equally broad group of education training providers). The *comparison* used in this study is the evaluation of costs between eLearning, other methods of instruction such as face to face, and alternate approaches to eLearning, or studies that do not make use of a comparator. The *outcome* was quantification and analysis of the difference in costs between and within the implementations. We defined costs from cost calculations used in economic evaluation, including cost-consequence analysis, cost-minimization analysis, cost-effective analysis, cost-utility analysis, and cost-benefit analysis [11].

Identifying Relevant Studies

Following consultation with an information scientist at the Imperial College London Medical School Library on literature search approaches, a search of the following databases was performed in December 2015 and repeated in December 2018: PubMed, Scopus, Education Resource Information Centre (ERIC), Web of Science, Embase, Global Health, Health Management Information Consortium (HMIC), Prospero, and OVID. In a second search, which was completed in December 2018, new papers were added to the original dataset but did not undergo exhaustive data charting; the data included provided a high-level summary of contents and relevance to previously categorized themes (these papers can be identified as studies from 2016 to 2018).

The search strategy included use of Medical Subject Heading terms and related keywords centered on eLearning and cost calculation with a population scope of health professionals in all countries. The search was limited to English-language studies. There was no restriction placed on literature publication date; although online technologies have changed rapidly over a short period of time, the authors felt that to provide a comprehensive overview of the literature, it would be useful to first explore research with no date restriction. The primary research questions were kept broad to ensure that there would be inclusion of all studies that recorded the costs to deliver eLearning globally. A high-level summary of the search strategy is detailed in Textbox 1; a full summary of the search strategy used per database is detailed in Multimedia Appendix 1.

Textbox 1. Sample search terms.

Cost-related terms

- Costs and Cost Analysis [Medical Subject Heading (MeSH) terms]
- Cost-benefit analysis [MeSH Terms]
- Costs and cost analysis [MeSH Terms]
- Cost*
- Economic*

Learning-related terms

- Learning [MeSH Terms]
- eLearning
- Blended learning
- Online learning

Study Selection

Following the process used in this scoping review method, study selection was based on study identification with data centered on studies that identified cost factors and variables in health professions education eLearning. The literature was reviewed independently by two researchers (JE and EM) to identify articles. A third researcher (CB) adjudicated disagreements when necessary. Article abstracts were first scanned for relevance to the research question and then full articles were downloaded to verify appropriateness. The inclusion criteria included studies and reviews that examined eLearning in health professions education, and captured data concerning design, development, and production costs. Papers that provided synthesis or editorializing of issues without data (ie, opinion pieces and commentaries) were excluded (Multimedia Appendix 2).

Charting the Data

The definition of cost in this review is centered on the hypothesized cost savings derived from a possible reduction in labor costs through scaling teaching via digital technology; cost was defined as the production and delivery costs (direct and indirect) of online learning [12]. Studies included were classified to explore different ways of comparing and analyzing factors influencing these costs. Studies were chartered into two groups: (1) studies detailing costs for eLearning implementations and (2) studies with detailed costing methods (approaches to capture costs) for eLearning but without implementation of specific data. Group 1 was further charted into two separate groups: (1) studies with comparison to other learning types and (2) studies without a comparator. For these two subcategories, we excluded studies disclosing that the cost data provided were incomplete.

Collating, Summarizing, and Reporting the Results

Each study was reviewed individually to understand the implementation aspects of each reported eLearning instance. The studies were then summarized into four categories: (1) studies that detail eLearning costs without a comparator, (2) studies that detail eLearning costs with a comparator, (3) related data from two related systematic reviews, and (4) studies that detail costing approaches. The results are presented as a narrative summary of the principal aspects of each study organized via main classification themes to present evidence that can inform the development and deployment of eLearning by defining the factors that influence implementation costs and the criteria that should be used to explore cost optimization.

Results

Overview of Included Studies

In total, 7344 articles were returned from the search of the literature (Figure 1). Of these, 232 were relevant to associated keywords or abstract references to cost following screening. Full-text review resulted in 168 studies being excluded. Of these, 61 studies were excluded because they were unrelated to eLearning and focused on general education. In addition, 103 studies were excluded because of lack of detailed information regarding costs; these studies referred to cost in ways either indicating cost favorability or unfavorability, but without data to support findings. Finally, 4 studies were excluded because of limited cost data insufficient for analysis. In total, 42 studies

(Table 1) provided data and analysis of the impact of cost and value in health professions education. Completeness of data extracted varied, which resulted in some datasets in the final inclusion data charts to be designated as not available/applicable to reflect inability to abstract usable information; however, these studies remained within the inclusion set because of partial data that contributed to the narrative analysis. These studies contrasted to studies excluded at the earlier screening stage because of cost being a secondary outcome of the investigation and the cost data being of greater focus than those of the excluded studies. The most common data source was the total cost of training (n=29). Other sources included cost per learner, meaning the cost per student (n=13). The population most frequently cited was medical students (n=15), although a group of articles focused on multiple populations (n=12). A further 22 studies provide details of costing approaches for the production and delivery of eLearning. These studies offer insight into the ways that eLearning has been budgeted and project-managed through implementation.

Figure 1. PRISMA (Preferred Reporting Items in Systematic Reviews and Meta-Analyses) flow diagram of search and screening for costs of eLearning implementation.

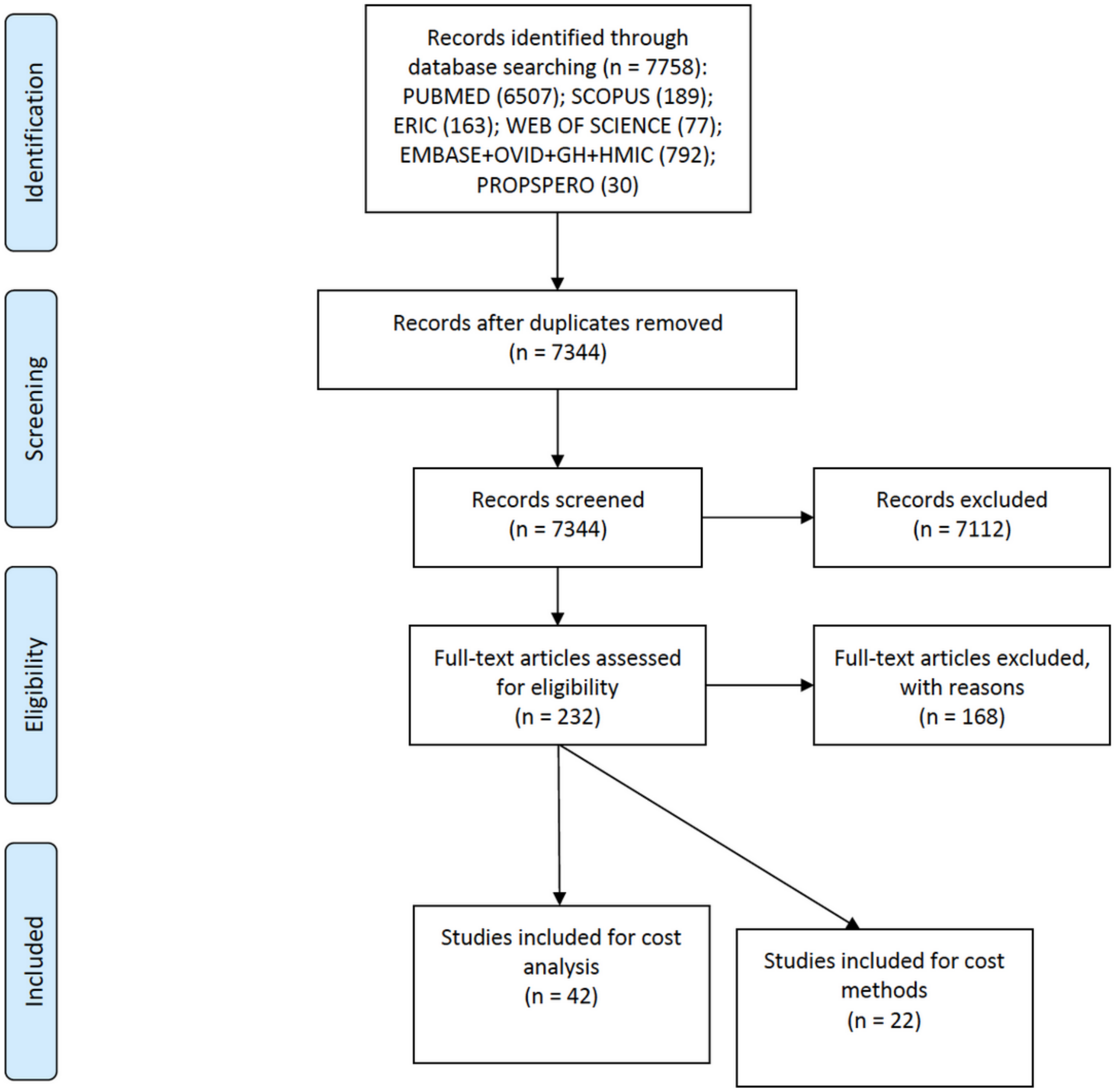

Table 1. Studies that provide costs for eLearning implementation.[a]

Reference	Year	Comparison	Study design	Subject	Cost source	HCP[b] population
Allan et al [13]	2008	None	Case	Evidence-based medicine	Total cost	Clinicians
Bandla et al [14]	2012	None	Case-control	Sleep medicine	Total cost	Medical students
Berger et al [15]	2009	Face to face	Case- control	Patient education	Per learner	Nurses
Butler et al [16]	2013	None	RCT[c]	Behavior change counseling	Per learner	Clinicians, nurses
Choi et al [17]	2008	Other learning	Case	Surgical anatomy	Total cost	Medical students
Collins et al [18]	2018	None	Course review	Nutrition	Total cost	AHPs[d], medical students
Downer et al [19]	2018	None	Case	Leadership and management in health	Total cost	AHPs, medical students, clinicians
Dumestre et al [20]	2014	Other learning	Systematic review	Microsurgical skill acquisition	Per learner	Clinicians, medical students
Glasbey et al [21]	2017	Face to face	Case	Surgical training	Total cost	Medical students
Grayson et al [22]	2018	None	Longitudinal	Hand hygiene	Total cost	AHPs, medical students, clinicians
Hardwick et al [23]	2011	None	Case	Pathology	Total cost	Clinicians
Jerin and Rea [24]	2005	None	Case	Emergency medicine	Per learner	AHPs
Joshi and Perin [25]	2012	Other learning	Case	Public health informatics	Total cost	AHPs
Kaufman [26]	2010	None	Case	Treatment of diabetes	Per learner	Patients (patient education used by HCP)
Knapp et al [27]	2011	Face to face	Case	HIV detection	Total cost	AHPs, clinicians
Kumpu et al [28]	2016	Face to face	Case	Global health	Total cost	AHPs, medical students, clinicians
Letterie et al [29]	2003	None	Literature review	Computer-assisted medical education	Total cost	AHPs, medical students, clinicians
Likic et al [30]	2013	None	Cohort	Rational therapeutics	Total cost	Medical students
Manring et al [31]	2011	None	Case	Psychotherapy	Total cost	Clinicians
McConnell et al [32]	2009	None	Case	Pharmacy CPD[e]	Per learner	Pharmacists
McDuffie et al [33]	2011	None	Case	Experiential pharmacy training	Per learner	Pharmacists
Moreno-Ger et al [34]	2010	No Intervention	Case	Practical skills simulation	Per learner	Medical students
Nickel et al [35]	2015	Other learning	RCT	Laparoscopic cholecystectomy	Total cost	Medical students
Nicklen et al [36]	2016	None	Case	Physiotherapy	Total cost	Undergraduate AHPs
Padwal et al [37]	2017	Other learning	RCT	Weight management	Total cost	Patients (patient education used by HCP)
Padwal et al [38]	2013	Other learning	RCT	Weight management (study protocol)	Total cost	Patients (patient education used by HCP)
Palmer et al [39]	2015	None	Case	Clinical skills	Total cost	Medical students
Pentiak et al [40]	2013	None	Clinical review	Surgical skills	Per learner	Clinicians

Reference	Year	Comparison	Study design	Subject	Cost source	HCP[b] population
Perkins et al [41]	2012	Face to face	RCT	Advanced life support training	Per learner	AHPs
Reeves et al [42]	2013	Other learning	Literature review	Interprofessional education	Total cost	AHPs
Schopf and Flytkjær [43]	2011	None	Case	Interprofessional training -dermatology	Total cost	Clinicians, nurses
Shepler [44]	2014	None	Cohort	Advanced pharmacy practice experience	Total cost	Pharmacy students
Sivamalai et al [45]	2011	None	Case	Pathology	Total cost	Medical students
Spanou et al [46]	2010	Face to face	RCT (protocol)	Behavior change counseling	Total cost	Clinicians, nurses
Stansfeld et al [47]	2015	Other learning	RCT	Employee well-being	Total cost	AHPs
Stromberg et al [48]	2012	None	Cohort	Heart failure nursing	Total cost	Nurses
Thomas et al [49]	2010	None	Case	Family planning	Total cost	AHPs
de Ruijter et al [50]	2015	None	Case	Business engineering; surgical technician	Total cost	Medical students
Weiss et al [51]	2011	Other learning	Cohort	Antibiotic prescribing	Total cost	Clinicians, pharmacists
Williams et al [52]	2009	None	Cohort	Practice-based research networks	Per learner	Clinicians
Young et al [53]	2017	None	Case	Research skills	Per learner	AHPs
Zhou et al [54]	2018	None	Case	Resource stewardship	Per learner	Medical students, clinicians

[a]These studies were all assigned the prefix "INC," indicating that this group was inclusive of both comparator and noncomparator studies (for eLearning costs); the combination of the prefix and study number can be used to provide a unique ID to refer to studies.

[b]HCP: health care provider.

[c]RCT: randomized controlled trial.

[d]AHPs: allied health professionals.

[e]CPD: continuing professional development.

Studies Describing eLearning Costs Without a Comparator

Twenty-two studies [13,16,19,22,23,26,30-34,39,40,43-45,48, 50,52-55] provided analysis of implementation costs in eLearning without comparison to other learning platforms. These studies primarily reported total costs and cost per learner (Table 2). The studies suggested that eLearning should be less costly than face-to-face learning; however, without a comparator, it is not possible to substantiate these claims. Despite these deficiencies, these studies provide varying means of cost calculation across different forms of instructional design.

Table 2. Studies that detail eLearning costs without a comparator.[a]

Reference	Year	Instructional design	Sample size (N)	Total cost (US $)	Cost per learner (US $)	Notes
Allan et al [13]	2008	Asynchronous, blended	304	8209	24	No blended learning cost
Butler et al [16]	2013	Blended	80	2075	26	No explicit cost methodology/technique described
Downer et al [19]	2018	Asynchronous	53	23,000	394	No explicit cost methodology/technique described
Grayson et al [22]	2018	Asynchronous	1,989,713	N/A[b]	0.04	Provided aggregate cost per leaner
Kaufman [26]	2010	Asynchronous	787	N/A	1453	Reported overall cost per learner
Hardwick et al [23]	2011	Asynchronous	N/A	N/A	N/A	Provided cost modeling approach
Likic et al [29]	2013	Asynchronous	393	10,000	23	Use of online course deemed lower cost than face-to-face problem-based learning
Manring et al [31]	2011	Blended	35	5250	137	Only costs of physical implementation
McConnell et al [32]	2009	Asynchronous	8120	610	0.07	No explicit cost methodology/technique described
McDuffie et al [33]	2011	Blended	382	N/A	21	No explicit cost methodology/technique described
Moreno-Ger et al [34]	2010	Asynchronous	400	2630	6	No explicit cost methodology/technique described
Palmer et al [39]	2015	Synchronous	9	5000	506	No explicit cost methodology/technique described
Pentiak et al [40]	2013	Asynchronous	N/A	32,685	N/A	Total curriculum delivery
Schopf and Flytkjær [43]	2011	Asynchronous	88	84,229	858	No explicit cost methodology/technique described
Shepler [44]	2014	Asynchronous	580	N/A	N/A	US $148 savings per intervention
Sivamalai et al [45]	2011	Asynchronous	200	392,468	1782	Cost of digital microscopy 1/3 cost of physical microscopy
Stromberg et al [48]	2012	Asynchronous	183	N/A	N/A	Total cost reduction compared over previous methods
Thomas et al [49]	2010	Asynchronous	273	21,000	70	No explicit cost methodology/technique described
de Ruijter et al [50]	2015	Asynchronous	803	44,986	49	No explicit cost methodology/technique described
Williams et al [52]	2009	Asynchronous	103	3732	33	No explicit cost methodology/technique described
Young et al [53]	2017	Asynchronous	679	N/A	38	Did not report total cost
Zhou et al [54]	2018	Asynchronous	48	N/A	148	Did not report total cost

[a]These studies are given the prefix "SUM" to indicate that this group represents a summary of costs without a comparator; the prefix and number can be used to provide a unique ID to refer to studies.

[b]N/A: not available/applicable.

The studies in this set engaged the scope of the review question focused on the costs associated with eLearning in health professions education but lacked the comparison variable of the PICO framework. Although these studies suggest that implementation of eLearning could provide self-reported high value through low-cost delivery, and thus cost-effectiveness, they offer no comparative framework to justify these assertions. Among the studies that quantify eLearning costs, three groups emerged. The first included studies demonstrating that eLearning was of low cost but had no or limited evidence of self-reported educational impact [13,16]. The second group demonstrated that eLearning was of low cost and had a high self-reported education impact [23,30-34,43-45,48-50,52-54]. A third group [19,22,26,39,40] demonstrated that eLearning was of high cost and had a high self-reported educational impact.

Allan et al [13] and Butler et al [16] present examples of low-cost eLearning delivery but without demonstrated educational impact, with low cost in these studies presented from the perspective of the cost per learner. In Allan et al [13], the key research question was whether this research group could implement an evidence-based medicine curriculum for clinicians. Although quantifying costs was an aspect of the reported results, like many of the studies included in this review, it was not a primary focus and was done so in an informal fashion without explicit unit cost breakdown or listing of all of the components that would impact learning production. In contrast to the use of a comprehensive program including multiple forms of learning and the establishment of a learning community, Butler et al [16] made use exclusively of blended learning in a course. They revealed that the complete training costs are not captured when creating online or blended courses in primary care. Despite comprehensively capturing unit costs of delivery in the implementation of the study (by providing segmentation of costs across administrators, actors, trainers, clinicians, nurses, and costs per practice), their study treated eLearning as a single-group cost reflecting the time per participant to complete the eLearning; however, there was no accounting of the required system implementation time and production time for the creation of eLearning. Similar to Allan et al [13], Butler et al [16] highlight cost omissions that are endemic in studies included in this review.

A second group of studies demonstrate eLearning as having low cost and high educational impact [23,30-34,43-45,48-50,52-54]. Of this set, Likic et al [30], McConnell et al [32], McDuffie et al [33], de Ruijter et al [50], Moreno-Ger et al [34], Thomas et al [49], Williams et al [52], and Young et al [53] each represent online courses making use of asynchronous online learning at low cost per learner (below US $68/learner). The key issue among the studies in this literature cluster is that although they may provide evidence of low cost per learner, without a comparison point to comparable face-to-face delivery, there is no way to assert with any certainty that eLearning is a lower-cost option.

The final group of studies in this set [19,22,26,39,40] indicated that eLearning was of higher cost and had high educational impact. This group shared similar data-recording issues as those from the previous set but also provide evidence to indicate the high start-up costs associated with eLearning production.

It is challenging to draw strong inferences based on an aggregation of the studies that summarize eLearning costs because of the different methods that were used in cost calculation, the difference in subjects instructed, the rapid changes in web platforms for learning, and other factors impacting the way costs were calculated. However, it is possible to observe some trends from this grouping. For pure online courses, the studies suggest that total costs per learner are low; however, there is often acknowledgment in the studies that not all implementation costs have been captured in the cost calculations. This lack of included costs, including sunk costs, indicates that reported costs are not accurate. Although some studies identified the costs that were not captured, many did not, and these gaps are only evident to researchers who have a background and understanding of the issues involved in the delivery of eLearning. Additionally, most studies are cases of specific instances of eLearning implementation, making it difficult to gauge what the results mean in contrast to face-to-face learning, and case study methods make it hard to generalize the results. Some studies indicated high total costs, but in those instances [40], the eLearning costs were embedded in total curriculum delivery.

Studies Describing eLearning Costs With a Comparator

Seventeen studies [14,15,17,21,24,25,27,28,34-37,41,46,47,51] compared eLearning costs to those of face-to-face learning or other types of learning (Table 3). These comparative studies offered more evidence that the use of eLearning demonstrated cost efficiencies than did the studies in the previous group, which provided no comparative data.

Table 3. Studies that detail eLearning costs with a comparator.[a]

Reference	Year	Instructional design	Comparison	Sample size (N)	Cost of eLearning (US $)	Cost of face-to-face learning (US $)	Notes from study
Bandla et al [14]	2012	Asynchronous online	Face to face	173	21,752	21,752	N/A[b]
Berger et al [15]	2009	Blended	Face to face	1661	4	110	Cost per learner
Choi et al [17]	2008	Asynchronous online	Other learning	34	N/A	N/A	Provided costs of online platforms without complete cost comparison
Glasbey et al [21]	2017	N/A	N/A	570	N/A	N/A	Online curriculum embedded; core costs not separated in study
Jerin and Rea [24]	2005	Asynchronous online	Asynchronous online	9353	3	52	Cost per learner
Joshi and Perin [25]	2012	Asynchronous online	Other learning	15	14,085	20,714	Online vs face-to-face total costs
Knapp et al [27]	2011	Asynchronous online	Face to face	91	157	4386	N/A
Kumpu et al [28]	2016	Blended	Face to face	28	2431	1054	N/A
Moreno-Ger et al [34]	2010	Asynchronous online	Face to face	400	7	2630	N/A
Nickel et al [35]	2015	Virtual reality	Other learning	84	3900	82,500	Virtual reality vs blended learning
Nicklen et al [36]	2016	Blended	Face to face	78	5904	6856	N/A
Padwal et al [37]	2017	Asynchronous online	Face to face	651	11,727	477,000	N/A
Padwal et al [38]	2013	Asynchronous online	Face to face	N/A	N/A	N/A	Protocol
Perkins et al [41]	2012	Blended	Face to face	3732	438	935	N/A
Spanou et al [46]	2010	Asynchronous online	Face to face	N/A	N/A	N/A	Protocol
Stansfeld et al [47]	2015	Asynchronous online	Face to face	350	N/A	N/A	Captured approach to total costs but incomplete comparison data to nononline approach
Weiss et al [51]	2011	Asynchronous online	Other learning	N/A	N/A	N/A	Cost reduction per inhabitant following education program

[a]These studies were given the prefix “COMP” to indicate that this group was a summary of costs with a comparator; the prefix and number can be used to provide a unique ID to refer to studies.

[b]N/A: not available/applicable.

The studies in this set can be divided into two groups: studies that demonstrated that eLearning was of lower cost but had no or limited evidence of self-reported educational impact, and studies that demonstrated that eLearning was of lower cost and had self-reported high educational impact [25,51].

Of the studies that demonstrated that eLearning was of lower cost and had a low education impact, the key data issue was that although these studies suggested that eLearning was lower cost, they consistently omitted key components in the design and production of eLearning, thereby creating an incomplete cost profile of the total costs of delivery. Two studies in this set demonstrated that eLearning was of lower cost and had a high education impact; although each study completed a full comparison demonstrating a reduction in costs (in some instances a dramatic reduction), the studies suffer from a lack of methodological consistency in the way they captured costs and evaluated effectiveness. As was the case in the previous set of study classifications, the continued differences in cost accounting, learning delivery platforms, and various forms of assessments make synthesis challenging.

Literature Reviews That Quantify eLearning Costs

Two review studies [20,42] analyzed the use of training where eLearning was used as a delivery platform. Both studies revealed that there was a lack of sufficient evidence to analyze whether training methods using aspects of online learning were more pedagogically effective. The studies were also unable to provide findings that created a holistic understanding of associated cost ingredients. Dumestre et al [20] suggested that within the field of microsurgical training, there are many available methods of implementing instruction and that cost is the determining factor in what method is used by institutions. Reeves [42] performed a Cochrane systematic review protocol that included 15 studies. The review showed that due to the small number of studies (N=15) and the heterogeneity of interventions and outcome measures, it is not possible to draw inferences about the key elements of interprofessional education and its effectiveness. To make such evaluation possible, there must be implementation of cost-benefit analysis, and separation of review within specific professions and studies using qualitative methods to evaluate effectiveness. Although both studies were concerned with evaluation of the effectiveness of specific education training, the way they engaged with the literature review question was limited, as both studies collected limited information on eLearning and only gave broad summary generalizations about cost reductions in their respective field of focus. Costs were identified by looking at the total costs of the delivery of programs; however, because the costs were not described as units, it is not possible to examine the extent and quality of the results. There was no accommodation for differential timing or impact of the consequences of cost decisions. These issues are similar to the weakness in cost analysis of the other studies included in this review.

Studies Describing Costing Approaches

Twenty-two studies [56-77] referenced economic evaluation (analyzing cost benefits or cost effectiveness) or used the ingredients method [78] to calculate costs in the production of eLearning (Table 4). Reflecting on the broader set of studies in this review, it is important to note that while many studies suggest the cost-effectiveness of eLearning, following completion of this review, we have only identified 5 cost-effectiveness analysis studies completed on eLearning. Regarding specific cost approaches, use of the ingredients method is referenced often in this set (12 times); however, the mechanisms for cost capture and subsequent project delivery management of production of learning within this group are inconsistent despite using the same methods.

Table 4. Studies detailing costing approaches or economic evaluation.

Reference	Year	Costing approach
Brown [56]	2014	Cost-benefit analysis
Buntrock et al [57]	2014	Cost-effectiveness analysis
Pettit et al [58]	2017	Ingredients cost method
Carlson et al [59]	2008	Ingredients cost method
Carpenter [60]	2016	Ingredients cost method
Chambers et al [61]	2017	Cost utility analysis
Chhabra et al [62]	2013	Cost-effectiveness analysis
Cousineau et al [63]	2008	Cost-effectiveness analysis
Curran et al [64]	2006	Ingredients cost method
Cook [65]	2014	Ingredients cost method
Delgaty [66]	2013	Ingredients cost method
Djukic et al [67]	2015	Ingredients cost method
Gallimore et al [68]	2012	Ingredients cost method
Isaacson et al [69]	2014	Ingredients cost method
Lonsdale et al [70]	2016	Cost-effectiveness analysis
Papadatou-Pastou et al [71]	2017	Multiple; survey of methods
Pardue [72]	2001	Ingredients cost method
Pickering and Joynes [73]	2016	Multiple; survey of methods
Rondags et al [74]	2015	Cost-effectiveness analysis
Sharma et al [75]	2018	Ingredients cost method
Tung and Chang [76]	2008	Perceived financial cost
Zary et al [77]	2006	Ingredients cost method

Discussion

Principal Findings

Our review was focused on identifying literature that would define the associated costs in the delivery of eLearning in health professions education. Broadly speaking, we were able to answer this question as we collected data that documented a trend of reported eLearning costs per learner and their general low cost. However, we have questions about how conclusive these data are because of the issue of consistency regarding cost data capture, the lack of standard mechanisms for cost data collection for online learning, and the lack of primary studies that focused on cost analysis as a primary research objective. Our review findings are consistent with views put forth in previous research that understanding of the relationship of cost in eLearning is not well developed [6,79,80]. The studies included provide a cross-section of various instances of eLearning across many disciplines in health professions education. This collection of studies allowed gaining a deeper understanding of the various ways in which eLearning is being used and the cost considerations when applying different platforms of education delivery. The key limitation of the included studies was the lack of consistency of methodology for cost analysis. Cost evidence provided by the included studies was challenging for the purposes of comparison due to these deficiencies.

Strengths and Limitations

The strengths of this review are that it completed a comprehensive search of the major literature databases. The search question and the associated terms provided a sufficiently broad scope to ensure that there was coverage to any study that recorded cost and maintained relevance to the inclusion criteria. The search approach was designed in consultation with leading researchers who investigate cost in education, and the final results provide a rich background of materials to explore the issues associated with the research question.

There are four limitations to the process used in this literature review. First, as only English-language papers were searched, relevant foreign-language papers could have been excluded, in addition to the publication bias of health science papers for positive results. Additionally, industry literature was not explicitly searched in the search strategy, further adding to the limitation of study papers under review. Second, due to the inconsistency in capturing costs and lack of standardization in cost reporting, a meta-analysis for quantifying costs is not possible because of the lack of predefined costing models for eLearning used in standard ways across studies, the significant variance in the way costs are recorded, variant experimental methods with different outcome conclusions, and the variance in implementation between different eLearning types. Third, a significant limitation is that in comparing costs of eLearning within the included studies of the review, each study was treated equally, whereas the costs for a team new to eLearning production will likely be higher than those of an experienced team who have produced many courses. Additionally, reported costs could have been on segments of the production process, resulting in inconsistency in reporting. Further research could explore specific aspects of design, development, and delivery to allow for more refined comparison and analysis, including quantitative cost analysis such as that of fixed versus variable costs. In addition to this cost analysis, further work could explore the relationship between learning impact and associated effort as attributed to cost. Lastly, a significant limitation is that this review was rerun in December 2018 to update results from spring 2016 in an original scoping of the literature completed in December 2015, but detailed analysis of new studies identified from 2016 to 2018 are not included in the narrative of this review. Although the newly included studies are incorporated into the data tables, because of time constraints, further analysis of these new studies will be completed in a separate update of this review.

Therefore, the review could be strengthened by taking further measures to either refine the research question into a narrower scope or attempting cost modeling with accepted deficiencies. Nevertheless, the review as completed provides a comprehensive scope of the current evidence, and highlights a gap in the literature indicating a need for a protocol that can capture costs in eLearning interventions to allow a basis for comparison in similar educational subjects or across variant curriculum implementations. Such a protocol would provide a systematic mechanism for calculating online learning costs to allow for a basis of various forms of economic evaluation. This would assist course designers in understanding the total costs in delivery of eLearning and address the standardization issues incumbent with a lack of a standard as evidenced by this review.

Conclusions

Although cost is a recognized factor in studies exploring eLearning design and implementation, the way cost is captured is inconsistent and is assessed in relation to a wide variety of factors or with an alternate study–related focus. Despite a perception that eLearning is more cost-effective than face-to-face instruction, there is not yet sufficient evidence to assert this conclusively. Among the many factors for considering implementing eLearning is the potential long-term cost-effectiveness of its delivery model in comparison to other education delivery formats. A rigorous, repeatable data capture method is needed, in addition to a means to leverage existing economic evaluation methods that can then test whether eLearning is cost-effective, and how to implement eLearning with cost benefits and advantages over traditional instruction. On the one hand, if proven to be more cost-effective, this could assist in addressing the high cost of delivering health professions education. On the other the hand, should evidence point the other way, having discrete data points will allow those involved in health education to identify ways to optimize costs in eLearning delivery to create cost efficiency. To evaluate and optimize cost in education delivery, there must be a rigorous standard through which to score and assess cost-effectiveness, which would enable analysis of whether investments are justified.

To gain a comprehensive understanding of the way cost impacts the deployment of eLearning in comparison to face-to-face instruction, a body of evidence that makes use of economic evaluation must be developed to allow for systematic analysis of how these results demonstrate the strengths and weaknesses of comparative cost delivery. This review has identified the limited use of economic evaluations to achieve this aim thus far. Moreover, even among studies that make use of cost summaries in their results, there is a lack of sufficient rigor to provide insight into the way in which these costs impact education delivery or to allow for comparisons to other forms of learning.

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Authors' Contributions

JC conceived the study topic, and EM (under supervision of JC) devised the primary research question, scope, structure, and methods of the investigation. EM drafted and completed the primary manuscript; the text has been adapted from EM's doctoral thesis in Clinical Medicine Research (with a concentration in Public Health) at Imperial College London. JE and CB completed peer review of papers for selection and analysis. SM, GR, DI, KW, and AM provided feedback on the draft texts. EM responded to peer review feedback. The final manuscript was approved by all authors. EM is the guarantor.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Full search strategy.
[DOCX File , 20 KB - mededu_v7i1e13681_app1.docx]

Multimedia Appendix 2
Eligibility stage search exclusions.
[DOCX File , 42 KB - mededu_v7i1e13681_app2.docx]

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Abbreviations

PICO: Population, Intervention, Comparison, Outcome

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Original Paper

Impact Evaluation of the Kenya Frontline Field Epidemiology Training Program: Repeated-Measures Study

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Abstract

Background: In 2014, Kenya's Field Epidemiology and Laboratory Training Program (FELTP) initiated a 3-month field-based frontline training, Field Epidemiology Training Program (FETP-F), for local public health workers.

Objective: This study aimed to measure the effect of FETP-F on participant workplace practices regarding quality and consistency of public health data, critical interaction with public health data, and improvements in on-time reporting (OTR).

Methods: Between February and April 2017, FELTP conducted a mixed methods evaluation via online survey to examine outcomes achieved among all 215 graduates from 2014 and 2015. Data quality assessment (DQA) and data consistency assessment (DCA) scores, OTR percentages, and ratings of the training experience were the quantitative measures tracked from baseline and then at 6-month intervals up to 18 months postcompletion of the training. The qualitative component consisted of semistructured face-to-face interviews and observations. Quantitative data were analyzed using descriptive statistics and one-way analysis of variance (ANOVA). Qualitative data were transcribed and analyzed to identify key themes and dimensions.

Results: In total, 103 (47%) graduates responded to the survey. Quantitative analyses showed that the training significantly increased the mean DQA and OTR scores but there was a nonsignificant increase in mean DCA scores. Qualitative analyses found that 68% of respondents acquired new skills, 83% applied those skills to their day-to-day work, and 91% improved work methods.

Conclusions: FETP-F improved overall data quality and OTR at the agency level but had minimal impact on data consistency between local, county, and national public health agencies. Participants reported that they acquired practical skills that improved data collation and analysis and OTR.

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KEYWORDS

field epidemiology; workforce development; Kenya; training

Introduction

Strengthened health systems played a key role in improving global life expectancy throughout the 20th century [1]. For the 21st century, public health workforce competencies have important implications for global health preparedness, local disease surveillance and response capacity, health systems infrastructure, and overall population health outcomes [2].

The Field Epidemiology Training Program – Frontline (FETP-F) is a 3-month competency-based, service-oriented collaborative training program that is anchored within the Kenya Ministry of Health (MoH) [3]. The partners of FETP-F include the Ministry of Agriculture, Livestock and Fisheries; the Centers for Disease Control and Prevention (CDC), Kenya Medical Research Institute (KEMRI), and county and subcounty health departments and hospitals [4].

The first phase of frontline training was implemented between September 2014 and December 2016 throughout all 47 counties in Kenya, with a goal of improving local frontline health workers' ability to detect, report, and respond to unusual health events [5].

Methods

Between February and April 2017, the Field Epidemiology and Laboratory Training Program (FELTP) used quantitative, semiquantitative, and qualitative methods to evaluate all FETP-F activities. A survey link was sent to all 215 graduates of Groups 1-6 because they graduated >18 months before the impact evaluation began.

Quantitative Measures

We used interrupted repeated measures on 3 quantitative values (data quality assessment [DQA], data consistency assessment [DCA], and on-time reporting [OTR]) at 6, 12, and 18 months postgraduation from FETP-F. For all quantitative measures, one-way analysis of variance (ANOVA) analysis was performed using Microsoft Excel's (Microsoft Corp) Data ToolPak.

DQA Scores

The participants completed a DQA for their field project, and we used those scores as baseline. The DQA tool was designed for the following tasks: (1) verify the quality of health facility data, (2) assess the system that produces that data, and (3) develop action plans to improve items 1 and 2.

DCA Scores

The DCA is an end-to-end data integrity process that focuses on the entire surveillance network. The first end is the generation of data at the health facility level. The middle is the county record, where the health facilities report their weekly and monthly tallies. The last end is when data are entered into the District Health Information System (DHIS) by the county Health Records and Information Officer (HRIO). The goal is to detect inconsistencies as data travel through the surveillance system and identify root causes for these inconsistencies.

Timeliness of Reporting

Timeliness is a key performance measure of public health surveillance systems. We used the results from the field project as baseline OTR measures, and then followed up at 6, 12, and 18 months postgraduation.

Semiquantitative Measures

At the beginning of each training course, we asked participants to score their knowledge and skills in 8 key competencies on a Likert scale from 1 to 5, with 1 representing limited knowledge/skills and 5 representing expertise. We used those scores to gauge the impact of FETP-F training on knowledge, skills, and change in work methods.

Semistructured interviews were conducted with randomly selected graduates from groups 1-6, because we wanted to examine the impact of the training at least 1.5 years postgraduation; this meant that we could only look at the impact of FETP-F on the work methods of the first 6 groups to complete the FETP-F process.

Ethics Approval and Consent to Participate

Informed consent was obtained from all FETP-F graduates who agreed to an evaluation visit. Personal identifiers were not included in the recorded data. Permission to conduct this evaluation was sought from and granted by the Ethical Review Board of the Ministry of Health (FAN: IREC 1795). This evaluation did not involve any animal subjects. The evaluation did not collect human subject data nor any human specimen samples. All subjects provided signed and oral consent for participation. Informed consent included consent to publish findings of this evaluation research. This research did not use any images, names, or other identifying information of any of those who consented for interview and participation in the evaluation. Therefore, a consent for publication was not needed from any of the research subjects.

Results

Demographics of Survey Respondents

Overall, 103 graduates representing all regions of the country were included in the analyses. Most (55%) were male and 60% (n=62) had <10 years of public health work experience. The breakdown by cadre was the following: 20% (n=21) medical officers, 15% (n=15) veterinary officers, 25% (n=26) public health officers, 15% (n=15) laboratory staff, 15% (n=16) nursing staff, and 10% (n=10) other.

DQA Scores

Descriptive analyses of 103 DQA scores from baseline to 18 months postgraduation showed an increase in the mean DQA score from 75.6% at baseline to 84.5% at 18 months postgraduation.

Table 1 shows a 10.5% improvement in the mean DQA score for this sample of health facilities and programs. The subsequent ANOVA analyses on the 103 respondents showed that although the improvement was only 10.5%, this represented a significant improvement in DQA mean scores since baseline.

Table 1. Repeated-measures scores for data quality assessment, data consistency assessment, and on-time reporting of Kenya Field Epidemiology Training Program–Frontline graduates, 2014-2015.

Results and time interval postgraduation	Mean (SD)
Analysis of variance results, data quality assessment mean scores[a]	
Baseline	75.64 (8.05)
6 months	74.88 (9.00)
12 months	75.08 (5.21)
18 months	84.53 (8.82)
Analysis of variance results, data consistency assessment mean scores[b]	
Baseline	73.22 (27.59)
6 months	68.11 (13.42)
12 months	78.22 (21.46)
18 months	82.66 (21.37)
Analysis of variance results, on-time reporting mean scores[c]	
Baseline	29.66 (15.58)
6 months	70.11 (23.39)
12 months	70.83 (180.1471)
18 months	74.88 (624.3399)

[a]Between-groups: F=70.71; f-crit=2.61; P<.001.

[b]Between-groups: F=0.765; f-crit=2.90; P=.52.

[c]Between-groups: F=20.37, f-crit=2.74, P<.001.

DCA Scores

Descriptive analyses of DCA scores showed that there was an 11.4% improvement in DCA scores between baseline and 18 months postgraduation. However, upon further analyses using ANOVA, results showed that the increase was not significant (Table 1).

OTR Proportions

We examined the proportion of monthly reports submitted on time from health facilities to county health departments for the preceding quarter (Table 1). Analyses show that there was a >60% increase in OTR between baseline and the 18-month assessment. The ANOVA showed this to be a significant development and improvement compared to baseline values.

Semiquantitative Self-assessment of Learning Scores

Knowledge/skill levels for the 8 assessed competencies were relatively low before the training. After training, we noted significant increases in the mean knowledge/skill scores in each of the 8 competencies. During the site visits, field workers also interviewed supervisors of the graduates and at least one colleague regarding any notable changes (positive or negative) after the graduate resumed his/her normal work duties. We used the same assessment scale as with the graduates. Comparisons of mean difference scores among FETP-F graduates, their supervisors, and their colleagues in 8 competency areas are outlined in Table 2, using a Likert scale between 1 and 5.

There was not much variation in the self-assessments of the graduates when compared to the assessments of competencies provided by their supervisors and colleagues. However, the supervisors and colleagues noted a marked increase in Microsoft Excel skills, knowledge, and expertise postgraduation.

For the larger group of graduates (n=103), we examined via online survey the mean skills and knowledge changes (pre-post) in the key competencies before training (pretraining), immediately after the 3-month session ended (posttraining), and 18 months after training (follow-up; Table 3).

Table 2. Learner, supervisor, and colleague assessment of pre-post scoring of learner knowledge and skill in key competencies.[a]

Competency	Self-score (n=19)	Supervisor score (n=12)	Colleague score (n=7)
Statistics	1	2	2
Epidemiology	3	2	3
Surveillance	2	2	2
Microsoft Excel	1	3	2
Data analysis	2	1	2
Field investigations	2	2	2
Data audits	3	3	3
Communicating public health data	2	2	Not reported

[a]The assessment scale ranged from 1 to 5 (1=no skills, 2=limited skills, 3=average skills, 4=good skills, and 5=mastery). Classification of the difference scores tabulated above are in terms of improvement: 0=none, 1=limited , 3=modest, and >3=significant.

Table 3. Changes in knowledge and skills of Field Epidemiology Training Program–Frontline graduates, 2014-2015 (n=103)[a].

Competency	Time of measurement		
	Pretraining, mean (SD)	Posttraining, mean (SD)	Follow-up, mean (SD)
Statistics	2.77 (0.81)	3.69 (0.61)	4.35 (0.72)
Epidemiology	2.68 (0.72)	4.11 (0.45)	3.74 (0.69)
Surveillance	2.82 (0.73)	3.84 (0.59)	3.99 (0.51)
Microsoft Excel	1.86 (0.75)	3.81 (0.55)	3.97 (0.62)
Data analysis	2.55 (0.96)	3.95 (0.69)	3.56 (0.49)
Field investigations	2.32 (0.89)	3.47 (0.82)	2.66 (0.74)
Data audits	2.86 (0.99)	3.89 (0.55)	3.82 (0.62)
Communicating public health data	2.73 (0.58)	3.94 (0.31)	4.02 (0.47)

[a]The ordinal scale ranged from 1 to 5 (1=no knowledge, 2=little knowledge, 3=average, 4=good, and 5=mastery). Pretraining occurred before the training, posttraining occurred immediately after completing the 3-month training process, and follow-up was performed at least 18 months postgraduation from the training program. Between-groups: F=30.02; f-crit=3.47; P<.001.

Qualitative Results

Field investigators visited 19 sites and conducted 38 one-on-one private interviews (with graduates, supervisors, and colleagues). We analyzed the transcripts of all interviews (n=19 graduates, n=12 supervisors, and n=7 colleagues). After transcription, we conducted 3 levels of analysis. The coding process was iterative and involved multiple stages that involved preparing and formatting the raw data so that they are available for evaluation.

After conducting the first-level analyses using keyword searches and generating word clouds, we had a list of 107 codes. During the second-level analyses, we reduced the codes from 107 to 37, which we later grouped into 25 themes. After the third-level review, we noted that the themes clustered into 3 key dimensions. Graduates, their supervisors, and their colleagues' comments were associated with "personal" aspects (benefits to self), organizational aspects (benefits to the agency or organization where the graduate worked or health partners in the graduate's community), and the FETP process itself (feelings and perspectives on the nominations/selection process, the execution of the course inclusive of its contents, and feedback on the quality of the faculty and facilitators) [6].

Discussion

Principal Findings

Field epidemiology training programs worldwide are based on multiple administrative models. Our evaluation results show the effectiveness of a localized field epidemiology and data management training process for improving the skills and capacity of frontline health workers. During the interviews, most graduates, their supervisors, and their colleagues reported that the course had helped them to make scientifically based decisions and improved their overall capacity to deal with a spectrum of public health challenges, from calculating thresholds to responding to cholera cases. Additionally, they reported that the course helped them to become better leaders by improving their communication skills, enabling them to make more evidence-based decisions, and empowering them to show colleagues how to practically interact more critically with the data they generate at their agencies. Our findings align with evaluation results from other FETPs. In both Japan and Mongolia, the positive effect this approach had on trainees was demonstrated in post–training of trainers evaluations and posttraining application of knowledge and skills [7,8].

Several other examples have clearly showed the success of FETP in responding to emergencies and disasters [9]. During the Middle East Respiratory Syndrome (MERS) outbreak in 2014 in Saudi Arabia, FETP graduates tackled numerous issues, including redesigning the system to enable simultaneous real-time electronic reporting of suspected and confirmed cases to public health professionals who needed to take essential control and preventive actions on new cases [10]. FETPs in the Eastern Mediterranean Region showed success in building the epidemiologic capacity of the public health workforce, improving countries' surveillance systems, and strengthening health systems [9].

One of the strengths of this study is that we assessed "the degree of applying what was learned" and "the degree to which outcomes occur as a result of the training," which are levels 3 and 4 of the Kirkpatrick model, respectively [10]. Another strength is that the evaluation was based on information from two sources, including the FETP graduates and program advisers, who are within the health system at a level where they can observe the impact of the program.

Our results were derived from an online survey, with all the potential strengths and limitations of that medium. The survey was anonymous and, thus, it is very likely that participants gave accurate answers without fear of exposing their identity. In addition, they were not under any pressure to give "desirable answers" to the survey questions. Although the response rate was only about 55%, this is more than expected with this type of survey.

Implementing this approach revealed some challenges: first, the approach requires assessment of participant learning needs and subsequent systematic training design; thus, facilitators must review and redesign curricula for each event. Second, participatory methods can be new and uncomfortable for individuals educated in formal or traditional styles, implying that programs with longer records and institutional memory may be hesitant to change. Third, systematically evaluating short- and long-term effects of this approach beyond pretest and posttest questionnaires was challenging; therefore, program administrators should develop careful impact evaluations that begin before training. Finally, the approach requires a facilitator who is skilled and comfortable with participatory methods.

Some additional limitations of the current evaluation should be noted. First, the bulk of the data collected are self-reported, including DQA, DCA, and OTR scores, as well as measurements of respondents' perceptions of learning and impact. It is possible that participants overrated or underrated their skills and knowledge when responding to survey items online. Second, the time gap from delivery of the course to data collection could have affected the information that graduates gave to us. Additionally, the data collection had to be rushed due to pending funding cuts. This will hinder subanalyses of the formative and summative evaluation data over the life of the project. Further efforts are needed to determine if skills and/or benefits from the course change over time and whether the documented improvements in health facility data quality, consistency, and OTR change over time, particularly as replications continue and the time gap since training widens and we lack a steady flow of their colleagues who can participate in such training.

Further, many of the graduates did not respond to the repeated-measures surveys, so we do not have relevant data about them; therefore, we are not able to conclude that respondents are a representative sample of graduates.

Finally, we know that FETP-F's participants take part in a never-ending array of trainings, so we do not know how those other trainings have impacted the findings that we have documented. In addition, we do not know the spectrum of participants' involvement in support networks, how the doctors' and nurses' strikes affected outcomes, the role of politics in who is nominated to participate in the training, local rates of job turnover, and if there is an effect on uptake among some younger public health workers associated with the fact that the FETP-F does not award a diploma.

In summary, FETPs that plan to build sustainable public health response capacity and expertise from its most local levels for handling public health threats across health sectors should consider incorporating this approach, which combines participatory methods and periodic follow-up assessments with retraining opportunities and concurrent impact evaluations. This will improve governments' understanding of their public health workforces' potential for improving capacity to meet global epidemiology goals [5].

Conclusions

FETP-F is a viable and effective method for improving Kenya's public health workforce's skills, knowledge, and practices in key competencies. This evaluation suggests many benefits and lessons on frontline field epidemiology training including the following: (1) the advantage of focusing on local health workers who are more familiar with contextual issues to allow tailoring of the training, (2) enhanced collaboration among multiple practice cadres to create a forum for networking and new partnership opportunities, (3) a more convenient method of training that eliminates the need to bring in external trainers or for participants to travel outside of their region, and (4) specific examples of how to improve future iterations of this kind of training. This evaluation suggests that the FETP-F model has increased the capacity of local health workers trained in field epidemiology and data analytics, while maintaining fidelity with the original objectives and frameworks of the original model, the advanced-level field epidemiology training program. The FETP-F met its aims and objectives satisfactorily, and resulted in positive shifts in knowledge, attitudes, and behavioral intentions of local health workers who graduated from the program. This suggests that this training strategy was effective and feasible in improving the capacity of local public health workers of all cadres.

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Authors' Contributions

ZG, JG, EO, WB, and JR conceived and developed the evaluation tools and overall plan. JG, EO, EK, and WQ supervised the implementation and collection of the evaluation data. JR, ZG, EO, and WB cleaned and analyzed the data. JR and ZG contributed to interpretation of the results. JR took the lead in writing the manuscript. All authors provided critical feedback and helped shape the research, analysis, and manuscript.

Conflicts of Interest

None declared.

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Abbreviations

ANOVA: analysis of variance
CDC: Centers for Disease Control and Prevention
DQA: data quality assessment
DCA: data consistency assessment
DHIS: District Health Information System
FELTP: Field Epidemiology and Laboratory Training Program
FETP: Field Epidemiology Training Program
HRIO: Health Records and Information Officer
KEMRI: Kenya Medical Research Institute

MoH: Ministry of Health
OTR: on-time reporting

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Original Paper

Evaluating the Instructional Design and Effect on Knowledge, Teamwork, and Skills of Technology-Enhanced Simulation-Based Training in Obstetrics in Uganda: Stepped-Wedge Cluster Randomized Trial

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Abstract

Background: Simulation-based training is a common strategy for improving the quality of facility-based maternity services and is often evaluated using Kirkpatrick's theoretical model. The results on the Kirkpatrick levels are closely related to the quality of the instructional design of a training program. The instructional design is generally defined as the "set of prescriptions for teaching methods to improve the quality of instruction with a goal of optimizing learning outcomes."

Objective: The aim of this study is to evaluate the instructional design of a technology-enhanced simulation-based training in obstetrics, the reaction of participants, and the effect on knowledge, teamwork, and skills in a low-income country.

Methods: A stepped-wedge cluster randomized trial was performed in a university hospital in Kampala, Uganda, with an annual delivery volume of over 31,000. In November 2014, a medical simulation center was installed with a full-body birthing simulator (Noelle S550, Gaumard Scientific), an interactive neonate (Simon S102 Newborn CPR Simulator, Gaumard Scientific), and an audio and video recording system. Twelve local obstetricians were trained and certified as medical simulation trainers. From 2014 to 2016, training was provided to 57 residents in groups of 6 to 9 students. Descriptive statistics were calculated for ten instructional design features of the training course measured by the 42-item ID-SIM (Instructional Design of a Simulation Improved by Monitoring). The Wilcoxon signed rank test was conducted to investigate the differences in scores on knowledge, the Clinical Teamwork Scale, and medical technical skills.

Results: The mean scores on the ten instructional design features ranged from 54.9 (95% CI 48.5-61.3) to 84.3 (95% CI 80.9-87.6) out of 100. The highest mean score was given on the feature feedback and the lowest scores on *repetitive practice* and *controlled environment*. The overall score for the training day was 92.8 out of 100 (95% CI 89.5-96.1). Knowledge improved significantly, with a test score of 63.4% (95% CI 60.7-66.1) before and 78.9% (95% CI 76.8-81.1) after the training (P<.001). The overall score on the 10-point Clinical Teamwork Scale was 6.0 (95% CI 4.4-7.6) before and 5.9 (95% CI 4.5-7.2) after the training (P=.78). Medical technical skills were scored at 55.5% (95% CI 47.2-63.8) before and 65.6% (95% CI 56.5-74.7) after training (P=.08).

Conclusions: Most instructional design features of a technology-enhanced simulation-based training in obstetrics in a low-income country were scored high, although intervals were large. The overall score for the training day was high, and knowledge did improve after the training program, but no changes in teamwork and (most) medical technical skills were found. The lowest-scored instructional design features may be improved to achieve further learning aims.

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KEYWORDS

simulation training; medical education; instructional design; low- and middle-income countries; obstetrics

Introduction

Maternity Care

The improvement of maternal and newborn care is a global priority. The United Nations constructed the Millennium Development Goals and the Sustainable Development Goals, in which the aim of reducing the maternal and neonatal mortality was included [1]. Targets for 2030 are to reduce the global maternal mortality ratio to less than 70 per 100,000 live births and to reduce neonatal mortality to at least as low as 12 per 1000 live births [1]. In Uganda, in 2015 the maternal mortality ratio was still 343 per 100,000 live births, and the neonatal mortality rate was 20.2 per 1000 live births in 2017 [2,3]. Shortage of trained staff, poor management of emergency obstetric care provision, poor referral practices, and poor coordination among staff are barriers that hinder or delay the ability to access emergency obstetric services [4]. Simulation-based medical team training may have a positive effect on these barriers.

Simulation-Based Training

Simulation-based training in low-income and middle-income countries usually focuses on improving capacity and providing safe clinical skills to directly reduce maternal and neonatal mortality and morbidity [5]. A review in 2010 about training programs in low-resource environments aimed at improving emergency obstetric care concluded that training programs may improve quality of care, but strong evidence was lacking [6]. Since this review, there have been numerous evaluation studies on the effectiveness of simulation training for obstetric emergencies in low-income and middle-income countries [7-40]. The results of these studies show that obstetric simulation training is associated with improvements in clinical outcomes, mostly neonatal outcomes [7,11,16,18,24,26,28,33,36,38,40]. A later review included 23 studies about the impact of multiprofessional emergency obstetric and neonatal care training in high-income, middle-income, and low-income countries [5]. The conclusion of this review was that this type of training does make a difference [5]. Progress was not only found with regard to individual knowledge, skills, and attitudes, but also with regard to longer-term change in behavior and improvements in maternal and neonatal morbidity and mortality [5]. Sufficient evidence exists to justify the expense and effort of it [5]. Draycott et al agreed with this, but also mentioned that not all training is clinically effective and results are not entirely consistent [41]. Further research on the evaluation of different training programs is necessary to understand why some training programs improve clinical outcomes, and others show no improvements or even deterioration in outcomes.

Evaluating Simulation-Based Training

Most evaluation studies on simulation-based training in low-income and middle-income countries used Kirkpatrick's theoretical model. This model is composed of four levels: reaction, learning, behavior, and results. Each successive level of the model represents a more precise measure of the effectiveness of a training program. The results on these Kirkpatrick levels are closely related to the quality of the instructional design of a training program [42]. The instructional design is generally defined as the "set of prescriptions for teaching methods to improve the quality of instruction with a goal of optimizing learning outcomes" [43]. Another name for these prescriptions is *affordances* with the purpose of maximizing the effect, effectiveness, and usefulness of an educational instrument [44]. The instructional design of the training program may influence the outcomes on the Kirkpatrick levels [45]. Therefore, if the learning aim is not met, this may have to do with an inappropriate design.

A review on postgraduate medical e-learning recommended not only to evaluate the outcomes of an educational intervention, but to start with evaluation of its design [45]. For simulation-based medical education, Issenberg et al and McGaghie et al have described essential instructional design features [42,46]. These include feedback, repetitive practice, ranging difficulty levels, defined outcomes, individualized learning, curriculum integration, multiple learning strategies, clinical variation, controlled environment, and simulator validity [42,46]. These features were integrated by Fransen et al in the ID-SIM (Instructional Design of a Simulation Improved by Monitoring), an evidence-based assessment tool that can be used to aid development and evaluation of the instructional design of a simulation-based team training [47].

Training for Life

A technology-enhanced simulation-based training in emergency obstetrics was developed in Mulago Hospital in Kampala, Uganda (Training for Life). The training focused on both medical technical skills and teamwork. To evaluate the training program, we conducted a stepped-wedge cluster randomized trial. In this paper, we present the results of the evaluation of the instructional design of this training program, the reaction of participants, and the effect on knowledge, teamwork, and medical technical skills (Kirkpatrick levels 1 and 2).

Methods

Recruitment

Between October 2014 and April 2016, a stepped-wedge cluster randomized trial was conducted to implement technology-enhanced simulation-based team training in obstetrics. This educational intervention took place at the Makerere University College of Health Sciences, situated in Mulago Hospital in Kampala, Uganda. In November 2014, a medical simulation center was installed with a full-body birthing simulator (Noelle S550, Gaumard Scientific), an interactive neonate (S102 Simon Newborn CPR Simulator, Gaumard Scientific), and an audio and video recording system. Mulago Hospital is a national referral hospital in Kampala with an annual delivery volume of approximately 31,000. Over 23,000 women deliver at a medium-to-high–risk ward, and the staff of this ward consists of 45 gynecologists, 60 residents (first-year, second-year, and third-year senior house officers [SHOs]), and 45 midwives. To be included in the study, SHOs had to work at the medium-to-high–risk maternity ward of Mulago Hospital. As this study was set up as a stepped-wedge cluster randomized trial, clusters of SHOs started in a control period. Therefore, recruitment was done before the official opening of the simulation center and the train-the-trainers course. Seven clusters of first-year, second-year, and third-year SHOs were randomly created by a scheduler. To evaluate clinical outcomes, the SHOs had to work in the hospital in these fixed clusters during the study period.

Training for Life used a train-the-trainer model in which training was cascaded down from master trainers to local facilitators to learners. The group of master trainers consisted of two Dutch obstetricians, one communication expert, and one simulation specialist. They were all certified simulation educators. Twelve local senior obstetricians finalized a four-day training program and were certified as facilitators. Course materials were developed in cooperation with staff members in Mulago Hospital and Medsim, a medical simulation center in Eindhoven, the Netherlands. All materials were provided in English.

After the train-the-trainers course, training was cascaded down to the SHOs. Each training was given by two recently certified local facilitators to 7 clusters of each 6 to 9 SHOs of different study years. The training comprised a one-day (8-hour) simulation-based acute obstetric training focusing on medical technical skills and teamwork/crew resource management (eg, closed-loop communication, leadership, speaking up). The two facilitators focused alternately on medical technical skills or crew resource management. Scenarios included postpartum hemorrhage, eclampsia, ventouse delivery followed by resuscitation of the newborn, breech delivery, and a repetition of postpartum hemorrhage with a different etiological mechanism. Every scenario was briefly introduced by the medical facilitator, and after each scenario, a debriefing with review of the video recordings was provided with feedback on medical technical skills and crew resource management. All scenarios were performed once, according to a fixed script with realistic clinical progress. At least three SHOs could participate actively in each scenario. After the main training, at least one half-day repetition training session was organized for each group.

As this study was set up as a stepped-wedge cluster randomized trial, all 7 clusters of SHOs started in the control condition. Then, all clusters received the training at consecutive time points, scheduled 7 weeks apart. The order of the switch per cluster was randomized by a computer. Eventually, all clusters switched from the control to the training condition.

Instructional Design

This study evaluates the instructional design of the training and the effect of the training on Kirkpatrick levels 1 and 2. The instructional design was measured using the ID-SIM [47]. This questionnaire is an assessment tool, specifically designed for the evaluation of the instructional design of a simulation-based team training [47]. It consists of 42 statements that can be answered by placing a mark on a line from “not at all/never” to “completely/always”. The questions are divided over ten instructional design features: feedback, repetitive practice, curriculum integration, difficulty range, learning strategies, clinical variation, controlled environment, defined outcomes, individualized learning, and simulation fidelity.

Kirkpatrick Levels 1 and 2

Kirkpatrick level 1 was measured by asking all participants to give an overall score for the training day by placing a mark on a line. Suggestions for improvement could be made in an open remark at the end of the evaluation questionnaire. Level 2, the effect on knowledge of the participants, was measured by a knowledge test consisting of 30 multiple-choice questions on medical technical skills and teamwork at the beginning and end of the main training (Multimedia Appendix 1). To obtain content validity, a team of Dutch and Ugandan obstetricians developed and evaluated the multiple-choice questions. Construct validity was tested by asking obstetricians and first-year, second-year, and third-year SHOs to complete the knowledge test. A Cronbach α coefficient was calculated to measure the internal consistency of the knowledge test.

The effect on technical skills and teamwork was evaluated by assessing the video-recorded scenarios. Three independent researchers assessed the first and last scenario for medical technical skills and teamwork together until consensus was reached. The topic of both scenarios was postpartum hemorrhage; however, the etiology differed. The assessors were blinded for the day of training and whether the scenario was the first or the last of the day. The assessment consisted of the Clinical Teamwork Scale (CTS) and a checklist of medical technical procedures. The CTS is a validated tool for assessing teamwork [48]. It consists of 15 items about communication, situational awareness, decision-making, and role responsibility, and each can be scored on a 10-point scale. The checklist of medical technical procedures is based on local protocols for postpartum hemorrhage, and it consists of 24 items that can be either scored as “done,” “not done,” or “not applicable.”

Statistical Analysis

This paper shows secondary outcome results. A sample size calculation was performed based on the primary outcome of the study (the combined mortality proportion including maternal and neonatal mortality ratios). For a stepped-wedge design, first the sample size calculation for a standard randomized clinical trial is required [49-51]. To show a reduction in combined mortality proportion of 20% with an α of .05 and a power of 80%, a total of 6398 deliveries were needed for a standard randomized clinical trial design. The design effect was then calculated assuming an intracluster correlation of 0.05, 7 clusters, and a cluster size of 3343 deliveries per year, which resulted in 2367 deliveries per cluster period. This resulted in a minimum duration of 5 weeks for each cluster period based on local delivery rates. For logistical reasons in staff scheduling, the duration of each step was set at 7 weeks. As exam and holiday periods were excluded from the cluster periods, the total duration of the study was anticipated to be 1.5 years. Data were analyzed using IBM SPSS Statistics, version 21 (IBM Corporation). Descriptive statistics were calculated for participant characteristics and for the results of the ID-SIM. The Wilcoxon signed rank test was conducted to investigate the difference in scores on the knowledge test, the CTS, and medical technical skills assessment. The difference in scores on the knowledge test between the SHOs in their first, second, and third years of study was analyzed using the Kruskal-Wallis test. Statistical significance was accepted at a 2-sided *P* value of .05.

Ethical Permission

Ethical permission was obtained from both the Mulago Research and Ethics committee (Protocol MREC: 674) and the Uganda National Council for Science and Technology (number SS 3927). All participants gave written informed consent before the study began, and they acknowledged that they cannot be identified via the paper. Data were fully anonymized.

Results

Learner Characteristics

From 2014 to 2016, 68 SHOs were invited to participate in the training program; 19 (28%) of them were female, and 49 (72%) were male. Of these, 57 SHOs (84%) participated in the main training, with an even distribution over the three years of their obstetric curriculum (20 first-year SHOs, 18 second-year SHOs, and 19 third-year SHOs). Of the 11 SHOs who did not participate in the main training, 3 finalized their specialization, 1 quit specialization, and 7 did not give any reason. Almost half of the SHOs (49%, 33/68) took part in at least one repetition training. The total number of trained SHOs was higher than the average working number, because of the organization of extra main training sessions for leaving SHOs and the new first-year SHOs who were added to an already trained cluster.

Instructional Design

All of the 57 SHOs who participated in the main training completed the ID-SIM. The mean scores of the ten instructional design features are shown in Table 1. Mean scores on the features differed between 54.9 and 84.3 out of 100. The highest mean score of 84.3 (95% CI 80.9-87.6) was given on *feedback*. The lowest scores of 62.8 (95% CI 55.8-69.8) and 54.9 (95% CI 48.5-61.3) were given on *repetitive practice* and *controlled environment*, respectively.

Table 1. Mean scores of senior house officers on the ID-SIM.

Variable	ID-SIM score, mean (95% CI)
Feedback	84.3 (80.9-87.6)
Repetitive practice	62.8 (55.8-69.8)
Curriculum integration	78.7 (74.5-82.9)
Difficulty range	74.0 (68.5-79.4)
Learning strategies	83.2 (78.9-87.4)
Clinical variation	80.0 (74.9-85.1)
Controlled environment	54.9 (48.5-61.3)
Individualized learning	81.9 (76.9-86.9)
Defined outcomes	74.2 (69.2-79.3)
Simulation fidelity	80.3 (76.9-83.7)

Kirkpatrick Levels 1 and 2

The overall score for the training day rated by the participants was 92.8 out of 100 (95% CI 89.5-96.1). The following suggestions for improvement were made in the open remark at the end of the questionnaire: (1) to incorporate other members of the team, (2) to add other scenarios, (3) to have repetition training more often, (4) to plan more time for the debriefing, especially relating to a real-life setting, and (5) to provide the training materials a day earlier.

Of the 57 participating SHOs, a total of 53 (93%) completed the knowledge test before and after the main training. One SHO completed the knowledge test only after the training. Construct validity was tested using the Kruskal-Wallis test to compare knowledge test results of obstetricians and first-year, second-year, and third-year SHOs and showed a significant result (*P*=.03). A Cronbach α coefficient of .67 was calculated to measure the internal consistency of the knowledge test. Mean scores of the knowledge test are listed in Table 2. The mean score of the knowledge test increased from the beginning to the end of the training day. This result was also found for each study year separately. The improvement in score on the knowledge test between the three study years was not significantly different (P=.24).

Table 2. Mean scores of senior house officers on the knowledge test.

Year of study	Score before training, mean (95% CI)	Score after training, mean (95% CI)	*P* value
All	63.4 (60.7-66.1)	78.9 (76.8-81.1)	<.001
1st year	62.3 (58.3-66.4)	77.7 (72.5-82.8)	<.001
2nd year	60.9 (56.1-65.7)	78.9 (76.7-81.1)	<.001
3rd year	68.1 (62.5-73.7)	80.7 (77.2-84.1)	.001

To evaluate teamwork and medical technical skills, the recordings of the first and last scenarios of 8 teams were evaluated. Out of 16 recordings, 2 could not be assessed because of recording issues. No differences in scores on the CTS between the first and last sessions were found (Table 3). The scores of the technical skills assessment only improved statistically significantly for the provision of drugs (Table 3). During the first scenario, none of the teams reached the moment to tamponade the uterus. For 5 out of the 8 teams, the last scenario was stopped before they had to tamponade the uterus, hence this item was scored as not applicable. The scenarios were stopped by the local facilitators at the moment when they judged that the SHOs had reached sufficient learning subjects to discuss in the debriefing sessions.

Table 3. Mean scores of senior house officers in clusters on the Clinical Teamwork Scale and the medical technical skills assessment.

Item	First scenario score, mean (95% CI)	Fifth scenario score, mean (95% CI)	*P* value
Clinical Teamwork Scale			
Overall score	6.0 (4.4-7.6)	5.9 (4.5-7.2)	.78
Overall communication	6.5 (5.5-7.6)	6.0 (4.5-7.5)	.4
Overall situational awareness	4.4 (2.8-6.0)	5.4 (4.5-6.2)	.1
Overall decision making	4.6 (3.4-5.7)	6.0 (5.1-6.9)	.07
Overall responsibility	6.6 (5.6-7.7)	6.0 (5.3-6.8)	.59
Patient friendliness	5.6 (4.1-7.1)	6.0 (4.8-7.2)	.79
Medical technical skills			
Overall score	55.5 (47.2-63.8)	65.6 (56.5-74.7)	.08
Ask for help	100	100	>.99
Airway, breathing, circulation	58.9 (45.9-72.0)	54.6 (43.0-66.2)	.89
Establish cause	50.0 (25.2-74.8)	76.2 (41.9-110.5)	.34
Massage uterus	57.1 (18.5-95.8)	66.7 (31.1-102.3)	.59
Provision of drugs	28.6 (12.6-44.5)	56.0 (46.3-65.6)	.04
Shift to theatre	85.7 (63.2-108.3)	78.6 (53.9-103.3)	.56
Tamponade	N/A[a]	N/A	N/A

[a]N/A: not applicable.

Discussion

Principal Results

In this article, we investigated the instructional design of a technology-enhanced simulation-based training in obstetrics, the reaction of participants, and the effect on knowledge, teamwork, and medical technical skills of SHOs. Most instructional design features were scored high, although intervals were large. The highest-rated instructional design feature was *feedback*, and the lowest-rated were *repetitive practice* and *controlled environment*. The overall rating of the SHOs for the training program was high, with a mean score of 92.8 out of 100. Knowledge did increase after the training program, but no changes in teamwork and (most) technical skills were found. Results of the ID-SIM showed suggestions for improvement of the instructional design of the training program to achieve learning aims.

Strengths and Limitations

This study evaluates both the instructional design of a technology-enhanced simulation-based training in obstetrics and the effect on Kirkpatrick levels 1 and 2 in a low-income country at one of the biggest maternity wards in the world. The validated ID-SIM was used to evaluate the instructional design of the training program. A limitation of the study may be that the ID-SIM was scored by the SHOs, who may not have much expertise in evaluating an instructional design. However, Fransen et al mentioned that the ID-SIM may be helpful for less-experienced individuals who are challenged with the development or evaluation of a simulation-based team training course [47]. Nevertheless, validation of participants' ratings, instead of expert opinion, on the ID-SIM could be an item of further research.

Another limitation of this study is the level of expertise and the composition of the training groups. SHOs of different study years were divided into groups with a different team leader in the first and last scenario of the day. This means that the level of knowledge, skills, and teamwork of the team leader can differ between sessions. Other limitations include the ratio of male to female participants with 72% male participants, and missing data due to the dropout of 7 of the 68 SHOs without known reason, 4 SHOs who didn't fill in the knowledge test, and 2 missing video recordings due to technical issues. Moreover, only 33 SHOs participated in at least one repetition training. Information on motivation and reasons for not participating in further training sessions should be included in further evaluation studies to optimize learning results. Furthermore, it was hard to specifically define the level of knowledge, teamwork, and medical technical skills in advance. This may have resulted in learning objectives that were not challenging enough for all SHOs. Additionally, the item *tamponade the uterus* in the medical technical skills could not be scored in the way it was originally planned, as most scenarios were stopped before the clusters reached the moment to practice this skill. Hence, evaluation on Kirkpatrick levels 3 and 4 will probably not show any effect of this training subjective. Finally, the training teams only consist of SHOs, as it was not feasible to create working schedules with fixed teams including midwives, interns, SHOs, obstetricians, anesthesiologists, and pediatricians. To measure the effects of the training program using a stepped-wedge cluster randomized trial in one hospital, fixed teams were necessary. As the SHOs are the first responders after the midwives in emergency care at the labor ward, we chose to focus on these care providers. However, we are aware that teamwork is critical to provide safe obstetric care. All of the previous studies that have reported improvements after training have implemented "in-house" training programs and have trained almost 100% of their staff [52]. These features seem to be two of the active components of effective training [52]. For future training, a multiprofessional training program is recommended.

Comparison With Prior Work

De Leeuw et al have identified and compared the outcomes and methods used to evaluate postgraduate medical e-learning, including simulation [45]. Of the theories, Kirkpatrick's hierarchy was the most used method [45]. However, many other ways to carry out an evaluation were found, and it is probable that many ways to do so are correct [45]. A recommendation by De Leeuw et al was to evaluate not only the outcomes of an educational intervention but to start with the evaluation of its design [45]. Robust instructional design is required to achieve an effective training course. Moreover, to perform comparisons between simulation-based team training courses, Eppich et al recommended standardized reporting of these instructional designs [42,53]. Issenberg et al translated the literature into ten important design features [46]. Five out of these ten features corresponded to the educational theory of deliberate practice by Ericsson et al [54,55]. Cook et al confirmed the effectiveness of several of Issenberg's instructional design features [46,56]. The features were incorporated into two guidelines for designing an effective simulation-based training by the Association for Medical Education in Europe [57,58]. Later, Fransen et al developed, based on previous findings, an evidence-based assessment tool for evaluation of the instructional design of a simulation-based team training: the ID-SIM [47]. Table 1 shows the instructional design features of the technology-enhanced simulation-based training in obstetrics evaluated in this study. The table identifies the weaknesses in the instructional design of this training: *repetitive practice* and *controlled environment.*

Repetitive Practice

There is increasing evidence of the beneficial effect of repetitive practice. Cook et al analyzed over 600 studies in a systematic review and meta-analysis and reported that the distribution of learning activities over more than one day was consistently associated with larger effect sizes [59]. Bluestone et al also described that repetitive, time-spaced education exposure resulted in better knowledge outcomes, better knowledge retention, and better clinical decisions compared with single interventions and live instruction [60]. Additionally, improvement in skills was demonstrated after various types of refresher courses [61-64]. A study from van de Ven et al reported that the beneficial effect of a one-day, simulation-based, multiprofessional obstetric team training seems to decline after 3 months [65]. Repetitive training sessions every 3 months are therefore recommended. However, in low-income and middle-income countries conflict may arise because having adequate time and support for simulation-based training can be a challenge. Several studies describe challenges of pulling staff both as learners and educators out of their workplaces because of staff shortages or complex schedules [14,17,66,67]. In particular, longer courses have struggled with high on-site dropout rates because of night call schedules [67]. More research is necessary to determine the optimal training intervals in low-income and middle-income countries. The effects of training programs with different intervals between repetition sessions on the four Kirkpatrick levels, but also on participants' dropout rates and participants' and trainers' motivation, should be investigated in order to optimize this instructional design feature in low-income and middle-income countries.

Controlled Environment

The other lower-scored item on the ID-SIM was *controlled environment*. In a controlled clinical environment, learners can make, detect, and correct errors in patient care without adverse consequences. Moreover, instructors can focus on learners instead of patients. The low score in this study on this item may have to do with staff shortages and complex schedules. Training sessions were frequently interrupted by phone calls. Interference with clinical obligations may be a bigger issue in low-income and middle-income countries compared with high-income countries due to a shortage of personnel. Moreover, the educational system of Uganda differs from the system in high-income countries. In low-income to middle-income countries, health professionals may not be as familiar with simulation-based education as in high-income countries [68,69]. Moran et al even described the educators' lack of comfort with leading simulations as one of the key challenges in simulation-based training [69]. To increase the effectiveness of the training program, the *controlled environment* has to be improved.

Conclusions

Most instructional design features of a technology-enhanced simulation-based training in obstetrics in a low-income country were scored high, although intervals were large. The highest mean score was given on *feedback*, and the lowest scores on *repetitive practice* and *controlled environment*. The overall score for the training day was high, and knowledge did improve after the training program, but no changes in teamwork and (most) medical technical skills were found. The lowest-scored instructional design features, *controlled environment* and *repetitive practice*, may be improved to achieve further learning aims. Future studies should also include evaluation of the instructional design of a training program in order to understand why some training programs are effective and others are not.

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Conflicts of Interest

None declared.

Multimedia Appendix 1
Knowledge test.
[DOCX File , 547 KB - mededu_v7i1e17277_app1.docx]

Multimedia Appendix 2
CONSORT checklist.
[DOC File , 220 KB - mededu_v7i1e17277_app2.doc]

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Abbreviations

CTS: Clinical Teamwork Scale
ID-SIM: Instructional Design of a Simulation Improved by Monitoring
SHO: senior house officer

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Original Paper

Using Machine Learning Algorithms to Predict People's Intention to Use Mobile Learning Platforms During the COVID-19 Pandemic: Machine Learning Approach

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Abstract

Background: Mobile learning has become an essential instruction platform in many schools, colleges, universities, and various other educational institutions across the globe, as a result of the COVID-19 pandemic crisis. The resulting severe, pandemic-related circumstances have disrupted physical and face-to-face contact teaching practices, thereby requiring many students to actively use mobile technologies for learning. Mobile learning technologies offer viable web-based teaching and learning platforms that are accessible to teachers and learners worldwide.

Objective: This study investigated the use of mobile learning platforms for instruction purposes in United Arab Emirates higher education institutions.

Methods: An extended technology acceptance model and theory of planned behavior model were proposed to analyze university students' adoption of mobile learning platforms for accessing course materials, searching the web for information related to their disciplines, sharing knowledge, and submitting assignments during the COVID-19 pandemic. We collected a total of 1880 questionnaires from different universities in the United Arab Emirates. Partial least squares-structural equation modeling and machine learning algorithms were used to assess the research model, which was based on the data gathered from a student survey.

Results: Based on our results, each hypothesized relationship within the research model was supported by our data analysis results. It should also be noted that the J48 classifier (89.37% accuracy) typically performed better than the other classifiers when it came to the prediction of the dependent variable.

Conclusions: Our study revealed that teaching and learning could considerably benefit from adopting remote learning systems as educational tools during the COVID-19 pandemic. However, the value of such systems could be lessened because of the emotions that students experience, including a fear of poor grades, stress resulting from family circumstances, and sadness resulting from a loss of friends. Accordingly, these issues can only be resolved by evaluating the emotions of students during the pandemic.

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KEYWORDS

COVID-19; pandemic; mobile learning; fear; technology acceptance model; theory of planned behavior; prediction; intent; online learning; machine learning; behavior

Introduction

Background

Colleges and universities often actively aim to create web-based teaching environments with the help of relevant learning platforms and resources [1-3]. In addition, these higher education institutions attempt to achieve effective student results by providing various learning management platforms that enhance strategies and practices for teaching and learning. However, the COVID-19 pandemic has presented higher education institutions with several challenges, as students worldwide have been experiencing negative emotions and feelings with regard to their studies. Such emotions include fear, anxiety, and apprehension. A consequence of these negative emotions is stigmatization, which students who are mentally affected by fear often experience. In addition, students have experienced discrimination, loss, and various other psychosocial issues after COVID-19 was declared a pandemic [4-6]. The lockdown effect has also had an impact on students' fear; the need for e-learning became critical when education institutes were forced to halt their contact learning and teaching practices. Furthermore, students' fear can manifest as a fear of taking risks, a fear of failure, a fear of missing out, and fear resulting from insecurity [7-10]. Students' fear can also impact technology adoption, as the COVID-19 lockdown has forced universities, colleges, and schools to implement distance learning in an attempt to lessen the harmful effects of COVID-19 and maintain student learning.

A considerable percentage of colleges and universities have experienced issues that relate to educators' experience with using technology for teaching and learning. The technological proficiency of students is also problematic, as classes need to be conducted via web-based methods [11-15]. However, adopting technology for distance learning is essential for efficiently validating the conduction of web-based classes [16-19]. According to the majority of technology adoption studies, there are complications with regard to the adoption process, as technology adoption can affect other teaching and learning factors, such as learning strategies, learning contexts, and technology availability.

Although several researchers have focused on technology adoption in their research, the adoption of creative teaching methods (eg, the use of mobile learning apps) as a result of the COVID-19 pandemic and other similar disasters has yet to be explored. It has become quite easy to find mobile learning apps on both the Apple Store and Google Play Store. Users can access mobile learning apps from these stores, which are responsible for automatically updating these apps. In addition, users have been increasingly accessing these apps because of app stores' freemium approach [20,21]. However, students' and educators' thoughts on implementing a mobile learning platform during the pandemic must be considered. Therefore, the need for mobile learning platforms and the issues surrounding the COVID-19 pandemic need to be addressed [22]. As the use of mobile learning platforms is a relatively new practice, there is a lack of research on how mobile learning can influence higher education. Furthermore, although the technology adoption domain has undergone extensive research, there has been a lack of focus on the emotion of fear when considering the adoption of technology during the COVID-19 pandemic. Past studies have mostly dealt with the technological factors in teaching and learning, without paying any attention to psychological factors. The impact of fear on technology adoption has yet to be clearly understood, and this is often the reason why technology has not been used to its full potential when it comes to the education domain [23].

After taking into consideration the limitations of technology adoption in education, we aimed to provide educational information on appropriate technology use, for times when learners and educators are fearful of technology. This is particularly relevant at times (eg, the COVID-19 pandemic) when technology use becomes imperative for providing better education to both learners and educators, who are often novices in terms of using technological applications for teaching and learning.

When it comes to the academic research adoption model, studies have found that using the technology acceptance model (TAM) and the theory of planned behavior (TPB) model as a hybrid model is effective for technology adoption. With the help of these models, it becomes possible to determine users' willingness to accept and use technology [24,25]. Accordingly, this study focuses on understanding students' and educators' willingness to use mobile learning systems, by using the TPB model and TAM, in addition to 2 external factors (ie, subjective norms [SNs] and fear). As a result, we were able to use the TAM and TPB model to investigate students' and teachers' thoughts on using machine learning methods during the spread of COVID-19. In addition, assessments of fear during the COVID-19 pandemic and how fear directly affects the TAM and TPB model have been limited. After considering the lack of research, we aimed to develop a hybrid model that can determine the different fears that both learners and educators may face during the COVID-19 pandemic. Since we investigated the factor of fear, we believe that our research paper has an increased chance of providing both teachers and app developers with the technology and education-related information needed for developing and implementing new technologies during the COVID-19 lockdown period.

The unique educational problems that have emerged during these unordinary times can be highlighted if more information on the factors of machine learning adoption at the time of the COVID-19 pandemic is gathered. COVID-19–related literature on the technology adoption domain can benefit higher education institutions on a theoretical and practical level.

Literature Review

Previous research studies on technology adoption have focused on the various forms of fear [23,26]. For example, anxiety is an important factor that helps manage technology approval and apprehension. Within the education sector, the adoption of technology by students is influenced by anxiety [27]. Furthermore, apart from anxiety, a lack of experience and skills may also influence technology use. The fear of using technology, combined with poor technological literacy and anxiety, negatively affects the adoption of technology. Hence, it is essential for teachers and educators to focus on psychological development and help students accept the use of technology. Other factors of the fear of using technology within the educational sector include technical readiness and preparedness; technology adoption is negatively influenced by both of these factors [28-30].

The education sector is not the only sector that has exhibited a fear of technology adoption. Medical sector students usually perceive risks and exhibit negative anxiety when technology is used [31,32]. In addition, health anxiety is one of the top concerns of the health care sector. Health anxiety includes the apprehension of patients and the fear of receiving results about a severe illness. With regard to the banking sector, various kinds of fear that relate to customers' perceptions and attitudes toward technology have been recognized. Customers do not want to use their data for mobile payments. Customers fear the use of technology in mobile banking and are negatively influenced by the frauds that have occurred. As a result, they lack both technological experience and trust in technology [33,34]. With regard to the household sector, the main reasons why technology is not being used include the fear of using technology and the fear that technology will increase the number of family tasks [23].

Various research studies have assessed the issues that relate to technological acceptance and fear. These research studies are based on the TAM [29,30,32-35] and several other models [28,31,36,37], and most of these research studies have assessed how the fear of technology can influence technology acceptance. Various technology users have provided justifications for their fear of technology use. For example, several users have stated that their fear is related to self-confidence. Errors are made when a human is assigned to a job, and excessively worrying about this fact enhances fear [38]. Moreover, several users have stated that they do not use technology because they believe that technology is time-consuming, and therefore does not allow them to complete their tasks [39]. Various technology acceptance studies have assessed the influence of fear on the breach of data privacy, and this is why privacy and security awareness are emphasized in technology research studies [40].

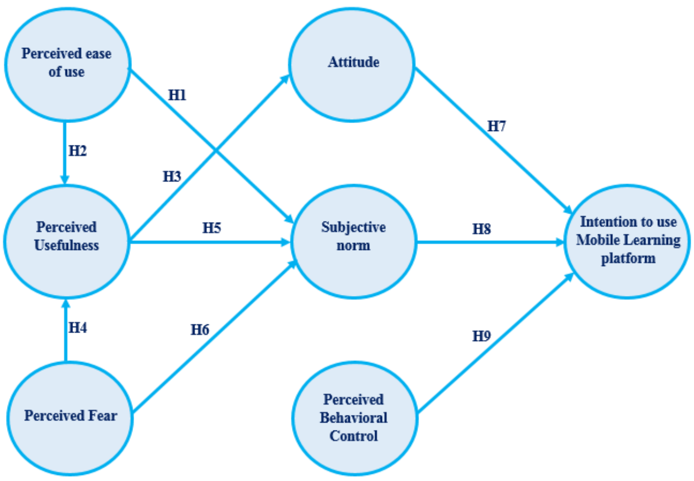
Previous studies have not provided sufficient empirical research on the use of mobile learning in United Arab Emirates (UAE) institutions, nor have they considered the factors that influence students' actual technology use. When it comes to methodology, technology acceptance researchers have typically analyzed theoretical models by using structural equation modeling and machine learning algorithms. After considering various theoretical models, we conducted this study with the following 2 objectives: (1) examine how students use mobile learning by integrating the TAM [41] and TPB model [42] into 1 theoretical model, and (2) validate the created theoretical model with the help of machine learning and partial least squares-structural equation modeling (PLS-SEM) algorithms.

Theoretical Model and Research Model

Model Design

In this study, the research model was developed to integrate the SN and fear constructs into 2 kinds of theoretical models—the TAM and TPB model. We believed that the SN and fear would influence the perceived ease of use (PEOU) and perceived usefulness (PU) of mobile learning systems. Additionally, we believed that attitude and perceived behavioral control (PBC) would be influenced by the continuous intention to use mobile learning systems. The proposed theoretical model is presented in Figure 1.

Figure 1. Study model.



TAM

One of the main objectives of the TAM is to validate external factors based on personal belief. The model is considered quite powerful, since it can be used to explain individuals' ability to accept the technology at their educational institutions [41,43-45]. According to the TAM, the 2 kinds of perceptions that can be measured are PU and the PEOU. This means that the behavioral intention of the user can be influenced directly. PU should be considered because this factor helps with measuring the degree to which technology must be evaluated by an individual, and assessing whether a technology is useful enough to be adopted and accepted. However, the PEOU refers to the degree to which an individual believes that technology is manageable and attainable [41].

In the context of technology acceptance, attitude has been defined as a user's desire to use a system [46]. Previous mobile learning studies have indicated that behavioral intention and attitude are related to each other. Previous research has also suggested that the intention to use mobile learning systems is significantly influenced by attitude [47-50].

Keeping in mind the previous assumptions, it can be concluded that if technology is considered to be easy to use, then users will retain a positive attitude. Therefore, user perceptions are quite important. If users have a positive attitude, it is believed that the users will adopt technology. The following hypotheses were proposed after applying the previous assumptions to the research model: (1) the PEOU will predict the SN (ie, H1), (2) the PEOU will predict PU (ie, H2); (3) PU will predict attitude (ie, H3), (4) PU will predict the SN (ie, H5), and (5) people's attitudes will predict their intention to use a mobile learning platform (ie, H7).

SN

Individual perceptions can be measured by using a tool called the SN, which is a type of perception that is based on the presence of individuals who exhibit similar attitudes and behaviors toward technology. The TAM is strengthened by the SN, since the TAM has been enabled to integrate user behaviors that are present within a user group [51]. The SN is an external factor that includes students' intentions to adopt mobile learning technology for classmate group meetings.

Various literature on technology adoption or acceptance have shown that the SN also influences behavioral intention, PU, and the PEOU [45,52-54]. The SN and TAM have recently been used as external factors in a study by Huang et al [55], who stated that the TAM-embedded factors from various research studies had a significantly close relationship with external factors. However, they found that the external factor SN was not efficiently or deeply implemented in other studies. Previous studies have stated that the intention of using mobile learning platforms is significantly influenced by the SN [49,50,56-58]. Hence, the following hypothesis was developed: the SN will predict people's intention to use a mobile learning platform (ie, H8).

Perceived Fear

On December 2019, the novel COVID-19 disease was observed in China, and with time, it spread throughout the world. Based on recent studies, the reaction toward the perceived threat of the SARS-CoV-2 virus has been fear. Additionally, the Health Anxiety Inventory scale has shown that fear is at the highest level [59]. Even though fear is perceived to be positive when real dangers are present, fear in the context of the COVID-19 pandemic may be burdensome and chronic. There are various forms of fear that are related to the COVID-19 pandemic, including health anxiety, uncertainty, and the fear of the risk of losing loved ones. The COVID-19 pandemic has resulted in the development of 2 vital issues, as follows: a high degree of worrying and a high possibility of being affected by the disease [4,60].

This study aimed to analyze the association between the adoption of technology and the external factor perceived fear (PF), through the use of the TAM. In this study, TAM limitations needed to be overcome. Such limitations include the implementation of external factors that are specific to the analysis of a TAM for PF, including PU, the PEOU, and the SN [61]. Hence, the following hypotheses were developed while keeping these factors in mind: PF will predict PU (ie, H4), and PF will predict the SN (ie, H6).

PBC

PBC is defined as "people's perception of the ease or difficulty of performing the behavior of interest" [62]. Previous research has shown that the intention to use mobile learning platforms is significantly affected by PBC [49,50,63]. Hence, the following hypothesis was proposed: PBC will predict people's intention to use mobile learning platforms (ie, H9).

Our hypotheses were used to develop the proposed research model, as indicated in Figure 1. The theoretical model was presented as a structural equation model and analyzed with machine learning methods.

Methods

Context and Subjects

University students were the target population for this study. The questionnaire was disseminated to university students in the UAE. In total, 7 well-known universities in the UAE were chosen for this study, namely the University of Sharjah, the Higher Colleges of Technology, The British University in Dubai, United Arab Emirates University, the University of Fujairah, American University in UAE, and Ajman University. We used a web-based survey to collect data from May to June 2020. The surveys were completed by the participants, who did not ask for any compensation. In this study, the convenience sampling technique was used for data collection. In total, 2000 surveys were distributed, and a 94% response rate was recorded (ie, 1880 students completed the whole survey). The number of males and females who completed the survey was 1102 (58.6%) and 778 (41.4%), respectively.

The percentage of participants aged 18-29 was 40.3% (758/1880), and the remaining 59.7% of participants (1122/1880) were older than 29 years. Furthermore, 33.3% (626/1880) of the participants were undergraduate students, 45.2% (849/1990) were master students, 11.1% (209/1880) were PhD students, and 10.4% (196/1880) were diploma students. A comprehensive view of the collected data is provided in Tables 1 and 2.

Table 1. Number of students (N=1880) in participating universities.

University	Number of students, n
United Arab Emirates University	568
University of Sharjah	439
Higher Colleges of Technology	365
Ajman University	287
The British University in Dubai	103
University of Fujairah	68
American University in United Arab Emirates	50

Table 2. Summary of students' demographic characteristics.

Variables	Participants, n (%)
Gender	
Male	1102 (58.6)
Female	778 (41.4)
Age (years)	
18-29	758 (40.3)
30-39	635 (33.7)
40-49	367 (19.5)
50-59	120 (6.5)
Level of education	
Diploma	196 (10.4)
Bachelor degree	626 (33.3)
Master degree	849 (45.2)
PhD degree	209 (11.1)

Study Design

This study's design consisted of 2 parts. The first part focused on collecting participants' demographic data. The second part focused on collecting responses that were related to the factors in the conceptual model's 5-point Likert scale. To assess the 7 constructs (ie, attitude, intention to use a mobile learning platform, SN, PBC, PF, PEOU, and PU) in the questionnaire, 20 items were included in the survey. The sources of these constructs are presented in Table 3.

Table 3. Constructs and their sources.

Construct	Number of items, n	Source, authors
Attitude	3	Al-Emran et al [49], Cheon et al [50]
Intention to use a mobile learning platform	2	Al-Emran et al [49], Tan et al [64], Bao et al [65]
Subjective norm	3	Al-Emran et al [49], Cheon et al [50]
Perceived behavioral control	3	Al-Emran et al [49], Cheon et al [50]
Perceived fear	3	Developed in this study.
Perceived ease of use	3	Al-Emran et al [49], Tan et al [64], Bao et al [65]
Perceived usefulness	3	Al-Emran et al [49], Tan et al [64], Bao et al [65]

Questionnaire Pretest

Before conducting the final survey, it was important to make sure that the questionnaire items were reliable by conducting a pilot study with a random selection of 100 students from the target population. We calculated Cronbach α values to measure the internal reliability of the items of each construct. Nunnaly and Bernstein [66] have suggested that an acceptable reliability coefficient should equal at least .70. Table 4 shows that this study's constructs had Cronbach α values of >.70. Therefore, each construct was reliable. This meant that each construct could be used in the final research model.

Table 3 shows that the questionnaire's 5-point Likert scales were reliable. Therefore, the measurement scales could be used in this study.

Table 4. Cronbach α values for the pilot study (Cronbach α≥.70).

Construct	Cronbach α
Attitude	.736
Intention to use a mobile learning platform	.755
Subjective norm	.864
Perceived behavioral control	.859
Perceived fear	.847
Perceived ease of use	.887
Perceived usefulness	.803

Results

Data Analysis

The theoretical model developed in this study was evaluated by using 2 different techniques. The first technique involved PLS-SEM and the use of the SmartPLS (SmartPLS GmbH) tool [67]. This study used the PLS-SEM technique, mainly because both the structural and measurement models could be concurrently analyzed through PLS-SEM, thereby increasing the preciseness of results [68]. As for the second technique, we predicted the dependent variables of the conceptual model with the help of machine learning algorithms in Weka (University of Waikato) [69].

Model Reliability and Validity Assessment

We assessed the validity and reliability of the measurement model [70]. Model reliability was tested by using Cronbach α and composite reliability measures. It has been suggested that these measures must equal at least .70 to be acceptable [70]. As per the results in Table 5, model reliability was confirmed, as satisfactory values were attained for both measures.

According to Hair Jr et al [70], discriminant and convergent validities can be evaluated to test model validity. We calculated the factor loading and average variance extracted values of each construct item to determine convergent validity. It has been suggested that the average variance extracted and factor loading values must equal at least .50 [71] and .70 [72], respectively, to be acceptable. As per the results in Table 5, convergent validity was confirmed, as accepted values were attained for both measures. Furthermore, Henseler et al [73] have suggested that the Heterotrait-Monotrait ratio of correlations can be calculated to determine discriminant validity. Heterotrait-Monotrait ratio values must fall below .85 to be acceptable. As per the results in Table 6, discriminant validity was confirmed, as accepted Heterotrait-Monotrait ratio values were attained.

Table 5. Convergent validity test results. Acceptable values (ie, factor loading, Cronbach α, CR[a]≥0.70, and AVE[b]>0.5) were obtained.

Constructs and items	Factor loading	Cronbach α	CR	AVE
Attitude		.798	.823	.760
ATT1	.726			
ATT2	.886			
ATT2	.800			
Intention to use a mobile learning platform		.739	.789	.703
INT1	.846			
INT2	.805			
Subjective norm		.758	.811	.716
SN1	.819			
SN2	.795			
SN3	.883			
Perceived behavioral control		.843	.771	.652
PBC1	.822			
PBC2	.873			
PBC3	.778			
Perceived fear		.779	.798	.593
PF1	.808			
PF2	.845			
PF3	.866			
Perceived ease of use		.769	.746	.633
PEOU1	.872			
PEOU2	.832			
PEOU3	.857			
Perceived usefulness		.715	.750	.785
PU1	.878			
PU2	.906			
PU3	.848			

[a]CR: composite reliability.

[b]AVE: average variance extracted.

Table 6. HTMT[a] ratios of correlations between each construct.

Construct	Attitude	Intention to use a mobile learning platform	Subjective norm	Perceived behavioral control	Perceived fear	Perceived ease of use	Perceived usefulness
Attitude, HTMT ratio	—[b]	.480	.519	.377	.330	.549	.651
Intention to use a mobile learning platform, HTMT ratio	.480	—	.299	.583	.514	.350	.504
Subjective norm, HTMT ratio	.519	.299	—	.516	.460	.393	.511
Perceived behavioral control, HTMT ratio	.377	.583	.516	—	.602	.657	.542
Perceived fear, HTMT ratio	.330	.514	.460	.602	—	.263	.494
Perceived ease of use, HTMT ratio	.549	.350	.393	.657	.263	—	.333
Perceived usefulness, HTMT ratio	.651	.504	.511	.542	.494	.333	—

[a]HTMT: Heterotrait-Monotrait ratio.

[b]Not applicable.

Hypotheses Testing and Coefficient of Determination

The 9 hypotheses we proposed were tested by using the structural equation modeling procedure [74]. Analyses were carried out to determine the variance (ie, the R^2 value) of each path, the variance of the research model, and the significance of each hypothesized path association. Figure 2 and Table 7 show the standardized path coefficients and path significances.

The R^2 values for attitude, intention to use a mobile learning platform, the SN, and PU ranged between 0.391 and 0.575, as shown in Table 7. Hence, these constructs had a moderate predictive power [75]. Based on the hypothesis data analysis, the empirical data supported every hypothesis (ie, H1, H2, H3, H4, H5, H6, H7, H8, and H9).

Table 8 and Figure 2 summarize the results of the hypotheses tests, which indicated that the SN significantly influenced the PEOU (β=.756; *P*=.001), PU (β=.227; *P*=.03) and PF (β=.480; *P*=.04). These results supported hypotheses H1, H5, and H6, respectively. PU had significant effects on attitude (β=.801; *P*<.001), which supports hypothesis H3. The results also revealed that the intention to use a mobile learning platform significantly influenced attitude (β=.707; *P*<.001), the SN (β=.553, *P*<.001), and PBC (β=.148, *P*<.001). These results supported hypotheses H7, H8, and H9, respectively. Additionally, the results show that PU was significantly influenced by the PEOU (β=.264; *P*=.002) and PF (β=.358; *P*=.04). These results supported hypotheses H2 and H4, respectively.

Figure 2. Hypotheses testing results. The R^2 values reported are for perceived usefulness, attitude, the subjective norm, and the intention to use a mobile learning platform. The β values and statistical significance of each path are also reported. *significant at *P*<.05, **significant at *P*≤.01.

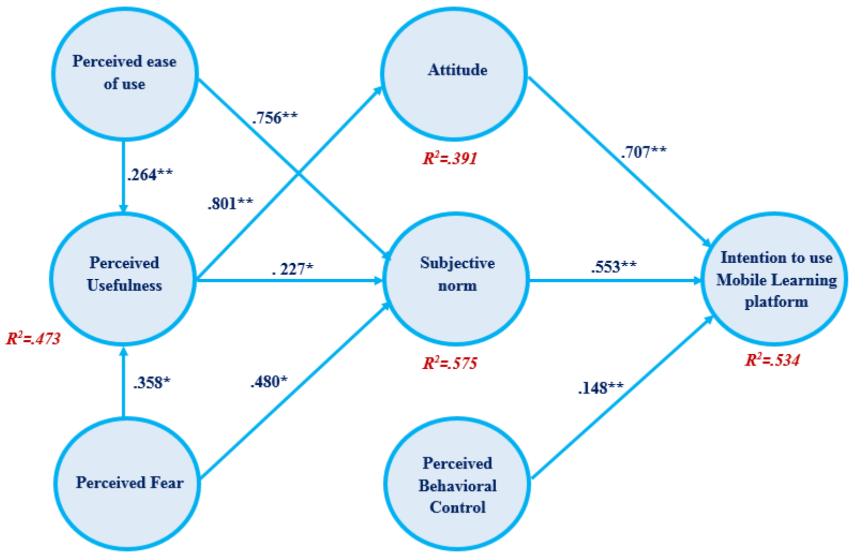


Table 7. R^2 values of the endogenous latent variables.

Constructs	R^2	Predictive power
Perceived usefulness	0.473	Moderate
Attitude	0.391	Moderate
Subjective norm	0.575	Moderate
Intention to use a mobile learning platform	0.534	Moderate

Table 8. Summary of hypotheses testing results.

Hypothesis	Relationship	Path β	*t* test (df)[a]	*P* value	Correlation direction	Decision
H1	Perceived ease of use and subjective norm	.756	18.179 (1876)	.001	Positive	Supported[b]
H2	Perceived ease of use and perceived usefulness	.264	10.203 (1876)	.002	Positive	Supported[c]
H3	Perceived usefulness and attitude	.801	19.093 (1876)	<.001	Positive	Supported[b]
H4	Perceived fear and perceived usefulness	.358	4.936 (1876)	.04	Positive	Supported[d]
H5	Perceived usefulness and subjective norm	.227	4.660 (1876)	.03	Positive	Supported[d]
H6	Perceived fear and subjective norm	.480	5.892 (1876)	.04	Positive	Supported[d]
H7	Attitude and intention to use a mobile platform	.707	15.337 (1876)	<.001	Positive	Supported[b]
H8	Subjective norm and intention to use a mobile platform	.553	19.485 (1876)	<.001	Positive	Supported[b]
H9	Perceived behavioral control and intention to use a mobile platform	.148	18.089 (1876)	<.001	Positive	Supported[b]

[a]The *t* test conducted was 2-tailed.

[b]The hypothesis is supported based on a significant *P* value of ≤.001.

[c]The hypothesis is supported based on a significant *P* value of ≤.01.

[d]The hypothesis is supported based on a significant *P* value of <.05.

Hypotheses Testing With Machine Learning Algorithms

This study was conducted with the assistance machine learning classification algorithms, which were applied through various methodologies, such as neural networks, if-then-else statements, decision trees, and Bayesian networks. Machine learning algorithms were used to predict the relationships in the proposed theoretical model [69,76,77]. With the help of Weka (version 3.8.3), the predictive model was tested on the basis of different classifiers, such as the OneR, J48, Logistic, LWL (Locally Weighted Learning), AdaBoostM1, and BayesNet classifiers [78,79]. In terms of predicting the PU of mobile learning systems, the J48 classifier performed better than the other classifiers, as seen from the results in Table 9. In the 10-fold cross-validation, the J48 classifier had an accuracy of 83.76% when predicting PU. Accordingly, these results supported hypotheses H2 and H4. The J48 classifier performed better than the other classifiers because of its high true positive rate (.837), precision (.803) and recall value (.838).

In terms of predicting attitude, the J48 classifier performed better than the other classifiers, as seen from the results in Table 10. The J48 classifier was able to use PU to predict attitude with an accuracy of 80.13%. Accordingly, these results supported hypothesis H3.

The results in Table 11 suggest that the J48 classifier performed better than the other classifiers when it came to predicting the SN based on the PEOU, PU, and PF. By using these constructs, the J48 classifier could predict the SN with an accuracy of 89.37%. Accordingly, these results supported hypotheses H1, H5, and H6.

According to the results in Table 12, the J48 classifier performed better than the other classifiers when it came to predicting the intention to use a mobile learning platform based on attitude, the SN, and PBC. When predicting the intention to use a mobile learning platform, the J48 classifier had an accuracy of 86.66%. These results supported hypotheses H7, H8, and H9.

Table 9. Predicting perceived usefulness based on the perceived ease of use and perceived fear.

Classifier	CCI[a], %	TP[b] rate	FP[c] rate	Precision	Recall	F measure
BayesNet	80.11	.801	.295	.721	.801	.790
Logistic	81.02	.810	.308	.735	.810	.798
LWL[d]	80.54	.805	.339	.705	.810	.801
AdaBoostM1	82.10	.821	.338	.732	.821	.819
OneR	81.66	.816	.337	.712	.820	.816
J48	83.76	.837	.634	.803	.838	.828

[a]CCI: correctly classified instances.
[b]TP: true positive.
[c]FP: false positive.
[d]LWL: Locally Weighted Learning.

Table 10. Predicting attitude based on perceived usefulness.

Classifier	CCI[a], %	TP[b] rate	FP[c] rate	Precision	Recall	F measure
BayesNet	78.02	.780	.229	.735	.781	.726
Logistic	77.22	.772	.205	.737	.723	.728
LWL[d]	76.79	.767	.269	.700	.768	.687
AdaBoostM1	78.11	.781	.289	.745	.782	.776
OneR	79.61	.796	.301	.754	.800	.798
J48	80.13	.801	.480	.787	.801	.800

[a]CCI: correctly classified instances.
[b]TP: true positive.
[c]FP: false positive.
[d]LWL: Locally Weighted Learning.

Table 11. Predicting the subjective norm based on the perceived ease of use, perceived usefulness, and perceived fear.

Classifier	CCI[a], %	TP[b] rate	FP[c] rate	Precision	Recall	F measure
BayesNet	80.76	.807	.311	.760	.810	.758
Logistic	80.63	.806	.369	.762	.810	.759
LWL[d]	80.06	.800	.299	.756	.801	.748
AdaBoostM1	81.37	.813	.378	.763	.814	.760
OneR	82.79	.827	.409	.772	.833	.772
J48	89.37	.893	.598	.788	.894	.782

[a]CCI: correctly classified instances.
[b]TP: true positive.
[c]FP: false positive.
[d]LWL: Locally Weighted Learning.

Table 12. Predicting the intention to use a mobile learning platform based on attitude, the subjective norm, and perceived behavioral control.

Classifier	CCI[a], %	TP[b] rate	FP[c] rate	Precision	Recall	F measure
BayesNet	81.10	.811	.303	.753	.812	.750
Logistic	81.23	.812	.371	.758	.813	.752
LWL[d]	80.73	.807	.389	.751	.812	.750
AdaBoostM1	81.44	.814	.369	.762	.815	.761
OneR	83.76	.837	.396	.770	.841	.768
J48	86.66	.866	.595	.802	.872	.798

[a]CCI: correctly classified instances.

[b]TP: true positive.

[c]FP: false positive.

[d]LWL: Locally Weighted Learning.

Discussion

Principal Findings

To test our proposed model, we used a complementary approach that combined the use of PLS-SEM and machine learning classification algorithms. There are few studies that have aimed to use machine learning algorithms to predict the actual use of mobile learning systems. Accordingly, studies that use a complementary multianalytical approach can play a major role in information systems literature and research. It should also be noted that PLS-SEM can help with predicting a dependent variable and validating a conceptual model that aims to extend an existing theory [80]. Similarly, a dependent variable can also be predicted with the help of supervised machine learning algorithms (ie, machine learning algorithms with a predefined dependent variable) and independent variables [69]. Another aspect of our study was the use of various classification algorithms in conjunction with the application of various methodologies, including if-then-else rules, neural networks, association rules, Bayesian networks, and decision trees. The J48 decision tree typically performed better than the other classifiers, as determined by our findings. Furthermore, we used a nonparametric decision tree to classify both categorical and continuous (ie, numerical) variables to obtain homogeneous subsamples from our main sample, on the basis of the main independent variable [69]. In other words, we used the nonparametric PLS-SEM technique to determine the significance of coefficients by using sample replacements, which were drawn from numerous subsamples on a random basis. This analysis provided empirical evidence for the impact of using mobile learning platforms during the COVID-19 pandemic. Our hypotheses (ie, H1, H5 and H6) significantly and positively supported the relationships between the SN and PEOU (P=.001), the SN and PU (P=.03), and the SN and PF (P=.04). Numerous research studies have assessed the relationship between the SN and PEOU, the SN and PU, and the SN and PF [23,41,43-45]. Moreover, our analysis provided empirical evidence for the effect of the PEOU on PU, as proposed in hypothesis H2. Our results showed that this effect was positive and significant (P=.002). Therefore, hypothesis H2 was in line with the findings of various studies [47-50].

Our analysis also provided empirical evidence for the effect of PU on attitude, as proposed in hypothesis H3. Our results showed that the effect was positive and significant (P<.001). Therefore, hypothesis H3 was in line with the findings of various studies [41,43-45,49]. PF also had a significant effect on PU (P=.04), which supported hypothesis H4 [23]. The seventh, eighth, and ninth hypotheses (ie, H7, H8, and H9) were developed to determine whether attitude, the SN, and PBC affected people's intention to use a mobile learning platform. Our results showed that the effects attitude (P<.001), the SN (P<.001), and PBC (P<.001) on people's intention to use a mobile learning platform were positive and significant. Therefore, H7, H8, and H9 were in line with the findings of various studies [49,50,56-58,63]. Our analysis strongly supported the proposed research model. The findings of other researchers [23,41,43-45,47-50,56-58,63] and our results have similarities.

Research studies have assessed the influence of the COVID-19 pandemic on modern technology, specifically the effects of the pandemic on technology that is used for learning and teaching. Technology is an effective tool that provides a new and viable platform for enabling the continuation of teaching and learning during lockdown [81]. Therefore, this study aimed to analyze the influence that COVID-19 has on teaching practices, by using machine learning algorithms. Our research model emphasized the effects of PF, which had an extraordinary influence on measuring the effects of COVID-19 on student and teacher groups. Furthermore, our analysis was able to assess the influence of the pandemic on mobile learning technologies that are used for teaching. Hence, our study helps with removing the identified gaps in the field and establishing a basis for future research on mobile learning and teaching practices.

Theoretical and Practical Implications

Our analysis contributes to existing literature by exploring the primary impediments that hinder the effective use of mobile learning systems during the COVID-19 pandemic. This study provides several important practical findings with regard to the use and adoption of mobile learning systems in limited-income states, such as the UAE. For instance, previous research has only highlighted infrastructure as the main impediment to the use of e-learning systems [16-19], but in reality, various other factors also pose a challenge to mobile learning technology adoption. These impediments include specialized issues that relate to mobile learning frameworks. Such issues include changes in management, problems related to course designs, computer knowledge issues, and monetary issues. Based on the results of our study, we can provide helpful proposals to policy makers, designers, developers, and researchers. These proposals will enable them to achieve greater familiarity with the important elements of successful mobile learning system adoption.

The first proposal is that important technical resources for the continuous technical maintenance of mobile learning platforms must be provided by university administrations and technical support staff, to encourage the extensive adoption of mobile learning materials and prevent specialized issues or postponements. The second proposal is that the successful implementation of mobile learning technologies by students and instructors should only occur if the essential hardware, software, and internet connectivity are provided by university administrations. Additionally, these university administrations should provide consistent upgrades for technological resources. The third proposal is that designers and developers need to develop mobile learning systems that are user-friendly, easy to use, and not complicated. When students and instructors find that mobile learning systems are easy to use and user-friendly, they will be encouraged to use mobile learning systems. The fourth proposal is that policy makers at UAE universities should resort to new policies and guidelines that encourage the use of mobile learning systems among students and teachers. In addition, policy makers should adjust educational policies to guarantee an adaptable transition from traditional learning to mobile learning. Support from top management is imperative in technology progression. Moreover, technology progression requires training programs to ensure that mobile learning system–related institutional principles are being promoted and strictly followed by teachers. The fifth proposal is that the outcomes of our study can help university policy makers concentrate on enhancing teachers' educational technology knowledge by arranging training programs on methods for using mobile learning systems. Such training programs are essential, since teachers' educational technology–related knowledge and skills are likely to convince students to use mobile learning systems, which will lead to better teacher performance and improved student efficiency. The sixth proposal is that universities need to concentrate on promoting mobile learning systems through training courses that highlight the benefits of using mobile learning systems. Universities must also focus on developing students' competency in using information technology. The main reason for this is that students' expertise in computer studies and positive views on mobile learning systems have a favorable impact on the success of mobile learning systems. Based on the outcomes of our study, we can provide a better understanding of mobile learning systems and offer recommendations for effectively implementing mobile learning systems during the course of the COVID-19 pandemic.

Limitations and Future Research

It is necessary to report on various key limitations of this study. First, caution needs to be taken when generalizing our results to other institutes in the UAE or other parts of the world. This is attributed to the fact that we only collected data from 7 education institutions. Additionally, participants were selected based on a convenience sampling technique. If these limitations are considered, future research can contribute to the generalization of our results. Second, this study only evaluated students' actual use of mobile learning systems. Future research should also focus on teachers' actual use of mobile learning systems, so that more information on influencing factors and system implementation can be determined.

Recommendations

With regard to web-based teaching, a mobile learning platform is considered to be a safe environment. During the COVID-19 pandemic, web-based teaching systems have been recommended. During the lockdown, web-based teaching systems have been considered a temporary solution. The availability of machine learning has promptly provided students and teachers with self-sensing security and communication tools. For example, in the UAE, Sharjah City was affected by the spread of the SARS-CoV-2 virus, and as a result, a web-based mobile learning tool has proved to be quite useful. This mobile learning platform has various advantages over other communication platforms. First, this platform can be used on laptops and smartphones; the students of the University of Sharjah have joined and participated in classes by using this platform on their smartphones. Second, the links to each class period can be used at various times, thereby allowing students to communicate with teachers at any point in time during the day. Third, the students have been much more confident, and their feelings of fear have been minimized.

Conclusion

This study's results are similar to those presented in earlier research studies on the importance of variables in the TAM and TPB model [41,42,44,45]. We observed that during the COVID-19 pandemic, students were much more accepting of technology if mobile learning technology was the only available tool for learning. Our PU-related and PEOU-related results are also similar to those of other studies that have assessed the influence of PU and the PEOU on students' acceptance of mobile learning technology. Therefore, PU and the PEOU should be considered indicators of students' willingness to use mobile learning platforms during the COVID-19 pandemic. Furthermore, PU was highly affected by the PEOU, which indicates that if a technology is easy to use, then it is also considered useful. Additionally, according to our results, there was a significant association between students' acceptance of mobile learning technology and the subjective norm (P<.001).

Studies have indicated that students' behavior within the classroom, their behavior in daily life, and their reactions to the use of mobile learning technology highly affect their acceptance of mobile learning technology. Previous research studies [45,52-54] have also stated that the SN and students' acceptance of mobile learning technology are associated. In the UAE, students are considerably influenced by their classmates' behaviors. This influence has increased the sense of security and comfort of students who have attended classes during the pandemic. Furthermore, students are motivated to use mobile learning technology to spend time with people who attend the same class. Additionally, there were several variables that significantly influenced the SN, other than the PEOU and PU. According to our results, instructors' and students' attitudes also helped to promote the use of mobile learning platforms as a learning tool during the pandemic period. If students and teachers have positive attitudes toward the use of mobile learning tools, they will perceive such tools to be useful, enjoyable, and effort free.

Our findings are consistent with those of previous studies [82]. For example, it has been stated that peers, students, and instructors provide useful feedback that affects students' attitudes and perceptions toward technology effectiveness. Due to the COVID-19 pandemic, fear has been on the rise. This should be considered an essential topic for future research, as the human population continues to be severely affected by the COVID-19 pandemic. The SARS-CoV-2 virus has a high probability of transmission, which is why there is a need for complete lockdown and stay-at-home strategies throughout the world [83]. In this study, we developed a model that is useful for conducting future studies, as our model can help with assessing the influence of COVID-19 during the pandemic period. Based on our study results and the rise of fear during the pandemic period, we believe that mobile learning technologies are important and useful tools that help to reduce students' and instructors' fear. In our study, PF highly affected PU and the PEOU. Furthermore, according to the responses we received, fear was quite evident during the pandemic period. However, mobile learning platforms maintained a high degree of PU and PEOU, which reduced fear and encouraged students to participate in their scheduled classes.

Conflicts of Interest

None declared.

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Abbreviations

LWL: Locally Weighted Learning
PBC: perceived behavioral control
PEOU: perceived ease of use
PF: perceived fear
PLS-SEM: partial least squares-structural equation modeling
PU: perceived usefulness
SN: subjective norm
TAM: technology acceptance model

TPB: theory of planned behavior
UAE: United Arab Emirates

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Viewpoint

Twitter as a Mental Health Support System for Students and Professionals in the Medical Field

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Abstract

Twitter is a rapidly growing social media site that has greatly integrated itself in the lives of students and professionals in the medical field. While Twitter has been found to be very helpful in facilitating education, there is also great potential for its usage as a social support system. Social support has become more essential as society grapples with declining mental health, particularly in the medical sector. In our previous paper, we saw that Twitter provides a promising tool to learn more about the online conversation about dementia and, in particular, the supportive network that can be created. Inspired by this, we decided to investigate the potential of using Twitter as a support system for students and professionals in the medical field. In this paper, we explore the current state of mental health in the medical field and suggest practical implementation methods for using Twitter.

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KEYWORDS

Twitter; social media; mental health; health professionals; community; social support; depression; physician suicide

Introduction to Twitter

Twitter is a free social networking and microblogging site that was launched in 2006. Users can send out brief, 280-character messages to either the public or to a specific subset of approved followers. These messages can then be retweeted and shared with another user's followers, which can lead to a ripple effect, with messages spreading to larger social networks. Upon seeing the tweets, others can immediately respond, allowing for almost instantaneous dialogue. Messages can include a hashtag (#) for specific words or phrases, allowing users' messages to be searchable.

In the past decade, Twitter has been used more frequently by the medical community [1-3]. A 2011 research letter published in *JAMA* describes how physicians frequently use Twitter to share medical information and discuss health topics [4]. A review from 2017 found that social media, including Twitter, can be a useful tool to be supplemented with the medical curriculum [5]. Another paper by Jayaram et al [6] noted that Twitter can be helpful for the medical community, as it provides a useful platform during conferences by fostering discussion and sharing content. Interestingly, a study published in 2018 investigating the use of the #TipsForNewDocs hashtag found that over the course of 2 days, 661 unique posts containing this hashtag were posted by doctors, health care professionals, and patients. While most of the tweets were focused on improving personal or professional qualities, there was a significant number of tweets on socialization and creating a welcoming community [7]. While Twitter can greatly facilitate academic discussion among health professionals and students, Twitter can also provide a supportive community for these individuals by fostering a sense of community and allowing individuals to support each other through tweets, likes, and comments. In this paper, we investigate the current state of mental health in the medical field and suggest some practical implementations of using Twitter.

Mental Health Concerns in the Health Profession

Mental health is a rising concern for individuals in the health profession. One study using data from 43 countries found that 27.2% of medical students showed depression symptoms, while only 15.7% sought treatment [8]. Similarly, it has been found that 20% of medical residents had symptoms of depression, with 74% of them satisfying criteria for burnout [9,10]. These concerns are detrimental not only for the students themselves but also for their patients, as it was found that residents with depression were 6.2 times more likely to make medication errors than nondepressed residents [10]. A study from 2004 showed that the suicide rates among male and female physicians are higher than those of the general population [11]. Finally, in a 2014 article, Dr Sinha [12] brought to light the issues of physician suicide and revealed his own experiences with the stresses of the medical profession. Several papers note that there may be negative consequences for physicians who acknowledge their mental health problems, as they may lose their medical license or the opportunity for career advancement [13-15]. If physicians are afraid to speak out or seek help, the problem may become worse. Thus, there is a great need for increased platforms to safely share these personal experiences and difficulties in a supportive community, especially in a way that can normalize mental health issues. Twitter provides a promising technological tool for this.

Value of a Supportive Online Community

A supportive online community can play a large role in improving health by helping to reduce feelings of social isolation. Although excessive social media use can be detrimental to mental health and getting adequate sleep [16], a limited amount of social media use, in which one engages in a supportive network with shared experiences, can be beneficial. Using technology for such social interactions removes limitations of geography, time zones, work schedules, and illnesses [17]. Online platforms can promote individuals to share health information and advice and encourage one another to adhere to recommended lifestyle changes [17]. It has even been found that people with serious mental illness report benefits from interacting with peers online due to greater social connectedness and feelings of group belonging through connecting through personal stories and coping strategies [18]. Although there are many types of social support (ie, informational, emotional, instrumental), this paper focuses on the emotional support that social media can provide.

Research has shown that Twitter can provide valuable psychological support. Our previous paper showed that Twitter has potential to create a valuable social support network for individuals affected by dementia and their family members [19]. Meanwhile, using the hashtag #WhyWeTweetMH, Berry et al [20] found that most people tweeted about mental health because of the sense of community, to raise awareness and combat stigma, and to have a safe space for expression and empowerment, creating a potential therapeutic effect.

Finally, a study by Sugawara and colleagues [3] showed that cancer patients can empower themselves by tweeting information about their own medical condition and treatment, providing a valuable forum for open discussion. After a thorough selection process described in the paper, the researchers focused on the account from one female cancer patient. The researchers noticed a majority of the tweets were related to psychological encouragement. User 1 wrote that she had “cleared the blood test,” and this was followed by the comment “Glad to hear that you cleared the test!” from user 2. In this scenario, Twitter provided a space for an individual to share what she was doing and to receive encouragement from the online community.

As the papers by Berry et al [20] and Sugawara et al [3] show, Twitter can provide a supportive online community that allows individuals to write about their experiences or feelings and to receive positive or encouraging feedback.

Implications for Individuals in the Medical Field

Implementing a hashtag to discuss a particular topic, as was done in Berry et al [20] (#WhyWeTweetMH) and Hennessy et al [21] (#nlm2soton), can allow for the aggregation of relevant content in this open, searchable space that is the online community of Twitter. Similarly, for physicians, perhaps a hashtag such as #AnesthesiologistStruggles can be used to share stresses that they face on a daily basis and discuss coping methods.

Using specific hashtags would allow us to congregate information on a particular topic to see how people are feeling about that topic. Are they stressed out about an upcoming exam? Are they struggling with a procedure? One study on #colorectalsurgery provides an account of how a community of colorectal surgeons were able to come together to share experiences on surgical techniques [22]. Analyzing such topics of conversation can allow individuals in the medical field to come up with solutions to help solve some of these problems. Perhaps noticing an online community of colorectal surgeons struggling with a particular technique will encourage clinicians to rethink the way that technique is performed and realize it is okay to openly share their struggles or inspire a colorectal surgeon who sees that post to recognize that this is a common problem and to work toward a solution to help.

Posting about personal struggles will allow stigmas to become more normalized. If individuals read many posts about a topic, such as struggling with mental health, from people they know, it seems more normalized because they may think, “So many of my friends and classmates are going through these struggles, perhaps it is something common.”

One method of creating such a forum is described in Admon et al [23]. Their strategies for organizing a Twitter chat include (1) thinking about the purpose of creating a Twitter chat, (2) identifying appropriate moderators, and (3) effectively publicizing the chat [23].

It would be beneficial for these conversations to be regulated in order to limit irrelevant material, misleading or false information [18,24], derogatory comments from others [18], and accidental violation of patient privacy [4,24]. A paper by Hennessy et al [25] provides an overview of some guidelines for health professionals to follow when delving into the social media community. Although Hennessy et al [25] places an emphasis on using social media to interact with patients, which is not the focus of this paper, several of the guidelines presented are applicable in this case, such as (1) making sure that patient confidentiality does not get breached in any way; (2) being respectful of other people's ideas, opinions, and habits; and (3) not posting copyrighted material as the user's own [25].

Conclusion

Declining mental health in an important issue that students and professionals in the medical field face. Social media platforms, such as Twitter, provide a promising space for individuals to find a supportive community, share experiences, and receive helpful advice. Previous research on Twitter has found supportive communities for individuals affected by dementia, mental health, and cancer. Thus, Twitter could also provide a community for improving mental health for individuals specifically in the medical field. Using specific hashtags may be useful for facilitating such communities.

Online social networks have the potential to extend social circles at the cost of in-person social interactions, resulting in increased social isolation [17,26]. With this in mind, it is important to remember that social support provided by Twitter is not meant to replace valuable human interaction but rather to provide a convenient supplemental tool.

Conflicts of Interest

None declared.

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Viewpoint

A Web Platform (MOSAICO) to Design, Perform, and Assess Collaborative Clinical Scenarios for Medical Students: Viewpoint

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Abstract

Background: The collaborative clinical simulation (CCS) model is a structured method for the development and assessment of clinical competencies through small groups working collaboratively in simulated environments. From 2016 onward, the CCS model has been applied successfully among undergraduate and graduate medical students from the Universidad de Talca, Chile; the Universität de Barcelona, Spain; and the Universidad de Vic-Manresa, Spain. All the templates for building the clinical cases and the assessment instruments with CCS were printed on paper. Considering the large number of CCS sessions and the number of participating students that are required throughout the medical degree curriculum, it is impossible to keep an organized record when the instruments are printed on paper. Moreover, with the COVID-19 pandemic, web platforms have become important as safe training environments for students and medical faculties; this new educational environment should include the consolidation and adaptation of didactic sessions that create and use available virtual cases and use different web platforms.

Objective: The goal of this study is to describe the design and development of a web platform that was created to strengthen the CCS model.

Methods: The design of the web platform aimed to support each phase of the CCS by incorporating functional requirements (ie, features that the web platform will be able to perform) and nonfunctional requirements (ie, how the web platform should behave) that are needed to run collaborative sessions. The software was developed under the Model-View-Controller architecture to separate the views from the data model and the business logic.

Results: MOSAICO is a web platform used to design, perform, and assess collaborative clinical scenarios for medical students. MOSAICO has four modules: educational design, students' collaborative design, collaborative simulation, and collaborative debriefing. The web platform has three different user profiles: academic simulation unit, teacher, and student. These users interact under different roles in collaborative simulations. MOSAICO enables a collaborative environment, which is connected via the internet, to design clinical scenarios guided by the teacher and enables the use of all data generated to be discussed in the debriefing session with the teacher as a guide. The web platform is running at the Universidad de Talca in Chile and is supporting collaborative simulation activities via the internet for two medical courses: (1) Semiology for third-year students (70 students in total) and (2) Medical Genetics for fifth-year students (30 students in total).

Conclusions: MOSAICO is applicable within the CCS model and is used frequently in different simulation sessions at the Universidad de Talca, where medical students can work collaboratively via the internet. MOSAICO simplifies the application and reuse of clinical simulation scenarios, allowing its use in multiple simulation centers. Moreover, its applications in different courses (ie, a large part of the medical curriculum) support the automatic tracking of simulation activities and their assessment.

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KEYWORDS

collaborative clinical simulation; electronic simulation record; medical students; medical education; MOSAICO

Introduction

Medical education has progressed toward student-centered learning approaches that allow students to have a more active role in their learning and the development of competencies compared with classic teacher-centered approaches [1-3]. Clinical simulation (CS) [4] and computer-supported collaborative learning (CSCL) [5] are two of these paradigms that provide significant student-centered benefits [6,7]. Both methodologies can improve teamwork processes (eg, communication, coordination, and cooperation), and their implementation has been associated with improvements in the quality of patient care [8].

The CSCL environment empowers students to collaborate through technology, which positively influences their learning [7,9]. With the COVID-19 pandemic, the new educational environment includes consolidation and adaptation of didactic sessions creating and using available virtual cases [10] and taking advantage of different web platforms [11]. In particular, for medical students, some software helps to build clinical cases based on data from real patients [12], applying artificial intelligence [13], or recommendations by experts [14].

The collaborative clinical simulation (CCS) model is a structured learning model for the acquisition and assessment of clinical competencies through small groups working collaboratively to design and perform in simulated environments supported by technology [15]. CCS is presently a comprehensive model because it contains essential considerations and recommendations from both paradigms (ie, CS and CSCL) [15].

An essential feature of the CCS model is its capability to support the collaborative design of CS cases, which applies to a large part of the medical curriculum. The cases are created for untrained medical students guided by a teacher. The process is based on what was learned in classroom sessions; it is an instance where students can learn collaboratively, integrating information in the construction of a clinical case while acquiring, reinforcing, and applying their knowledge and skills in a simulated clinical environment [16]. The medical students create a clinical case in small groups working separately. Each group is given 60 minutes for designing the simulated scenarios, with roles, medical records, nursing sheets, and assessments [15]. The designer groups apply the clinical cases created in the simulation session to another group (ie, performer groups) and evaluate their performance, with templates given by the teacher, during the collaborative simulation phase. The teacher monitors all the processes, supports the design, assesses the performance group, and conducts the debriefing [17].

From 2016 onward, the CCS model has been applied successfully among undergraduate and graduate medical students from the Universidad de Talca, Chile; the Universität de Barcelona, Spain, [17]; and the Universidad de Vic-Manresa, Spain. Throughout these CCS sessions, the templates for building the clinical cases and the assessment instruments were printed on paper. With printed templates, the students could design a case collaboratively in small groups, take notes, create laboratory tests, and assess their performance between peers.

Considering the large number of CCS sessions and the number of participating students that are required throughout the medical degree curriculum, it is impossible to keep a clean record when the instruments are printed on paper. Tracking simulation activity logs, scheduling simulation sessions, creating templates for assessment instruments, sharing patient data, monitoring the progress of students, and reusing clinical cases are impossible when the work is paper based. Moreover, managing all of the above information requires specialized software in order for a CS center to maintain systematized indicators, attendances, inventories, and simulation activity logs. A platform must support the management of a center with an emphasis on the teaching and learning processes with innovative tools for the collaboration between students and teachers.

To give computer support to collaborative simulation activities with the CCS model, we developed MOSAICO, a web-based platform. This platform allows for the designing, performing, and assessing of collaborative CSs through small groups working collaboratively in simulated environments supported by technology. The web platform enables a collaborative technological environment where each group works independently, while connected by the internet, to design clinical scenarios guided by the teacher, perform in the simulated clinical scenarios, and use all data generated for discussing and closing their learning gaps in the debriefing session with the teacher as a guide.

Considering the importance of tracking the progress of medical students adequately, the web platform was created to strengthen the CCS model [15], assist in the co-construction of shared understanding, and research the interactions between participants in simulation activities with technology [18]. The development of an electronic registry for CSs has the potential to positively affect the medical trainee workflow through different mechanisms, including reducing time spent in design, accessing cases, easing the process of data retrieval, providing greater remote access, and monitoring the progress of medical students [19].

The benefits of using simulations and tracking the progress of students in health care, construction, engineering, aviation, natural resources, and the military are widely documented [20]. The capabilities offered by simulations have created unlimited opportunities in areas such as aviation training, where the use of simulations is realistic, safe, and cost-effective and allows for tracking all the activities of the future pilots [21]. The tracking of simulated flight hours, the competencies developed, and the facilities to build and reuse different scenarios are essential characteristics of flight simulators. Medical education, like aviation, is driven by needs; use of simulations in this context allows for the tracking of activities of medical students.

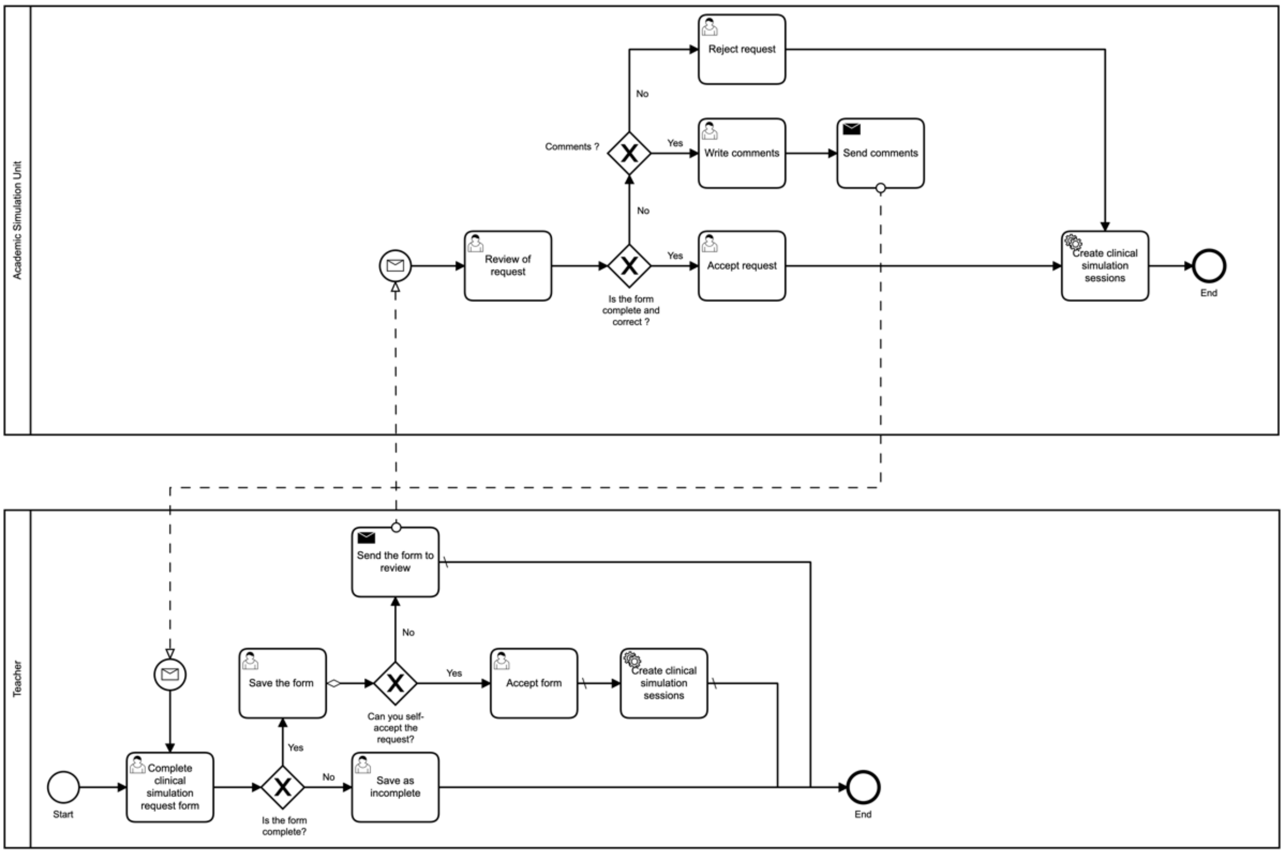
This paper aims to describe the MOSAICO web platform, which was created to facilitate and expand its application and track student progress across the curriculum. To reach this goal, this paper reports on the requirements elicitation, design, and development process for implementing MOSAICO in the Faculty of Medicine of both the Universidad de Talca, Chile, and the Universität de Barcelona, Spain.

Methods

The requirements elicitation was the first phase of the web platform development process. This phase is a critical aspect because it lays the foundation for all the subsequent project work, and it affects the success of the development project [22]. The CCS model [15] was the primary source of the requirements elicitation, which analyzes and documents the requirements via four phases. The process was conducted by the lead researcher of the web platform development (SGM) to ensure the quality and completeness of the CCS model.

In order to complement the features and structure of the web platform, we interviewed the personnel involved in academic activities, such as medical professors, students, and support staff. The interviews were semistructured for each CCS phase, and each meeting was recorded and documented. For the requirements elicitation from academics, we used an ad hoc instrument to document and analyze all the requirements. Furthermore, we modeled each process workflow involved in the functional requirements by module (eg, schedule simulation session, create a clinical guide, and assign group) with the Business Process Model and Notation [23] standard using the free software Camunda Modeler, version 4.4 [24] (see Figure 1).

Figure 1. Process of scheduling a simulation session. The Business Process Model and Notation diagram of the process to request a clinical simulation that involves the collaborative work of a teacher with the academic simulation unit.



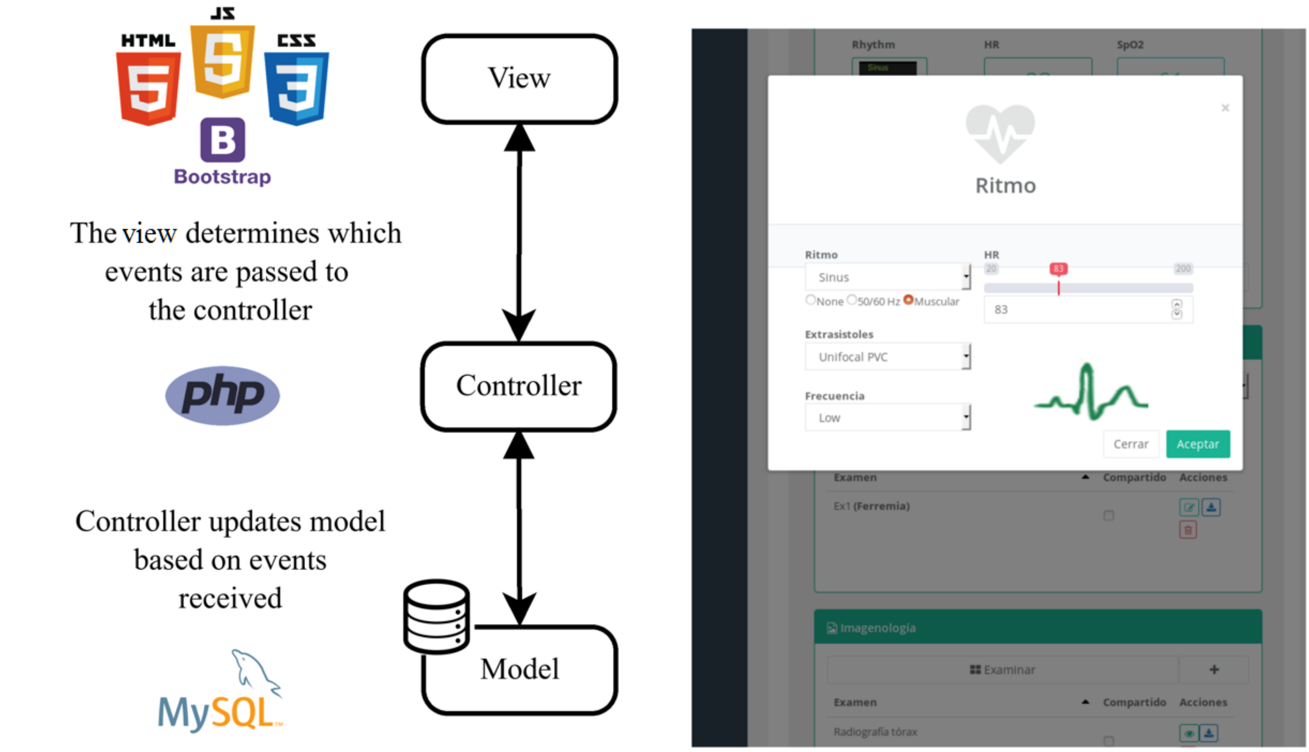
The documentation and analysis of the requirements to generate the web platform were divided into functional and nonfunctional. The functional requirements are the features that the web platform will be able to perform, such as schedule simulation, create a clinical guide, and design evaluation rubrics. Nonfunctional requirements describe how the web platform should behave, such as security, interoperability, and performance [25].

The web platform was designed to support each phase of the CCS by incorporating the functional requirements needed to run collaborative sessions. In this way, the system comprised four modules: (1) educational design, (2) students' collaborative design, (3) collaborative simulation, and (4) collaborative debriefing. Regarding the nonfunctional requirements, usability is essential to the design of functional interfaces [26] by considering specific characteristics of the medical curriculum, technological aspects, students' interactions, and instructional design [27,28]. Moreover, the interoperability is fundamental for sharing information between different platforms, exporting assessment instruments, sharing laboratory and multimedia tests, and reusing clinical cases.

On the other hand, the platform needs to secure users' authentication with different roles and permissions. Security and confidentiality are essential, since small groups of students need to generate clinical cases, which are monitored by an instructor, without the other students knowing the diagnosis. For the collaboration, all the interactions between students (ie, suggestions about patient conditions, sharing laboratory and multimedia diagnostic tests, and performance assessments) can be achieved with the assistance of mobile devices (ie, tablets or smartphones). At the end of the simulation sessions (ie, collaborative debriefing), it is necessary to store the information on simulated clinical cases and the evaluations of both students and instructors as well as keeping records of collaborative debriefing sessions.

After designing the web platform, we considered its development to include all the functional and nonfunctional requirements. The software was built under the Model-View-Controller architecture [29] to separate the views from the data model and the business logic. Figure 2 shows the software architecture and the technologies employed. Since usability is one of the most important nonfunctional requirements, views use web technologies, such as HTML5, JavaScript, and Cascading Style Sheets 3 (CSS 3), to ensure suitable access to different web browsers. The Bootstrap framework, version 3.7, gives the software responsive capability to fit different screen resolutions (ie, mobile and desktop devices). The model defined Hypertext Preprocessor (PHP) classes that represent the database schema and defined methods to update, select, and insert data into the database. Controllers call the model classes and use their methods to access the data. Both the model and controller were written with PHP 5.6 code. MySQL (Structured Query Language) 14.14 was used as the database management system (see Figure 2).

Figure 2. The software architecture and technologies implemented. The platform applies the Model-View-Controller architectural pattern. Controllers manage all requests from the view layer and update the model based on events or data received. The view layer renders the data sent from the model layer through a controller, and the web-based responsive interface uses technologies on a wide variety of devices, such as smartphones, tablets, or desktop computers. CSS: Cascading Style Sheets; JS: JavaScript; PHP: Hypertext Preprocessor; SQL: Structured Query Language.



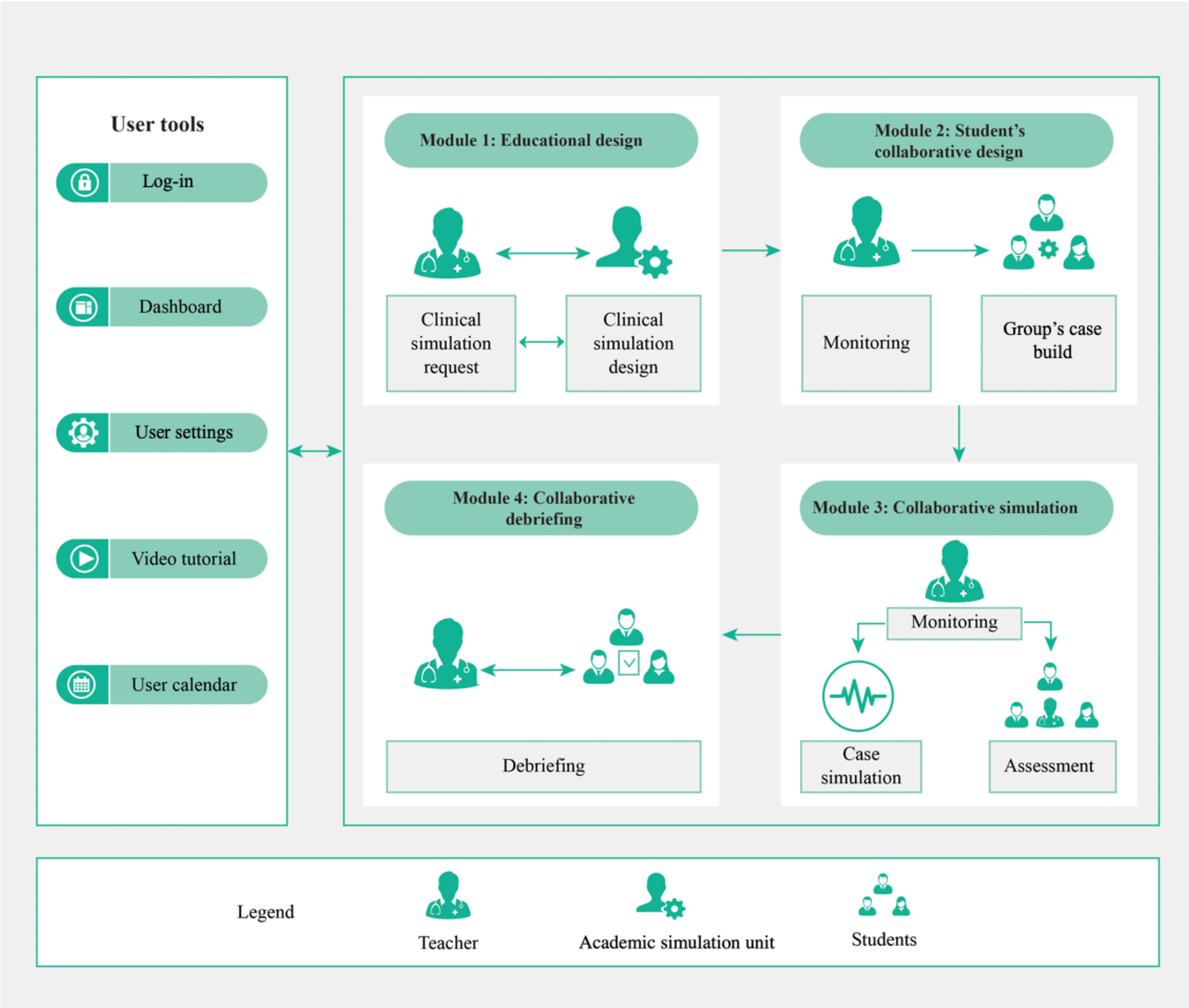
A full-time bioinformatics engineer (JGD) and the lead of the biomedical informatics laboratory (SGM) designed and developed the web platform. They took 12 months to create the prototype and 6 months to make modifications during the pilot application. As of 2020, the pilot application is operative for undergraduate medical students at the Universidad de Talca in Chile.

Results

Overview

MOSAICO has four modules and three different user profiles: academic simulation unit, teacher, and student. These users interact under different roles in collaborative simulations. The academic simulation unit profile includes the platform administrator, who oversees user accounts, courses, supplies, and room settings; generates reports; and works collaboratively with a teacher in order to validate and schedule simulation sessions. On the other hand, the teacher profile generates clinical guidelines with differential diagnosis and supports the platform execution with medical students. Finally, the student profile participates in modules 2, 3, and 4, which involves designing, executing, and debriefing a clinical case in small groups, collaboratively (see Figure 3).

Figure 3. The different sequential layers designed and developed by the collaborative clinical simulation (CCS) software MOSAICO. Each module supports the CCS phases and uses technology to design, develop, and assess collaborative clinical scenarios for medical students.



The results of the functional requirements engineering process involved elicitation, documentation, and analysis [25], which were obtained directly from the foundational paper of the CCS model [17]. These results were complemented with different interviews and discussions about the functionalities and attributes to build a web platform for a collaborative CS. Table 1 shows the results of the most critical requirements to design the software classified by the four CCS model phases. Moreover, the nonfunctional requirements, which specify how the web platform should behave and were obtained from professors, students, and support staff, are listed in Table 1.

Table 1. Results of functional and nonfunctional requirements to design and develop the web platform MOSAICO for the collaborative clinical simulation (CCS) model. Functional requirements were obtained from Guinez-Molinos et al [15].

CCS model phases [15]	Platform software requirements	
	Functional	Nonfunctional
Module 1: educational design	• Schedule simulation session (date and time, educational objectives, and materials) • Create a clinical guide • Design evaluation rubrics	• Interoperability • Usability • Access security (authentication)

Module 2: students' collaborative design	• Record attendance
	• Assign groups
	• Create collaborative clinical scenarios (small groups) including:
	  ◦ Patient history
	  ◦ Vital signs
	  ◦ Laboratory tests
	  ◦ Roles
	  ◦ Multimedia tests
	• Monitoring student progress (online)
		• Interoperability
		• Usability
		• Access security (authorization, authentication, and privacy)

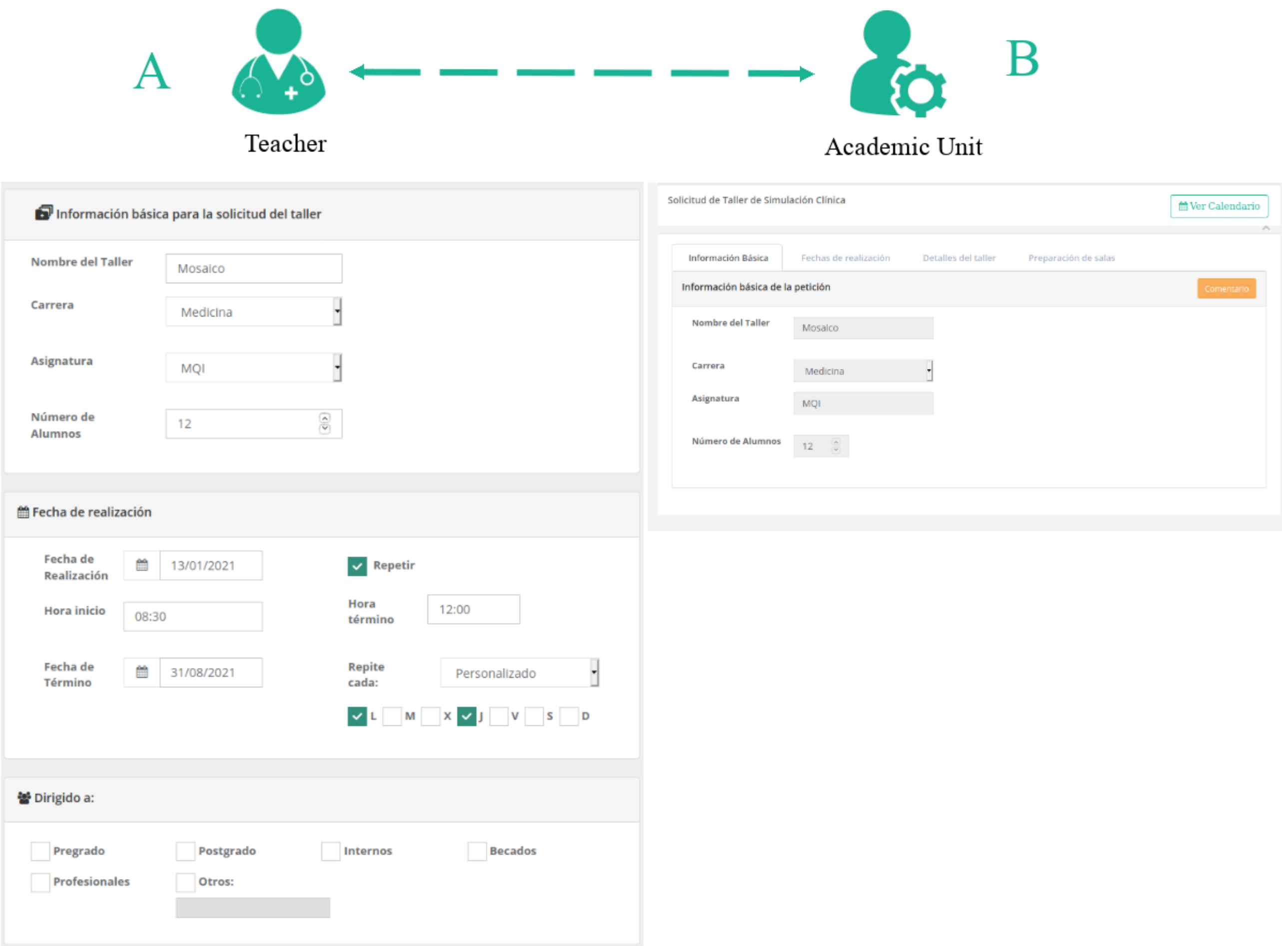
Module 3: collaborative simulation	• Share patient data (laboratory and multimedia tests and vital signs) • Apply evaluation rubric	• Interoperability • Usability • Mobile usability

Module 4: collaborative debriefing	• Debriefing module with:
	  ◦ All scenarios
	  ◦ Evaluations
	  ◦ Videos (if possible)
		• Interoperability
		• Usability
		• Storage capacity

Module 1: Educational Design

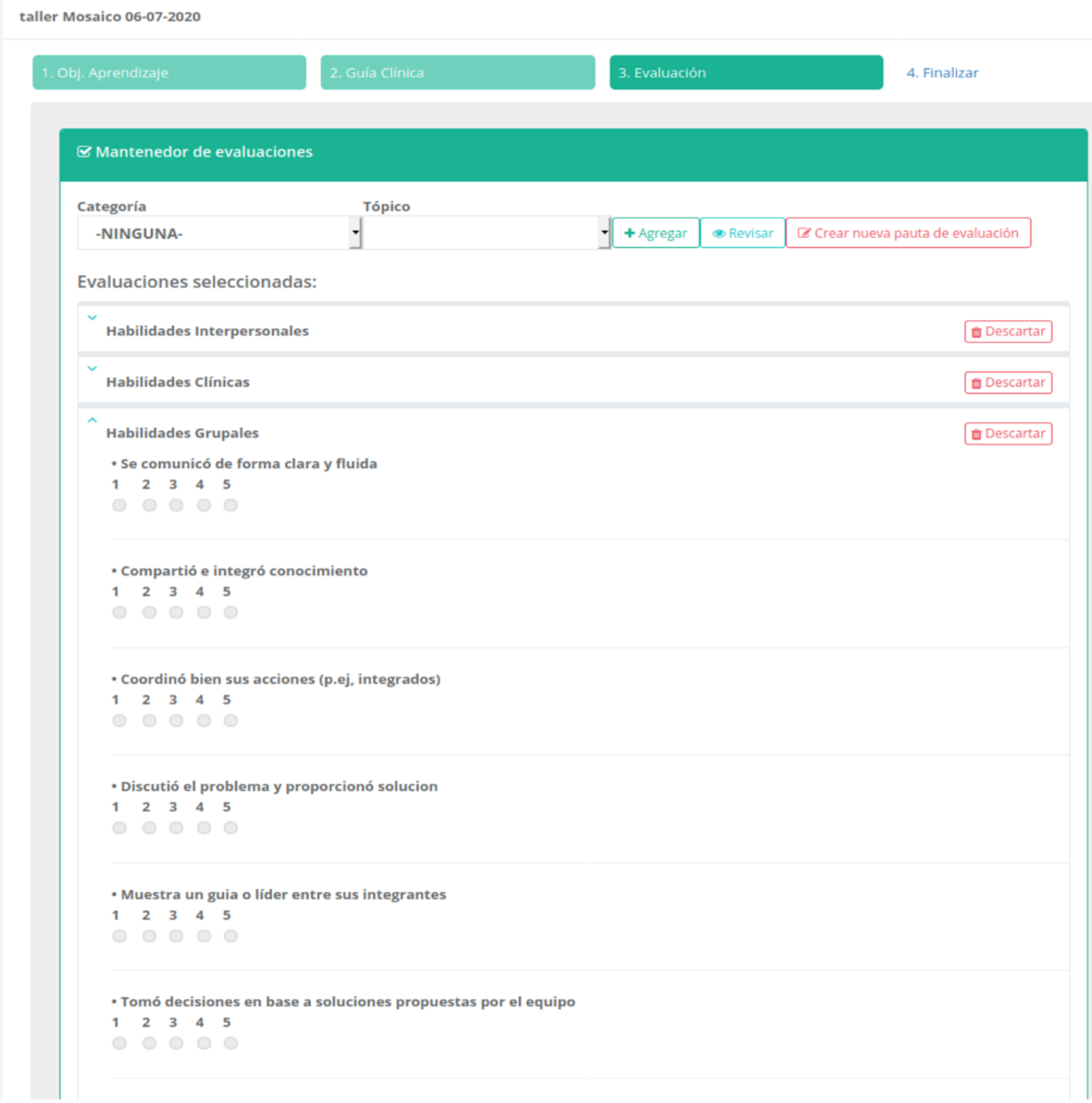
To schedule CS sessions, the teacher requests the academic simulation unit through the educational design module where it is possible to create, edit, review, check status, and delete the request (see Figure 4). To create a new request in MOSAICO, the teacher must define a name for the clinical session, select the audience (ie, undergraduate or graduate course, number of participants, academic degree, and competencies), propose to schedule the rooms, and create educational objectives. The teacher and the academic simulation unit profiles must design the components of the CCS (ie, objectives, materials, case scenarios, and assessment items) collaboratively according to the medical curriculum and student needs [30].

Figure 4. Educational design module. Form to request a clinical simulation to the academic simulation unit director (A), who reviews the request and sends comments to the teacher (B).



In an iterative process supported by MOSAICO, the teacher and the academic simulation unit can incorporate progressive changes, which might be necessary to complete the CS request (see Figure 4) adequately. Thus, the request may take the status of incomplete (ie, in preparation), waiting (ie, sent to be reviewed by the academic simulation unit), commented (ie, reviewed by the academic simulation unit, where a teacher must make changes for it to be accepted), and accepted or rejected. Once that request has been approved and scheduled by the academic simulation unit, the teacher should upload the clinical guides, multimedia tests (eg, videos, x-rays, laboratory results, and electrocardiograms), and assessment items, based on existing templates or from scratch (see Figure 5). With this information, the system schedules a new CS session.

Figure 5. Design of the simulation session module. Once the request by the academic simulation unit is approved, the teacher can design the session with a clinical guide and rubric to assess the competencies.

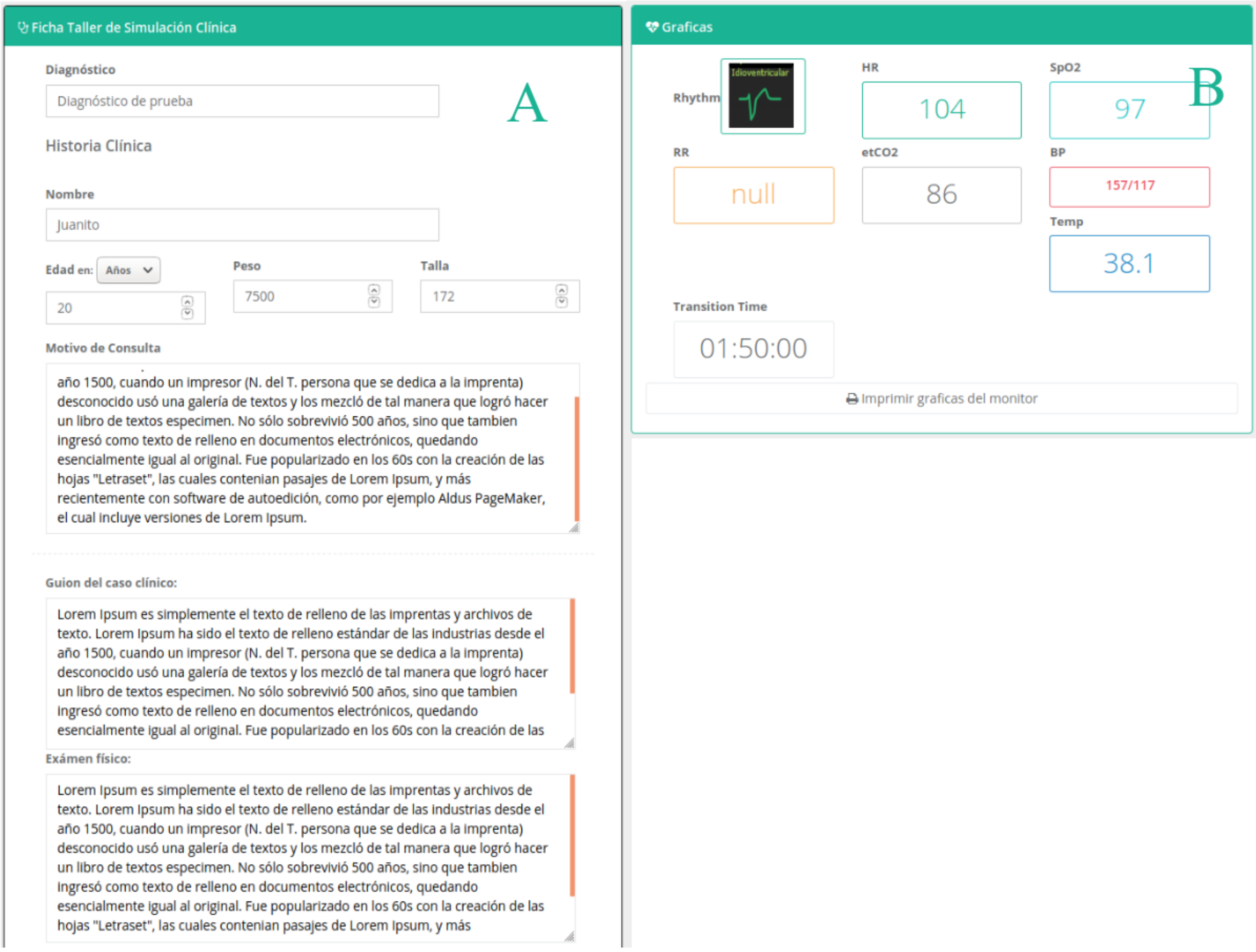


Module 2: Students' Collaborative Design

MOSAICO can track simulation activity logs of medical students, generating recorded activities [31,32]. Toward this goal, each time the medical students are about to start simulation activities, they register their attendance through a fingerprint reader; they must register their entry, select the simulation session, and register the exit when the activity has ended.

The instructor divides the students into at least three small groups of 3 to 5 students, which are deployed to different rooms [15,33]. Each group has access to a computer connected to the internet. Each group designs a clinical case in the students' collaborative design module, according to the differential diagnosis assigned by the teacher (see Figure 6).

Figure 6. Students' collaborative design module. (A) and (B) are the views of the web platform's graphical interface. (A) shows a view of the students' case design form, where the designer group enters information to support their case design. (B) shows a teacher's view from where he or she can monitor the students' activity remotely and in real time.

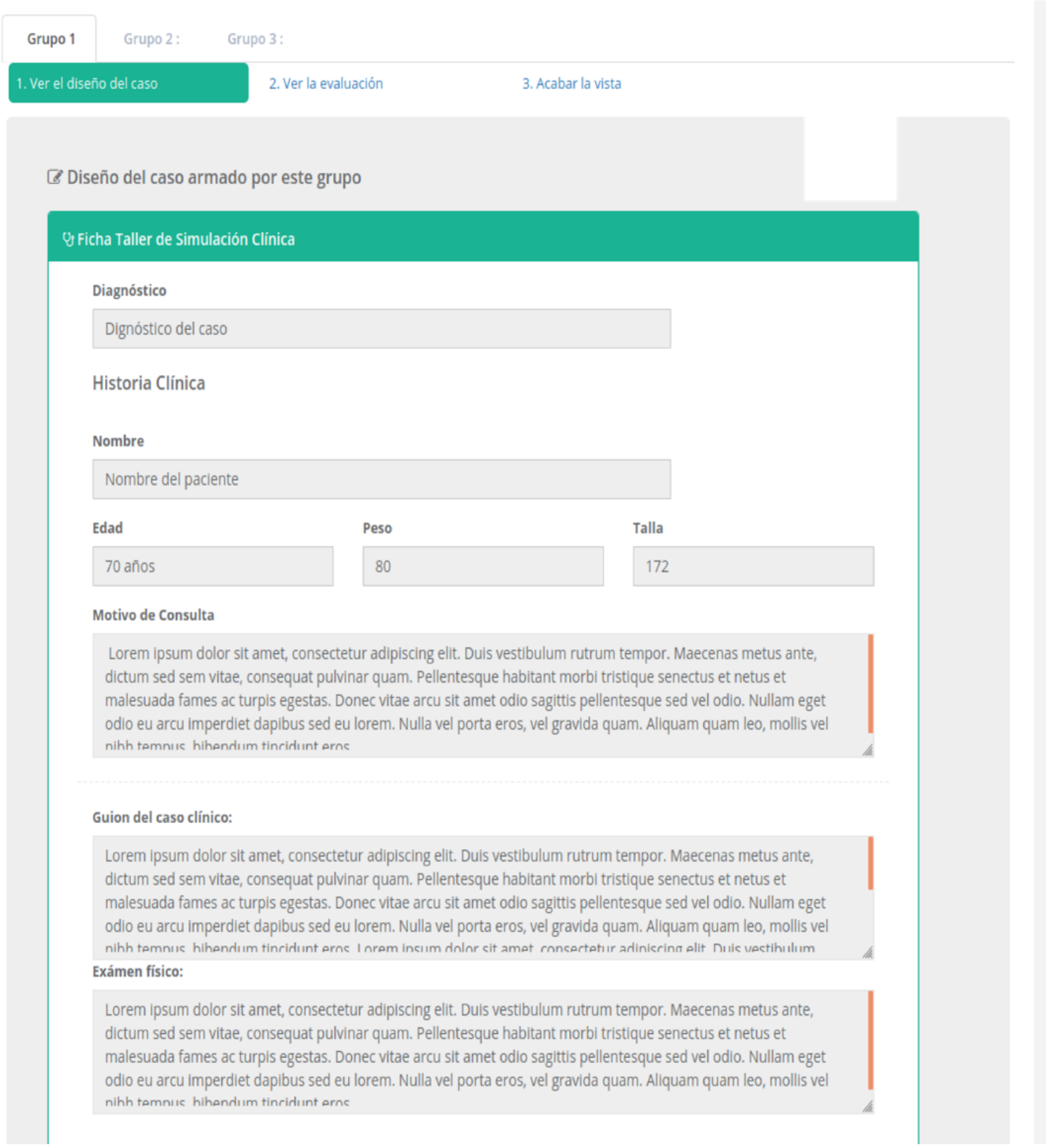


For the collaborative design of a clinical case, MOSAICO provides standardized templates with all the required information. The students write down relevant information about the clinical case (see Figure 6A), including age, sex, weight, size, physical exam, vital signs, laboratory tests, images, or videos (see Figure 6B). Moreover, the students describe the roles they play in the next phase (ie, collaborative simulation) for each designer group member (eg, patient, nurse, and family member).

Medical students collaboratively design a clinical case by forming small groups in person—before the COVID-19 pandemic—at the Clinical Simulation Center, where one student writes the required information with the group's consensus on the web platform. This year, with the COVID-19 pandemic, the semiology course in medicine is using MOSAICO to teach online academic activities. This web platform allows students to design a clinical case collaboratively via the internet while at home. One of MOSAICO's strengths is that it allows communication between students in person or online through the web platform.

Throughout the students' collaborative design process, the teacher supervises and facilitates the design process through the web platform via the internet, providing advice, clarifying doubts, and guiding each group in the preparation of the short clinical case scenario [15] (see Figure 7).

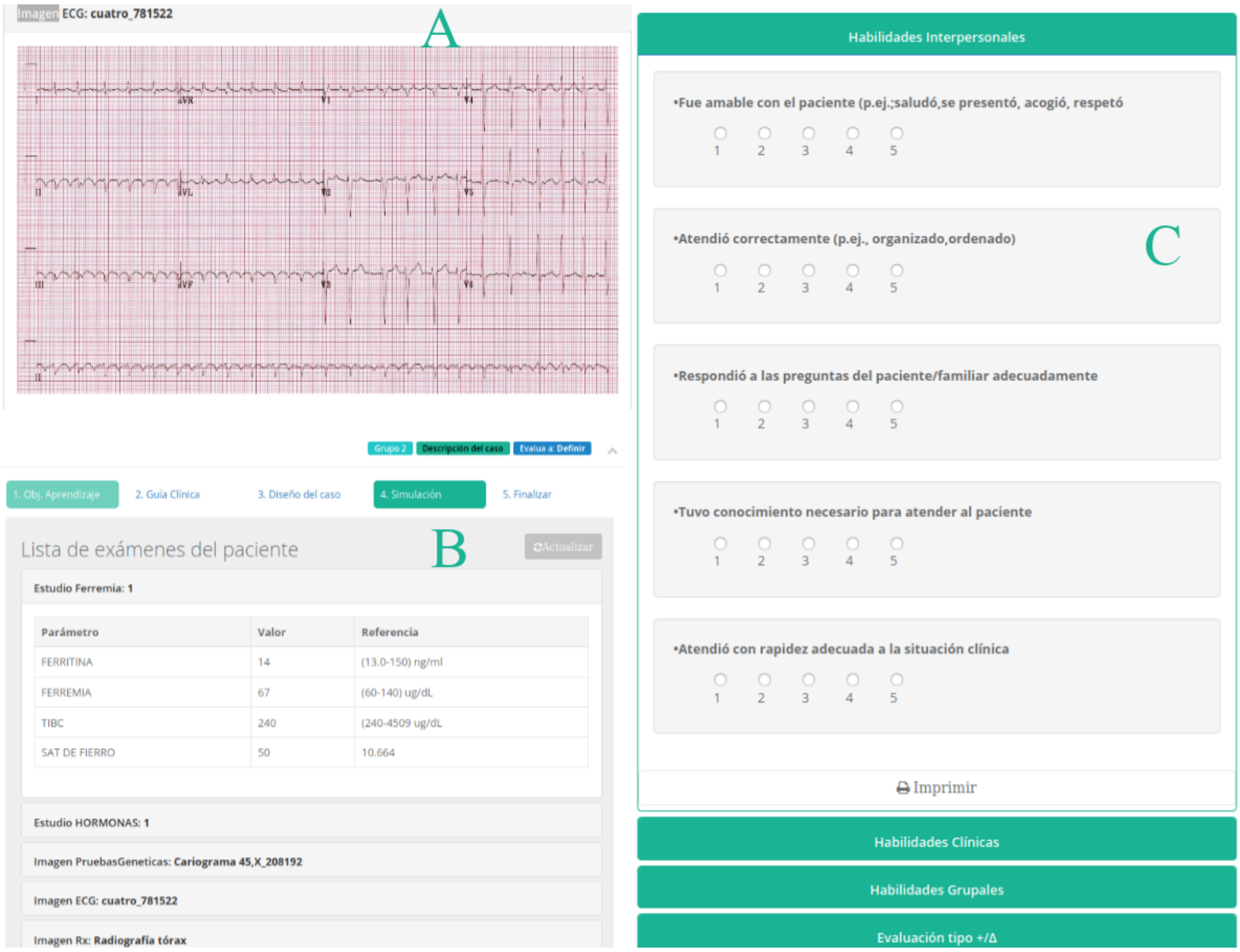
Figure 7. Teacher monitoring module. In this module, the teacher can monitor each group working in the collaborative design process in real time.



Module 3: Collaborative Simulation

Collaborative simulation is a face-to-face activity that is executed in a simulated clinical environment, which provides a controlled and safe environment for the acquisition of clinical skills [34-36]. The members of the designer group prepare the scenario and simulate its case, perform roles, and present the case (ie, brief) to members of the executing group, who assume the role of the medical team. Members of the executing group, based on their knowledge and information, must obtain the anamnesis, perform a physical examination, request and interpret complementary exams and laboratory tests, diagnose, and treat the simulated patient [15] (see Figure 8).

Figure 8. Collaborative simulation module. (A) and (B) are views of the performer group during the collaborative clinical simulation where an electrocardiogram and laboratory test are shown, respectively. (C) is a view of the assessment tool available for the evaluation of the performer group by the evaluator group. In the web platform, there are rubrics previously defined by the teacher that allow for assessment of the performance of the performer group in the simulation.



All information is provided by the designer group as requested by the performer group when handling the patient inside the simulated room. The performer group may request laboratory results and exams, in images or video clips, and may visualize them on a desktop computer or mobile device. In parallel, the teacher controls the time and observes actions from a mirror room, ideally, and guides the designer group, which receives instructions through a hidden earpiece to help the performer group.

The third group, the evaluator group, observes the development of the case and evaluates the performance of the performer group in a separate room using the evaluation guidelines and the structured Plus/Delta assessment strategy in MOSAICO. This enables participants to consider the “pluses” (ie, what went well) and the “deltas” (ie, what they would like to change about the performance) in the web platform [37].

Module 4: Collaborative Debriefing

For the last phase of the CCS session, MOSAICO offers a summary module with all the logged activities, assessments by peers and the teacher, and video recordings for the three simulated clinical cases. This module is specially adapted so that the teacher and students can perform a collaborative debriefing, where each case is discussed deeply by the design, performance, and scoring carried out in the three groups (see Figure 9). At the end of the simulation, students can give, through the platform, their perception of the CSs and what they learned.

Figure 9. Collaborative debriefing module. Both (A) and (B) are views for the teacher. During the debriefing, the teacher can access the assessment done by each group. (A) shows the evaluations done for members of a group, while (B) shows summary charts of all the evaluations done for the students.

Discussion

Principal Findings

In this paper, a web platform, MOSAICO, is described in detail to facilitate the design, performance, and evaluation of collaborative clinical scenarios for medical students. MOSAICO was created to digitalize the collaborative simulation learning model that has been successfully applied for 4 years in the universities where the authors are based [15,17]. The web platform considers the CCS model's functional and nonfunctional requirements and medical experts' advice. The engineering software process (ie, design and development of the web platform) was oriented to support each phase of the model and extend its capabilities for designing clinical cases online via the internet.

The process of building a clinical case is a complex cognitive task. The students must work collaboratively to design a scenario representing a hypothetical clinical situation with enough fidelity to allow other students in a simulation phase to act collaboratively as a doctor team (ie, performer groups) to deduce a diagnosis and proceed to the medical actions. The designer group must coordinate to provide details like personal data, clinical history, laboratory or multimedia results, and vital signs to the performer group. According to simulation methodology, the last part of the session is used to analyze and discuss among all participants the experience and consequent relevant actions for solving the simulated situation in the real clinical practice. The teacher leads and stimulates reflection, allowing the students themselves to discover and assess their future behavior.

In the collaborative designer module, MOSAICO enables tools for team collaboration, supporting positive interdependencies among the team's members as well as the diversity and depth of their clinical knowledge [38]. This is critical for the professional future of the medical students, where a physician does not work alone or is not isolated from a team. Instead, being part of a team has become a requirement, and leadership is a skill rather than a role [16].

Moreover, it is essential to include technologies that will be used in real-world settings into educational CSs to better prepare students for clinical practice and to promote patient safety [32]. In a recent perception study [39], European medical students believed that their curriculum lacked digital health education, with 84.9% (383/451) agreeing or strongly agreeing that it should be implemented in the medical curriculum. In Chile, the Universidad de Talca has implemented the CCS model since 2016 in the medical curriculum, creating the Biomedical Informatics course for medical students and funding the National Center for Health Information Systems (Centro Nacional en

Sistemas de Información en Salud [CENS]) with four Chilean universities [40].

Recently at the CENS, we published a model of referential competencies in health information systems [41], which focuses on the health transformation and technology areas. These areas orient the design of curricula, training programs, and new careers associated with health and data science.

In this sense, MOSAICO is oriented to introducing electronic recording technologies and developing technological competencies in the curriculum of a medical faculty. Future employers expect new graduates to be competent in information technology use upon graduation. Students are often not given the significant educational opportunities needed to gain these competencies [32].

Assessing collaboration in undergraduate education is complex and requires special dedication [15]. How teamwork is measured and assessed is often a concern, making it difficult to include these skills in the undergraduate curricula [42]. The development of assessment instruments with reliability and validity based on statistical analyses should be designed and supervised by psychometricians, who propose items and dimensions to assess [15]. MOSAICO supports the construction and application of assessment instruments for CCS scenarios. In the educational design module, the teacher can design both their assessment guidelines and the one that students will apply to each other. The students apply this instrument in the collaborative simulation phase measuring the technical and nontechnical skills, registering all the items in the web platform for discussion in the debriefing phase. Understanding and developing teamwork is essential, and health care lags significantly behind fields such as the military and aviation [42]. In Chilean and Spanish medical faculties, as it happens in many other faculties, the students do not have an electronic registry that records the number of hours of CS that they had during their undergraduate studies.

For this reason, MOSAICO has the capabilities to maintain individual and group records of the simulated competencies, the assessments, and the detailed hours that each of the students had in the simulation center. This replicates the current aviation simulation models [42]. Besides, with the registration of cases and evaluations, investigations could be designed between different simulation centers, for both undergraduate and graduate medical students, which could allow for a better and fairer design of the end-of-program grade assessments of students' performance.

The collaborative debriefing module is vital for enhancing learning and participating successfully in group discussions, with all the elements registered in the web platform. In this MOSAICO module, both teachers and students give feedback to learners and assess their participation in the activities [15]. Only 41% of the software programs used for medical training allow feedback to be given to students from the teacher or through automatic responses [13], but students work alone, before or after classes, without guidance along the learning process. The debriefing sessions are essential because they facilitate reflection, learning, conceptualization, abstraction, and connecting with real events [36].

The COVID-19 pandemic has significantly affected teaching within health career programs [10,43]; students have been without the possibility of doing rotations in hospitals, face-to-face classes, and CSs. In this scenario, MOSAICO has become a unique protagonist as a support web platform for the construction of online clinical cases, simulations via video conference, and debriefing with all the elements available (ie, cases, evaluations, and comments). Each stage in MOSAICO may happen in a different place, so the technology used should be flexible enough to support access from different devices, such as desktops or tablets, through the internet.

MOSAICO is growing; the next version (ie, version 2.0) should include more tools for the administration of simulation centers, modules for academic reports and supplies, different specialties (eg, psychiatry, obstetrics, and pediatrics), and improvement of the interoperability for the export of cases between different platforms or institutions.

During this online academic semester, MOSAICO is being evaluated by both teachers and medical students of the Universidad de Talca. For the evaluation, we are applying the mobile health (mHealth) App Usability Questionnaire (MAUQ) [44] to evaluate the usability of the web platform in mobile devices. This evaluation is a work in progress that considers two courses: (1) Semiology for third-year students (70 students in total) and (2) Medical Genetics for fifth-year students (30 students in total). In future work, we are planning to validate the application of MOSAICO in medical education, comparing it with similar platforms that use collaborative learning in CS. The application of MOSAICO in the CCS activities of cardiology courses at the Universität de Barcelona (120 students) and the Universidad de Vic-Manresa (64 students) in Spain will be assessed in a face-to-face or online modality, depending on the COVID-19 pandemic, during the next academic year.

Limitations

The platform, which works on computers or mobile devices, is only available in Spanish. The next version will support both English and Spanish languages. MOSAICO supports a collaborative clinical session with three small groups composed of 3 to 5 students each. It does not allow the incorporation of another group in the same session, making it necessary to create another session if four or more groups are needed.

Conclusions

MOSAICO was implemented online and is still currently being used correctly with different simulation sessions at the Universidad de Talca, Chile, where medical students work collaboratively connected by the internet. Both students and teachers have excellent comments about the use of the web platform. An essential strength of the platform is that it is possible to use it in face-to-face sessions or online via the internet without modifications.

The web platform supports all the stages of the CCS model satisfactorily, and the teachers use MOSAICO as technological infrastructure to schedule, design, and execute the simulation activities. Moreover, it allows for the teaching of clinical activities throughout the COVID-19 pandemic while the university campus is closed for student safety.

The use of the web platform simplifies the application and reuse of CS scenarios, permitting its use in multiple simulation centers. Moreover, its applications in different courses (ie, a large part of the medical curriculum) support the automatic tracking of simulation activities and their assessment.

MOSAICO could allow research to be conducted between different simulation centers by standardizing the information, structure of clinical cases, and assessment instruments. This is important in comparative studies and in research regarding medical students' learning.

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Conflicts of Interest

None declared.

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Abbreviations

CCS: collaborative clinical simulation
CENS: Centro Nacional en Sistemas de Información en Salud (National Center for Health Information Systems)
CORFO: Corporación de Fomento de la Producción de Chile
CS: clinical simulation
CSCL: computer-supported collaborative learning
CSS 3: Cascading Style Sheets 3
GINMAD: Grup d'Innovació en Metodologies docents actives per el desenvolupament i avaluació de les competències clíniques en Medicina
MAUQ: mHealth App Usability Questionnaire
mHealth: mobile health
PHP: Hypertext Preprocessor
SQL: Structured Query Language

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Letter to the Editor

Medical Students Respond: Question Precision and Gender Differentiation. Comment on "Understanding Medical Students' Attitudes Toward Learning eHealth: Questionnaire Study"

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KEYWORDS

eHealth; medical students; medical education

We read with great interest the article by Vossen et al [1] investigating the preparedness of medical students to take advantage of eHealth innovations in medicine and their attitude toward its implementation in medical education. The successful utilization of eHealth has never been more relevant than it is today, allowing for better workflows, fewer errors, scalability of record-keeping, and, importantly, remote consultations to reduce the transmission and risk of COVID-19 [2]. Therefore, this article comes at a critical time to allow for a better understanding of the factors affecting the willingness of medical students to interact with eHealth to allow for meaningful change to be implemented.

Although the authors have attempted to investigate the attitudes of students toward learning eHealth, the questions used provide a vague description of said eHealth. For example, the authors ask, "I feel prepared to take advantage of the technological developments within the medical field" without describing the nature of the technological options available. eHealth in clinical practice can vary from simple telecommunication consultations to complex diagnostic artificial intelligence; thus, as medical students, we would expect the questions to be more focused in order to successfully judge our preparedness and consequently contribute to more reliable and practical results. In their study, Walpole et al [3] described the specifics of eHealth in their questionnaire, for example, "use of computers and other information systems, including storing and retrieving information," allowing students to accurately respond to the questions, thereby producing reliable results. By describing the eHealth measure, there is less room for interpretation, which allows the results to be generalized to the general medical student population.

Additionally, responders to the survey were mainly female medical students (215/303, 71.0%), which may have skewed the results of this study. A similar study by Haluza et al [4] exploring eHealth behavior and gender demonstrated that females are more likely to engage in health technology. In the study, 89.6% of the females engaged in online health-related services compared to 77.8% of males, highlighting that there is a gender difference among eHealth users. Addressing this discrepancy would therefore produce reliable results that can be used to implement eHealth and telemedicine strategies that would promote digital skill use in medical practice. The role of gender needs to be assessed in a more extensive survey that would better represent the cohort.

Even though data regarding the technical skill level of participants were collected, the authors did not elaborate on the link between technical literacy and medical students' attitude toward implementing eHealth into their future work environment. Previous experience with technology can impact one's likelihood of taking advantage of eHealth in clinical practice. This was evident in a study by Olok et al [5], which showed that the level of ICT (information and communications technology) skill was a significant predictor of eHealth use among medical professionals. Therefore, understanding this association can guide future interventions to target specific groups of medical students to promote their engagement with eHealth.

We congratulate the authors on this research as it provides important insights into student doctors' attitudes toward eHealth. However, we recommend that the authors use a more descriptive set of questions, as well as adjust for the discrepancies in gender. This would allow for representative results that can be used to influence change in eHealth medical school curricula.

Editorial Notice

The corresponding author of "Understanding Medical Students' Attitudes Toward Learning eHealth: Questionnaire Study" did not respond to our invitation to reply to this commentary.

Conflicts of Interest

None declared.

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Abbreviations

ICT: information and communications technology

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Original Paper

Willingness to Use Digital Health Tools in Patient Care Among Health Care Professionals and Students at a University Hospital in Saudi Arabia: Quantitative Cross-sectional Survey

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Abstract

Background: The adoption rate of digital health in the health care sector is low in many countries. A facilitating factor for successful implementation and adoption of digital health is acceptance by current and future health care professionals.

Objective: This study was conducted to identify factors associated with willingness to use digital health tools in patient care among health care professionals and students.

Methods: This was a quantitative cross-sectional survey study conducted among health care professionals and students at a university hospital in Riyadh, Saudi Arabia. A nonprobability convenience sampling procedure was used to recruit participants. Data were collected using a self-completed e-questionnaire that was distributed by email. Chi-square tests, *t* tests, and logistic regression were used to analyze the data.

Results: We found that 181 out of 218 health care professionals (83.0%; 75.6% [59/78] physicians; 87.1% [122/140] nurses) and 115 out of 154 students (74.7%; 80.0% [76/95] medical students and 66.1% [39/59] nursing students) were willing to use digital tools in patient care. Willingness to use digital tools was significantly associated with attitude (Adjusted Odds Ratios [AOR] 1.96; 95% CI 1.14-3.36) and self-efficacy (AOR 1.64; 95% CI 1.17-2.30) among health care professionals, and with current year of study (AOR 2.08; 95% CI 1.18-3.68) and self-efficacy (AOR 1.77; 95% CI 1.17-2.69) among students. No significant difference in willingness to use digital tools was found between physicians and nurses (P=.113), and between medical and nursing students (P=.079).

Conclusions: The findings of this study should encourage policy makers and hospital managers to implement relevant eHealth interventions within routine health care systems in Saudi Arabia. For successful implementation, digital health education programs should be implemented simultaneously, so that current and future health care professionals are able to develop required positive attitudes as well as practical skills and competencies.

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KEYWORDS

attitude; digital health; electronic medical record; health care professionals; health care students; Saudi Arabia; self-efficacy; telemedicine; willingness to use

Introduction

The potential of digital health to support health systems in health care delivery, health promotion, and disease prevention has been recognized in many countries [1,2]. In hospital settings, digital health tools (also referred to as “eHealth tools”), such as patient–physician portals, telemedicine, electronic medical records, smartphone and tablet apps, or remote monitoring devices, can reduce demand for (in-house) consultations, medical procedures, and unnecessary hospitalizations as well as improve postoperative monitoring of patients [3,4]. In particular, digital tools may support self-management and preventive behaviors in patients with chronic conditions, such as diabetes, hypertension, asthma, or cardiovascular diseases [1,5].

Consequently, the use of eHealth tools in patient care is on the rise globally, as digital health interventions are being implemented in many countries [1,2,5]. Implementation quality and effectiveness, however, seem to vary widely by type of eHealth intervention and setting [5]. Digital health interventions can be challenging to implement, not only because they are often inherently complex but also because they may meet with a variety of barriers. Some impediments are systemic, such as lack of financial resources, poor fit with existing information and delivery systems, or disruption of established modes of interaction between health care professionals and patients [6]. Others are individual-level challenges, such as insufficient skills and competencies of health care professionals or unfavorable beliefs and expectations, such as using eHealth tools may create misunderstandings and mistrust in the patient–provider relationship or might limit professional autonomy or increase administrative burden [7,8].

Numerous studies have examined health care professionals’ willingness to use eHealth tools but level and quality of evidence in this area remain insufficient. This may partly be a consequence of an often narrow scope of individual studies, due to an exclusive focus on specific tools, such as telemedicine [9-12] and electronic medical record [13,14], one professional group (often medical doctors) [8,14-16], or one medical specialty [17-20]. Another reason is that findings often are discrepant [8,9,12-14,18,19,21,22]. For instance, many studies in the European region found low adoption rates when national strategies for the introduction of electronic medical records were first implemented [13,15,23], but some saw improvements over time [14,24], while others did not [12,25].

Similarly, health care professionals’ willingness to use digital tools has often but not always been found to be related to sociodemographic characteristics, such as age and gender or professional attributes [12,19,21,22,26]. Menachemi and Brooks [26], for example, reported that willingness to use computers and electronic medical records was significantly higher among male health professionals and those with longer years of professional experience. More recent studies by Saleh et al [19] and Grassl et al [12] noted that willingness varied between professional groups, with physicians being significantly more willing to use computers and telemedicine compared to other health professionals. Other studies, however, did not find significant differences in terms of age, gender, or professional education when it came to willingness to use various types of eHealth tools [16,17].

By contrast, there is large-scale consensus that sociocognitive factors, including attitudes toward eHealth tools and perceived benefits/costs as well as perceived ease of use, are important factors when it comes to health care providers’ willingness to use eHealth tools [10,13,15,16,20,27,28]. In particular, health care professionals’ perceptions that use of eHealth tools leads to improved communication as well as increased access to care and level of satisfaction among their patients have been found to lead to or be associated with higher willingness for adoption [20]. Perceived loss of autonomy and privacy, doubts about data safety, and anxiety about use, by contrast, seem to contribute to a lack of willingness [13,27].

When it comes to differences in implementation of eHealth on the country level, a main explanation might of course also be found in the wide variety between health care systems, quality of care, and specific eHealth strategies chosen, so that experiences may not necessarily be comparable between countries [29]. In fact, the World Health Organization (WHO) recommends that each country should have its own strategy to engage health care professionals in adopting digital health as part of their individual journey toward universal health coverage and patient-centered care [30].

Countries in the Gulf region, and Saudi Arabia in particular, are on their way to systematically introduce digital health systems, not at least due to an increasing burden of chronic, life style–related diseases. As many as 1 in 3 adults in Saudi Arabia is either obese or diabetic, and from 2000 to 2017, the population prevalence rates of diabetes increased from 26.2% to 34.5% in men and 21.5% to 28.6% in women [31]. In line with this, the proportion of people with cardiovascular risk factors, such as low-density lipoprotein cholesterol, hypertension, and low levels of physical activity, has increased over the recent decade, as reported by a recently published study [32]. The resulting increased demand for efficient patient management, in combination with the need of rural populations to cover large geographical distances to reach hospitals/care facilities [33], has led to an increased interest in eHealth tools and systems. Because population adoption rates of mobile phones/apps and use of social media are very high in the Saudi Arabian society, one might expect integration of eHealth into health care to be comparatively easy. However, not much is known yet about local health care professionals’ readiness to adopt eHealth tools in clinical practice and the factors associated with level of motivation.

To our knowledge, only 2 studies have investigated perceptions of eHealth and willingness to make use of these services in health care professionals working in Saudi Arabia [34,35]. The first study conducted by Albarrak et al [34] exclusively targeted physicians and found medium levels of knowledge about telemedicine and largely positive views toward using telemedicine. However, in that study, factors associated with willingness to use telemedicine in patient care were not investigated. The second study, by El-Mahalli et al [35], targeted physicians as well as other subgroups of health care professionals and investigated both willingness to use and actual adoption of telemedicine. It was noted that although the majority of health care professionals were willing to use telemedicine, the actual rate of adoption was low. Further, willingness to use telemedicine was not found to be associated with age, gender, professional education, and years of professional experience, while actual use was significantly higher among consultant physicians having more than 20 years of professional experience compared to more junior physicians and nonphysicians.

It is unclear to which extent these previous findings on willingness to use telemedicine can be generalized to other types of eHealth tools and devices. Besides, knowledge about readiness to use eHealth tools among other groups of health care professionals than medical doctors is insufficient. We believe that it is particularly relevant to include nurses, because they also play a major role in patient care. For a sustainable implementation of digital health services, it is further important that not only current health care professionals but also medical and nursing students as the future generation of health care providers are targeted [11,36]. Moreover, to our knowledge no study has as yet investigated whether and to which extent sociocognitive factors, such as eHealth-related attitudes, perceived benefits/costs, and self-efficacy, might function as potential barriers or facilitators for the willingness to use eHealth tools among health care professionals in Saudi Arabia.

Therefore, in this study, we aimed to investigate willingness to use digital tools in patient care among medical and nursing professionals and students in a clinical setting in Saudi Arabia. Further, we aimed to examine the associations of such willingness with sociodemographic and professional characteristics, with attitudes toward digital health tools in terms of their importance for patients' care, as well as with general perceived costs and benefits of using these tools and with self-efficacy.

Methods

Study Design and Approval

This was a quantitative cross-sectional survey study conducted among health care professionals and students from King Saud University Medical City Hospital (KSUMC). KSUMC is one of the biggest tertiary level, multifacility, public hospitals in Riyadh, Saudi Arabia. Ethical approval was received from the Institutional Review Board of KSU College of Medicine (ethical approval number 18/0657/IRB).

Study Participants

Physicians and nurses at KSUMC were targeted if they were employed in any of the following departments: internal medicine, cardiology, otolaryngology, obstetrics and gynecology, ophthalmology, orthopedics, pediatrics, psychiatry, intensive care unit, and surgery. These departments were chosen based on the rationale that they would have the highest potential to profit from the use of digital health tools.

The health care students included medical and nursing students from the College of Medicine and the College of Nursing, King Saud University (KSU), respectively. All medical and nursing students from the second year onward, as well as interns enrolled in the program were considered eligible. First-year students were excluded, as they would not yet have had relevant experience and direct contact with patients.

Sampling and Recruitment

The hospital departments were contacted and informed about the aims of the planned research and asked for permission to conduct the study. All contacted departments gave permission and subsequently forwarded an invitational email to all physicians and nurses. There were altogether 864 eligible health care professionals (547 physicians and 317 nurses), all of whom received the invitation email. To reach out to the students, the academic coordinators at both colleges sent an invitational email on behalf of the research team to students from the second year onward. Altogether, 2143 students (1599 medical and 544 nursing students) were eligible, and all of them received the invitation email.

The invitation included information about the study and a web address that linked to an informed consent form. Subsequent to filling out the informed consent form, an e-questionnaire was sent out to the participants in May 2019. A reminder email was sent to nonresponders every second week over the 2-month recruitment period.

A total of 3007 health care professionals and students were sent the invitation email, 662 of whom participated in filling in an e-questionnaire (response rate 22.02%).

Measurement

Questionnaire

The questionnaire was developed and administered via Survey-XACT. The dependent variable was "willingness to use digital health tools in patient care" and was measured by 1 question: "If digital health tools and services were (now or in the future) adopted by your department, would you be in favor of such a change?" (responses: 0=no, 1=yes, 2=not sure). The response "not sure," which was endorsed 59 times, was merged with the "no" response, so that the final response categories were "not willing to use or uncertain about use" versus "willing to use." This was based on the rationale that in the given cultural context it is often considered impolite to explicitly say "no." Therefore, an expression of uncertainty might instead be used as a more acceptable way of giving a negative answer. In a similar vein, the alternative option to just offer a dichotomous "yes–no" response format was rejected, because social desirability tendencies might have motivated skeptical respondents to answer with "yes" rather than saying "no." This would have led to even more serious misclassification effects.

The independent variables included sociodemographic characteristics, ever having received a training for digital health use, prior use of digital tools at the departmental level, attitudes toward using digital health tools, perceived costs and benefits of digital health tools, and self-efficacy regarding personally using digital health.

Sociodemographic Characteristics

These included age, gender, educational background (nursing/medicine), and professional background (nurse/physician/student). Additionally, we included number of years of direct contact with patients for health care professionals and current year of study for students.

Ever Received Training About the Use of Digital Health

This variable was based on the question: "Have you ever received any organized training or extended instructions about the use of digital health tools, which include patient–physician portals/websites, patient health records, remote monitoring devices, mobile apps, telemedicine, webinars, online encyclopedia and online peer groups?" (no/yes).

Use of Digital Tools at the Departmental Level

Prior experience was operationalized with 1 question: "Has your department ever implemented any digital health tools?" (no/yes).

Sociocognitive Variables

For the assessment of the sociocognitive variables, 3 new multi-item instruments were developed. A core team of 3 researchers (ST, FQ, and AL) reviewed qualitative and quantitative studies on health professionals' perceptions regarding use of eHealth in patient care to identify a preliminary list of items for the assessment of "attitudes toward using digital health tools," "perceived benefits/costs of digital health tools," and "self-efficacy." This pool of items was discussed in terms of content validity and core items selected accordingly. Subsequently, the remaining items were checked and improved in terms of their clarity/comprehensibility by the extended research team over several rounds of revision.

Finally, a pilot study with face-to-face cognitive interviews was conducted, including 2 physicians, 2 nurses, 1 medical student, and 1 nursing student. Based on the findings of these interviews, some items were edited to improve clarity and understanding, and redundant items were deleted.

Attitudes Toward Using Digital Health Tools

We developed a 10-item instrument, which specifically reflected the perceived relevance/value of different functions of digital tools for active engagement of patients in their own treatment/care. Example items are "How important would it be that your patients can use remote monitoring devices (eg, glucometer, oximeter) to monitor their clinical condition by themselves?" or "How important would it be that your patients can see their medical test results and the record of treatments they have received in patient portals/website?" All items were presented with 5-point scales (1=not important at all to 5=absolutely important). Item responses were summed up, and a mean score was computed. Cronbach α for the total scale was .93.

Perceived Benefits/Costs of Digital Health Tools

Altogether, 20 items were used to assess expectations about potential positive (10 items) and negative consequences (10 items) of introducing digital health tools in clinical care for patients, professionals, and for the hospital. Example items are "If digital health tools were introduced into clinical care in hospitals, quality of care will be..."; "If digital health tools were introduced into clinical care in hospitals, quality of communication between health care professionals and patients will be...." All items were to be rated on 5-point Likert scales (1=much lower to 5=much higher). The subgroup of 10 items relating to the positive consequences of using digital tools was labeled as "perceived benefits," while the 10 items relating to the potential psychological, financial, technological, and administrative burden of using digital tools were labeled as "perceived costs." Item responses for perceived benefits and costs were summed up, and the means of the respective sum scales were used as final scores. Cronbach α was .89 for the perceived benefits scale and .81 for the perceived costs scale.

Self-Efficacy

We developed a 12-item instrument, which reflected the belief in one's own ability to successfully perform various specific actions related to the use of digital tools in patient care. All items were presented with response scales from 0 to 6 (0=not at all confident to 6=100% confident). An example item is: "How confident are you that you are able to monitor the patients' health data using mobile apps." All items were summed up, and the mean of the total scale was used as final score. Cronbach α for the scale was .94.

Because most health care professionals in KSUMC are expatriates, the questionnaire was made available in English only.

Data Analysis

Descriptive statistics were used to present all variables (percentages, means, and SDs). For bivariate analysis, independent samples *t* tests were conducted to compare the means for perceived benefits/costs of using digital tools in patient care between health care professionals and students. Further, chi-square tests and *t* tests were conducted separately for the samples of professionals and students to examine the bivariate associations of sociodemographic variables, ever having received eHealth training, experience of using digital tools at the departmental level, attitudes, perceived costs/benefits, and self-efficacy with the willingness to use digital tools in patient care. A *P*-value <.05 was considered statistically significant.

On the multivariable level, logistic regression analysis was used to identify individual factors associated with willingness to use digital health tools in patient care among health care professionals and students while adjusting for effects of potential other influencers. To maximize power, only factors associated with the dependent variable at a level of *P*<.10 in the respective bivariate analysis were carried forward to the multivariable logistic regression models. Adjusted Odds Ratios (AOR) and 95% CIs were calculated. All the data were analyzed using SPSS 24.0 for Windows (IBM).

Results

Overview

Among the group of nonresponders (n=290), students as compared to health care professionals (*P*<.001), male participants (*P*<.001), and younger ones (*P*<.001) were significantly less likely to complete the e-questionnaire (Multimedia Appendix 1). Questionnaires with missing values in the dependent variable, that is, willingness to use eHealth tools, and attitudinal variables were excluded from further analysis. A total of 290 out of 662 questionnaires were thus excluded, resulting in a sample size of 372 (questionnaire completion rate= 56.2% [372/662]).

General Characteristics of the Respondents

Of the 372 respondents who had completed the e-questionnaire, 268 were female (72.0%), and 194 were in the age group of 18 and 30 (52.2%). Medical students made up about one-quarter of the sample (25.5%; 95/372), 15.9% (59/372) were nursing students, while 21.0% (78/372) were physicians and 37.6% (140/372) were nurses (Table 1).

A total of 181 out of 218 professionals (83.0%) and 115 out of 154 students (74.7%) were willing to use digital health tools for patient care. Among the professionals, almost 70.6% (154/218) had previously received training on using digital tools in clinical care, and about 62.8% (137/218) had prior experience of using digital tools on the departmental level (Mean years of experience = 13 years).

Table 1. Characteristics of the study population.

Characteristics	Health care professionals (N=218), n (%)	Health care students (N=154), n (%)	Total (N=372)
Age (years)			
18-20	3 (1.4)	45 (29.2)	48 (12.9)
21-25	6 (2.8)	107 (69.5)	113 (30.4)
26-30	31 (14.2)	2 (1.3)	33 (8.9)
31-35	61 (28.0)	0 (0.0)	61 (16.4)
36-40	30 (13.8)	0 (0.0)	30 (8.1)
41-45	37 (17.0)	0 (0.0)	37 (9.9)
46-50	21 (9.6)	0 (0.0)	21 (5.6)
Over 50	29 (13.3)	0 (0.0)	29 (7.8)
Gender			
Male	53 (24.3)	51 (33.1)	104 (28.0)
Female	165 (75.7)	103 (66.9)	268 (72.0)
Willingness to use digital tools in patient care			
Yes	181 (83.0)	115 (74.7)	296 (79.6)
No	37 (17.0)	39 (25.3)	76 (20.4)

Perceived Benefits and Costs of Using Digital Health Tools Among Health Care Professionals and Students

Table 2 shows means of perceived benefits and perceived costs of using digital health tools in patient care among health care professionals and students. The most often perceived benefits by both, health care professionals and students, were increased quality of care, easy access to patient data, and increased work satisfaction. Regarding the perceived costs, health care professionals perceived that using eHealth tools would raise concerns about patient data safety, increase risk of technical errors, and increase financial costs for hospitals. Students, by contrast, perceived that use of eHealth tools would increase work-related stress, cause delay in the response to meet patients' needs, and increase financial costs for hospitals.

Compared to students, health care professionals were more likely to perceive that using digital tools provides easier access to patient data (*P*=.01), higher number of patients turning up in time for their appointments (*P*=.03), and improvement in patients' adherence to treatment (*P*=.009). Regarding potential costs health care professionals were more likely than students to perceive that using digital health tools in patient care would increase financial burden for hospitals (*P*=.03) as well as work-related stress among health care professionals (*P*=.01), and cause delay in the response of health care professions to meet patients' needs (*P*=.02).

Table 2. Perceived benefits and costs of using digital health tools among health care professionals and students (N=372).

Perceived benefits and costs of using digital health tools	Health care professionals (N=218), mean (SD)	Health care students (N=154), mean (SD)	*t (df)*	*P* value
Perceived benefits				
Quality of care	4.06 (0.9)	4.16 (0.9)	–0.93 (370)	.35
Easy access to patient data for health care professionals	4.16 (0.8)	3.92 (0.9)	2.60 (370)	.01
Work satisfaction among health care professionals	3.98 (1.0)	3.94 (0.9)	0.40 (370)	.68
Increased understanding of health conditions among patients	3.85 (1.0)	3.84 (1.0)	0.14 (370)	.88
Opportunities for self-care	3.64 (1.0)	3.69 (0.9)	–0.50 (370)	.61
Increased quality of communication between health care professionals and patients	3.83 (1.1)	3.60 (1.1)	1.84 (370)	.06
Higher number of patients turning up in time for their appointments	3.48 (1.2)	3.22 (1.1)	2.12 (370)	.03
Improved patients' adherence to treatment	3.88 (0.9)	3.62 (0.9)	2.63 (370)	.009
Increased patient satisfaction	3.87 (0.9)	3.77 (0.9)	0.99 (370)	.32
Improved trust between health care professionals and patients	3.74 (1.2)	3.64 (1.1)	0.79 (370)	.42
Perceived costs				
Concerns about data safety among patients	3.76 (1.0)	3.62 (1.0)	1.26 (370)	.20
Increased risk of technical errors (eg, tool breakdown, internet breakdown)	3.53 (1.2)	3.67 (1.1)	–1.11 (370)	.26
Increased financial costs for hospitals	3.53 (1.3)	3.23 (1.3)	2.13 (370)	.03
Higher risk of data misuse	3.27 (1.2)	3.23 (1.1)	0.31 (370)	.75
Increased financial cost for patients	3.06 (1.2)	2.89 (1.1.)	1.58 (370)	.11
Higher risk of medical errors	2.94 (1.2)	2.79 (1.1)	1.17 (370)	.23
Increased level of anxiety among patients	2.81 (1.1)	2.66 (0.9)	1.34 (370)	.18
Increased demand of time for health care professionals	3.06 (1.2)	3.05 (1.1)	0.11 (370)	.90
Increased work-related stress among health care professionals	3.31 (1.2)	2.98 (1.1)	2.44 (370)	.01
Delay in the response from health care professions to meet patients' needs	3.18 (1.2)	2.91 (1.0)	2.20 (370)	.02

Associations Between Willingness to Use Digital Health Tools in Patient Care and Sociodemographic Characteristics as well as Sociocognitive Factors

Tables 3 and 4 show the results of the bivariate analysis for willingness to use digital health tools and background characteristics as well as attitudes and beliefs among health care professionals and students, respectively.

Among health care professionals, being a nurse as opposed to being a physician was significantly associated with increased willingness to use digital tools in patient care (*P*=.03). Furthermore, significant positive associations with willingness to use digital tools were found for prior experience of using eHealth tools at the departmental level (*P*<.001), favorable attitudes (*P*<.001), perceived benefits (*P*<.001), and self-efficacy (*P*<.001) regarding personal use of these tools in patient care (Table 3).

Among students, being in the third or senior year as opposed to the second year was significantly associated with increased willingness to use digital tools in patient care (*P*=.01). Furthermore, significant positive associations with willingness to use digital tools were found for favorable attitudes (*P*=.01), perceived benefits (*P*<.001), and self-efficacy (*P*<.001) regarding personal use of these tools in patient care (Table 4).

Table 3. Bivariate associations between willingness to use eHealth tools and sociodemographic characteristics as well as sociocognitive factors among health care professionals.

Variables	Willing to use (N=181)	Not willing to use/uncertain about use (N=37)	*t* (*df*)	χ^2 (*df*)	*P* value
Age, n (%)					
Over 35 years	99 (54.7)	18 (48.6)	—[a]	0.45 (1)	.50
35 years or below	82 (45.3)	19 (51.4)			
Gender, n (%)					
Female	137 (75.7)	28 (75.7)	—	0.01 (1)	.99
Male	44 (24.3)	9 (24.3)			
Professional education, n (%)					
Nurses	122 (67.4)	18 (48.6)	—	4.70 (1)	.03
Physicians	59 (32.6)	19 (51.4)			
Ever received training on using digital tools in clinical care, n (%)					
Yes	130 (71.8)	24 (64.9)	—	0.71 (1)	.39
No	51 (28.2)	13 (35.1)			
Prior experience of using digital tools at the departmental level, n (%)					
Yes	124 (68.5)	13 (35.1)	—	14.65 (1)	<.001
No	57 (31.5)	24 (64.9)			
Years of experience, mean (SD)	13.5 (8.7)	12.4 (8.1)	0.63 (172)	—	.52
Attitude toward using digital tools in patient care, mean (SD)	4.1 (0.7)	3.2 (0.9)	6.32 (216)	—	<.001
Perceived benefits of using digital tools in patient care, mean (SD)	3.9 (0.6)	3.2 (0.6)	5.70 (216)	—	<.001
Perceived costs of using digital tools in patient care, mean (SD)	3.2 (0.7)	3.2 (0.6)	–0.38 (216)	—	.70
Self-efficacy about personally using digital tools in patient care, mean (SD)	5.4 (1.3)	3.8 (1.5)	6.41 (216)	—	<.001

[a]—: Not available

Table 4. Bivariate associations between willingness to use eHealth tools and sociodemographic characteristics as well as sociocognitive factors among students.

Variables	Willing to use (N=115)	Not willing to use/uncertain about use (N=39)	*t (df)*	χ^2 *(df)*	*P* value
Age, n (%)					
Over 21 years	85 (73.9)	24 (61.5)	—[a]	2.15 (1)	.14
18-21 years	30 (26.1)	15 (38.5)			
Gender, n (%)					
Female	75 (65.2)	28 (71.8)	—	0.56 (1)	.45
Male	40 (34.8)	11 (28.2)			
Professional education, n (%)					
Nursing students	39 (33.9)	20 (51.3)	—	3.71 (1)	.053
Medical students	76 (66.1)	19 (48.7)			
Current year of study, n (%)					
Third or senior years[b]	65 (65.0)	16 (41.0)	—	6.63 (1)	.01
Second year	35 (35.0)[a]	23 (59.0)			
Attitude toward using digital tools in patient care, mean (SD)	4.0 (0.8)	3.6 (0.9)	2.37 (152)	—	.01
Perceived benefits of using digital tools in patient care, mean (SD)	3.8 (0.6)	3.4 (0.7)	3.34 (152)	—	<.001
Perceived costs of using digital tools in patient care, mean (SD)	3.0 (0.6)	3.2 (0.5)	–1.40 (152)	—	.16
Self-efficacy about personally using digital tools in patient care, mean (SD)	5.1 (1.2)	4.02 (1.2)	4.16 (152)	—	<.001

[a]—: Not available

[b]N=100.

In the multivariable analysis for health care professionals, willingness to use digital tools in patient care was positively associated with attitude and self-efficacy. Among health care students, willingness to use digital tools in patient care was positively associated with self-efficacy and current year of study, with higher odds for third- or senior-year students compared to second-year students. No significant difference in willingness to use digital tools between nurses and physicians (*P*=.113), and between nursing and medical students (*P*=.079) was found. Furthermore, in both subsamples perceived benefits were no longer significant once attitudes were controlled for (Tables 5 and 6).

Another multivariable analysis conducted for the whole sample (ie, health care professionals plus students) found significant differences in willingness to use digital tools for perceived benefits (AOR 1.91; 95% CI 1.17-3.12) and self-efficacy (AOR 1.64; 95% CI 1.30-2.07). However, willingness to use digital tools did not vary significantly between the groups of health care professionals and students (*P*=.400; Multimedia Appendix 2).

Table 5. Multivariable analysis for health care professionals for the association between willingness to use eHealth tools and sociodemographic characteristics as well as sociocognitive factors.

Variables	Adjusted Odds Ratios (95% CI)
Age	
Over 35 years	1.82 (0.74-4.49)
35 years or below	Reference
Gender	
Female	0.71 (0.21-2.34)
Male	Reference
Professional education	
Nurses	2.35 (0.81-6.82)
Physicians	Reference
Prior experience of using digital tools at the departmental level	
Yes	2.40 (0.90-6.35)
No	Reference
Attitude toward using digital tools in patient care	1.96 (1.14-3.36)
Perceived benefits of using digital tools in patient care	1.90 (0.89-4.03)
Self-efficacy about personally using digital tools in patient care	1.64 (1.17-2.30)

Table 6. Multivariable analysis for health care students for the association between willingness to use eHealth tools and sociodemographic characteristics as well as sociocognitive factors.

Variables	Adjusted Odds Ratios (95% CI)
Age	
Over 21 years	0.67 (0.21-2.12)
18-21 years	Reference
Gender	
Female	0.66 (0.25-1.75)
Male	Reference
Professional education	
Nursing students	0.43 (0.17-1.06)
Medical students	Reference
Current year of study	
Third or senior years	2.08 (1.18-3.68)
Second year	Reference
Attitude toward using digital tools in patient care	0.69 (0.34-1.40)
Perceived benefits of using digital tools in patient care	2.20 (0.94-5.13)
Self-efficacy about personally using digital tools in patient care	1.77 (1.17-2.69)

Discussion

Principal Findings

Respondents had a largely positive view about the potential of eHealth tools for clinical practice. Interestingly, besides comparatively obvious advantages of eHealth tools, such as an easier access to patient data, it was most of all quality of care which was expected to benefit. Accordingly, large majorities in all subgroups expressed a willingness to use digital tools in patient care, with acceptance rates varying between 87.1% (122/140) and 75.6% (59/78) in nurses and physicians, and 66.1% (39/59) and 80.0% (76/95) in nursing and medical students, respectively. This is in line with findings from a previous study conducted in Saudi Arabia [35], which had more narrowly focused on telemedicine and reported that 78.9% of health care professionals were interested in adopting the technology for patient care [35]. Yet another Saudi Arabian study found an even higher telemedicine acceptance rate of

90.0% across several medical specialties, but comparability is limited because what was measured was not personal willingness but estimates of general acceptance/interest among physicians [34]. Apart from targeting a broader spectrum of eHealth applications beyond telemedicine, our study also enables a more differentiated view on subgroups of health care professionals in terms of professional background (medical doctors/nurses) and allows for comparisons between health care professionals and students.

In this study, multivariable comparisons between nurses and physicians showed no general differences in willingness to use eHealth tools. A few prior studies conducted in countries as different as Germany, Lebanon, and the United States have reported that physicians are more likely to use or accept eHealth tools compared to other health care professionals [12,19,37]. However, these studies were focused on specific tools, such as telemedicine [12] or use of eHealth records [37] or were conducted in settings very different from the present one (ie, primary health care) [19] or in very specific medical areas, such as pregnancy monitoring [12,37], which limits comparability. By contrast, another study, which also investigated willingness to engage with eHealth in general, did not find differences between professional groups, either [17]. In addition, it needs to be noted that our study was conducted at one of the largest and technologically most advanced university hospitals in the country which might have involved a more homogeneously motivated and “open” group of health care professionals compared to other, more diverse settings. Nurses in this hospital are already familiar with using digital tools for administrative purposes.

Similarly, we did not find an association between extent of professional experience (number of years in the profession) and willingness to use eHealth. By contrast, the previous study by El-Mahalli et al [35], which investigated not only willingness but also actual adoption of telemedicine by health care professionals in Saudi Arabian hospitals, suggested that compared to more junior physicians and nonphysicians, senior consultants with more than 20 years’ experience were significantly more likely to use telemedicine. This discrepancy between the 2 studies is most likely explained by their different focus on telemedicine versus eHealth in general. Willingness to practice telemedicine might require more long-standing professional experience with patients and resultant self-confidence regarding diagnosis/treatment than use of other eHealth tools, such as electronic patient records, webinars, or monitoring apps. Besides, the acceptance and use of telemedicine as well as other digital tools might have increased significantly over the years among health care professionals of all age group and years of experience [38].

Further, previous use of eHealth tools at the departmental level, which can be seen as a proxy variable for personal experience, was not identified as a relevant factor in this study. The initial bivariate test had indicated a significant association (P<.001), which however was not confirmed in the multivariable analysis. It is likely that the effect of prior experience was mediated by attitudes as well as self-efficacy, which might have increased with experience, so that after adjustment for these factors in the multivariable analysis, prior experience was not significant anymore.

Among the subgroup of students, willingness to use digital tools did not significantly differ in terms of sociodemographic characteristics such as age, gender, and professional education (medicine versus nursing). However, willingness was positively associated with current year of study, with higher odds for third- or senior-year students compared to second-year students. At KSU, the subject “medical informatics” is taught in the third year of study for medical students, and recently, a new subject “nursing informatics” has been offered to third-year nursing students. Thus, the association between year of study and increased willingness to use eHealth tools emphasizes the importance of a structured, formal eHealth curriculum for health care students [39]. Noor [40], based on the data from a survey study, reported that only 10 out of 109 higher education institutions in Saudi Arabia provide specific courses on medical informatics. Further, the author noted a need for standardized, accredited programs in this field as well as integrating well-structured eHealth courses into nursing and medical education programs and health care practice.

As for the role of expected benefits and positive attitudes, the findings of our study are in line with past research [16,21] and theoretical models, such as the Technology Acceptance Model [41] or the related Unified Theory of Acceptance and Use of Technology [42], which have specifically emphasized the role of “perceived usefulness of technology for intention to use and actual use.” However, this study also indicates some specificity of effects for different subgroups. Thus, positive attitudes in terms of the importance attributed to different eHealth tools for patient (self-) management were related to higher willingness to use these tools among professionals but not the students. This is plausible insofar students, because of their lack of clinical practice and experience, might be more uncertain than health care professionals about the importance of eHealth tools for patients. These observations were also made by Wernhart et al [11] in their study investigating differences in perceptions regarding eHealth and telemedicine among health care professionals and students at the teaching hospital of the University of Vienna, Austria.

Regarding the motivation of health care professionals to use eHealth tools, it is further interesting to note that the tools’ potential to actually benefit patient (self-) management makes a difference, while the sum of different expected positive consequences for the hospital, doctors/nurses, or patients were less relevant in comparison. This factor had been significant (P<.001) in the bivariate analysis and showed a very similar trend for an effect like attitudes in the multivariable analysis, but lost significance once attitudes were controlled for. For one thing, due to their clinical experience, health care professionals might feel more certain about specific effects of eHealth for patients than for the hospital or work conditions in general [25]. Additionally, physicians’ and nurses’ professional role identity as patient advocates might make the function of eHealth tools to serve patients’ needs particularly salient. Besides, it might be argued that an implementation of eHealth tools via improving patients’ self-management capacities will also facilitate physicians’ and nurses’ work.

Interestingly, an additional analysis combining the health care professionals with the students showed a somewhat different result. The similar nonsignificant trends for perceived benefits in both subgroups added up to a significant effect based on the higher statistical power due to increased sample size, while the positive effect for attitudes, which was only present in health care professionals, was no longer relevant. This indicates the importance of subgroup-specific analysis, because actual differences might otherwise be missed.

Of note, perceived costs/negative consequences did not seem to make a difference. This finding does, however, not imply that perceived costs might be similarly irrelevant when it comes to actual adoption [13,25]. General willingness might mainly require a positive motivation or a clear rationale in favor of change while costs might become more apparent once actual experience is initiated.

Finally, we found that evaluation of own competences to use eHealth tools is important for their adoption by health care professionals as well as by students. The relevance of self-efficacy has also been shown by previous studies [7,16,28]. This emphasizes the need for capacity building in eHealth for both professionals and students, which can be achieved by regular education, training, and evaluation with feedback [7]. This would, however, require support structures, which in a recent review were identified as still lacking in most Middle Eastern countries, including Saudi Arabia [43].

Although implementation of some types of eHealth tools, such as electronic medical records and telemedicine, has been discussed or promoted on a political level, such tools have not yet been adopted in Saudi Arabia on a large scale [33-35]. The findings of this study suggest that most nurses, physicians as well as medical and nursing students are generally willing to adopt eHealth tools in patient care, which is an important prerequisite for the successful implementation of eHealth interventions. Further, education programs about eHealth interventions and their potential positive consequences for patients as well as programs teaching skills to competently use eHealth tools may enhance current and future health care professionals' readiness to adopt such interventions. The present findings, which indicated no systematic differences between males/females, age groups, or physicians and nurses, also suggest that eHealth educational and promotional activities should take a broad, inclusive approach, targeting health care professionals in general, irrespective of their gender and professional background.

Limitations

This study has some limitations. First, because of the cross-sectional nature of the study we were not able to establish causality beyond plausibility assumptions. Further, data were collected via an e-survey method with a response rate of 22.02% (662/3007) and a questionnaire completion rate of 56.2% (372/662), which limits the generalizability of the study results. This response rate is lower than the rates reported by the previous Saudi Arabian studies by Albarrak et al [34] and El-Mahalli et al [35]. This might be due to the considerable length of the questionnaire, which included not only standard single items but also several multi-item instruments to enable a valid assessment of sociocognitive factors. The overall low response suggests that the high level of willingness to use e-tools may to some extent be due to an overrepresentation of those who already held more positive attitudes about and a stronger interest in eHealth and were therefore more motivated to participate in the first place or to complete the questionnaire in full.

In addition, although all respondents were assured about anonymity/confidentiality, we cannot be certain that responses were not influenced by social desirability. Because respondents probably were aware that eHealth was considered a desirable strategy by the hospital leadership, they might have responded more positively. Two of the response categories for the outcome "willingness to use" had to be merged, that is "not sure" responses were collapsed with the "no" responses. Therefore, the results can only be interpreted as "full willingness" versus "uncertain about use plus nonwillingness." Finally, we were not able to take into account the potential impact of local contextual factors on health care professionals' decisions about using digital tools. Investigating such context factors (eg, cultural factors, social influences), as well as the needs and the level of eHealth literacy of the patient groups was out of the scope of this study and should be addressed by future research.

Conclusions

Our findings suggest that most nurses, physicians as well as medical and nursing students in a major Saudi Arabian university hospital are willing to adopt eHealth tools for patient care. The most important factors with respect to motivation for adoption by health care professionals are favorable attitudes related to positive impacts for patients and a sense of self-efficacy. For those still undergoing education, being a senior student and having self-efficacy are most relevant. The findings of this study should encourage policy makers and hospital managers in Saudi Arabia to introduce and implement relevant eHealth interventions into routine health care programs. In addition, students as well as current health care professionals should be targeted by eHealth education programs with an aim to develop required positive attitudes. In particular, the aim is to create awareness about the value that eHealth tools can have for many patients as well as to promote and refine practical skills. Future research should include organization-level factors which might facilitate or hinder eHealth implementation as well as willingness among patients to use these tools.

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Authors' Contributions

ST, AA, JBN, and AL were all responsible for conceptualizing the protocol and overall design of the study. FQ and AA conducted the pretesting interviews and the fieldwork for data collection. ST and AL performed the analysis. ST prepared the initial draft of the manuscript, which was then circulated among all the authors for critical revision.

Conflicts of Interest

None declared.

Multimedia Appendix 1
Characteristics of nonresponders.
[DOCX File , 13 KB - mededu_v7i1e18590_app1.docx]

Multimedia Appendix 2
Multivariable models for the association between willingness to use eHealth tools and sociodemographic characteristics and sociocognitive factors (both health care professionals' and students' groups combined).
[DOCX File , 13 KB - mededu_v7i1e18590_app2.docx]

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Abbreviations

AOR: Adjusted Odds Ratios
KSU: King Saud University
KSUMC: King Saud University Medical City Hospital
WHO: The World Health Organization

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Original Paper

The Impact of Electronic Health Record–Based Simulation During Intern Boot Camp: Interventional Study

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Abstract

Background: Accurate data retrieval is an essential part of patient care in the intensive care unit (ICU). The electronic health record (EHR) is the primary method for data storage and data review. We previously reported that residents participating in EHR-based simulations have varied and nonstandard approaches to finding data in the ICU, with subsequent errors in recognizing patient safety issues. We hypothesized that a novel EHR simulation-based training exercise would decrease EHR use variability among intervention interns, irrespective of prior EHR experience.

Objective: This study aims to understand the impact of a novel, short, high-fidelity, simulation-based EHR learning activity on the intern data gathering workflow and satisfaction.

Methods: A total of 72 internal medicine interns across the 2018 and 2019 academic years underwent a dedicated EHR training session as part of a week-long boot camp early in their training. We collected data on previous EHR and ICU experience for all subjects. Training consisted of 1 hour of guided review of a high-fidelity, simulated ICU patient chart focusing on best navigation practices for data retrieval. Specifically, the activity focused on using high- and low-yield data visualization screens determined by expert consensus. The intervention group interns then had 20 minutes to review a new simulated patient chart before the group review. EHR screen navigation was captured using screen recording software and compared with data from existing ICU residents performing the same task on the same medical charts (N=62). Learners were surveyed immediately and 6 months after the activity to assess satisfaction and preferred EHR screen use.

Results: Participants found the activity useful and enjoyable immediately and after 6 months. Intervention interns used more individual screens than reference residents (18 vs 20; *P*=.008), but the total number of screens used was the same (35 vs 38; *P*=.30). Significantly more intervention interns used the 10 most common screens (73% vs 45%; *P*=.001). Intervention interns used high-yield screens more often and low-yield screens less often than the reference residents, which are persistent on self-report 6 months later.

Conclusions: A short, high-fidelity, simulation-based learning activity focused on provider-specific data gathering was found to be enjoyable and to modify navigation patterns persistently. This suggests that workflow-specific simulation-based EHR training throughout training is of educational benefit to residents.

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KEYWORDS

electronic health records; medical education; simulation; usability; training

Introduction

The use of electronic health records (EHRs) has expanded significantly over the past 20 years. Spurred by the Health Information Technology Act of 2009 for adoption and meaningful use of the EHR, there was a 6-fold increase in EHR use after over US $19 billion was allocated to facilitate their adoption [1]. Consequently, the EHR is now the central health information storehouse used to facilitate clinical decision making.

With the widespread adoption of EHRs, there have been a number of unintended consequences. The first is the increase in patient harm if the information is not entered, retrieved, or processed correctly, coined e-iatrogenesis [2]. A recent retrospective review showed 2000 medical errors directly related to EHR use over 3 years in the state of Pennsylvania alone, and this may be an underrepresented number given the underreporting of events [3]. Second, there is an increase in provider burnout because of the burden of EHR use [4-6]. The complexity of EHRs has increased the amount of time providers spend documenting outside of work hours, reduced the amount of time spent with the patient, and increased documentation time overall [7-9].

Central to addressing both of these issues is the improvement in EHR education to ensure providers are capable of safe, effective, and efficient use of the EHR in the context of their specific, daily workflow. As a result, multiple groups have developed competencies for EHR training and their integration into medical education; however, effective implementation remains elusive [10,11]. Furthermore, these studies focus primarily on improved efficiency and data entry, although most of the time spent by residents with the EHR focuses on data gathering [12]. Through the use of eye and screen tracking, we have previously demonstrated that there is a lack of a standard approach to use the EHR concerning screen navigation, with only a very small subset of screens used universally by residents. This is associated with a decrease in the number of embedded safety items recognized within simulated EHR charts and subsequent massive variance in perceived diagnosis and plan [13-15]. *Safety items* were defined as data elements that should trigger new diagnoses or clinical management changes if appropriately recognized. Furthermore, these studies identified specific screens and data gathering patterns on screens associated with a greater likelihood of identifying critical patient issues within the charts. These studies not only delineate a framework for metrics to use to design and assess an educational curriculum but also highlight the significance of this variance in patient care.

Multiple challenges with implementing EHR education persist despite the relatively ubiquitous use of the EHR in health care delivery and the growing awareness that EHR use comprises a large portion of a resident's daily work [16]. A number of studies suggest that physicians believe their basic, standard EHR training, typically associated with onboarding when they start their residencies, is inadequate. A recent study suggests that surgery residents spend the first 8 months of their residency becoming proficient with the EHR [17-19]. Residents desire more EHR-related education, which is more likely to be positively received when taught by peers [18,20]. In terms of specific EHR-related education for medical trainees, although there have been some educational interventions to facilitate learning at the medical school level reported in the literature, there is scant literature on educational activities designed to improve resident workflow in the EHR [21]. Residents typically learn EHR skills by emulating their supervisor or peer EHR use, which generally focuses on comprehensive documentation to optimize billing rather than communicating clinical reasoning or quantifying the patient's clinical status [22].

The utilization of EHR simulations that feature patient records has gained traction as a solution for these problems in EHR education because, as stated by a national consensus conference, simulation is capable of matching EHR training with provider-specific workflow [22-24]. Critical to this is to ensure that the EHR chart has the appropriate degree of realism (which is termed *Fidelity*) to allow for reproduction on workflow. This includes having the appropriate density and quality of data, the ability to house charts in the same system used clinically, to maintain user and system customizations, and to shift charts temporally so that data are current and thus, consistent with the day of activity [24-26]. Our group has previously developed high-fidelity simulated patient cases to assess safe and effective EHR use [13,15,27,28]. Participation in EHR-based simulation improved recognition of embedded patient safety issue recognition upon repeat simulation testing [27]. We have also described the ability to integrate EHR-based simulation into an intern boot camp, demonstrating wide variance in the content of resident-generated notes [29]. Therefore, given the previous data on the lack of standardized use of the EHR and its impact on clinical workflow, we hypothesized that a high-fidelity simulation exercise focused on an ideal EHR navigation strategy would not only be well liked by learners but would also allow for greater standardization of EHR use with a shift toward the use of screens designed to facilitate ideal data gathering.

Methods

Cohort and Lesson Plan

Our intervention interns consisted of 71 first-year internal medicine residents at Oregon Health and Science University (OHSU) who completed training and simulation-based learning sessions. There were 33 participants (14 males and 19 females) in 2018 and 38 participants (24 males and 14 females) in 2019. Four participants in 2019 were preliminary neurology residents. All subjects received a dedicated EHR training using high-fidelity simulation-based learning (as described below). The training session occurred during a week-long boot camp in their second or third month of training, the details of which have been previously described [29,30]. Here, we also provide historical data on established workflow from reference residents participating in multidisciplinary simulation for assessing intensive care unit (ICU) safety with regard to EHR use. Reference residents consisted of 33 first-year, 12 second-year, and 13 third-year internal medicine residents. These reference residents used the same or similar simulated charts as the intervention interns. In these studies, residents were assessed for their ability to recognize embedded safety items within the charts; eye and screen tracking were integrated to define navigation patterns and assess the use of specific screens associated with improved identification of said items [14,15]. All participants underwent Epic (Epic Systems Corporation) training as part of their initial onboarding.

Each simulation session performed with our intervention interns consisted of 5-7 participants, 1 instructor, and 1 teaching assistant. Each learner had an individual workstation. The instructor screen was projected to be visible to learners during both guided reviews and debriefing. All subjects completed a survey assessing prior EHR experience and other demographic characteristics at the beginning of the session. The learning activities were divided into 3 sections. In section 1 (duration approximately 1 hour), learners were provided a detailed script on optimal EHR navigation strategies and a number of *high-yield* and *low-yield* screens for effective navigation. These were determined by expert opinion and analysis from previous simulation activities based on the impact of recognizing embedded safety items within simulated charts [15]. The instructor then provided a guided review of a simulated EHR chart demonstrating all aspects of the script and emphasizing the EHR navigation pattern. In section 2, learners were provided a 1-hour didactic on ICU bedside patient presentation skills, though this section was limited to 20 minutes in 2019 because of externally imposed time constraints. In section 3, learners had an independent activity consisting of a 20-minute review of a second simulated ICU patient case. After this, participants in 2018 gave individual mock ICU bedside patient presentations, although this was excluded in 2019 again because of time constraints. A 20-minute group debriefing of the case content concluded the activity, illustrating how the recommended EHR navigation pattern can uncover embedded patient safety issues within the case. The flow of both years' lessons can be found in Multimedia Appendix 1.

Simulation Description

Our research group has developed multiple high-fidelity simulated ICU patient charts with accompanying relevant patient data, including vital signs, fluid intake and output, laboratory values, microbiology results, imaging reports, active and inactive medications, active and inactive orders, documentation, and previous encounters. A copy of Epic, which duplicates user preferences without displaying authentic patient charts, is used to host the simulated cases. Cases are copied and transposed forward in time to the date of the simulation, as previously described [13,27]. In addition, screens available in the Epic interface were divided into high- and low-yield categories, as determined by a survey given to senior critical care attending and fellow physicians at the institution and results of previous simulation exercises. Due to copyright conflict, we are not allowed to show these screens or other images of the EHR in this publication.

Measures

Background demographics, including previous exposure to various EHRs and self-assessment of the facility inpatient EHR navigation ability using a 5-point Likert scale, were collected via a survey immediately before the activity to determine whether any learner-specific factors impacted performance. Individual computer screens were recorded during the solitary review of the second case using open-source software CamStudio [31] to assess the impact of the activity on screen navigation patterns and screens employed. To determine the immediate learner perception of the activity's utility, global satisfaction and usefulness data for the boot camp were gathered for the 2018 cohort via an anonymous Qualtrics (Qualtrics) survey but given low response rate is excluded. As a result, the intervention interns in 2019 completed an immediate postactivity satisfaction and usefulness survey using a 5-point Likert scale. Finally, to assess the persistence of the perceived benefit of the activity and self-reported EHR use patterns, all intervention interns were assessed again 6 months after the activity via the Qualtrics survey. To eliminate confusion about which screen each question in this survey referred to, we included both screenshots of the specific screens and the screen name.

Analysis

Screen recordings from the solitary review of the second case were reviewed for the EHR navigation pattern. Excel (Microsoft Corporation) and Prism (GraphPad Software) were used for statistical analyses. Participant use of high-yield screens, low-yield screens, unique screens, and total screens used were compared with historical controls using Pearson chi-square and 2-tailed Student *t* test.

Results

Intervention group interns included 33 (100%) of the 2018 OHSU first-year residents and 38 (100%) of the 2019 first-year residents. A participant in 2018 was unable to participate in the independent portion of the activity and was therefore excluded from the analysis. A total of 47% (33/71) of the participants were female (Table 1), 67% (48/71) had rotated in the ICU, and 77% (54/77) had experience with the EHR before the activity. When asked to rate themselves on their ability to use the EHR efficiently and comprehensively, intervention interns ranked themselves as *average* with no differences between years.

A total of 38 (100%) intervention interns in 2019 responded to the satisfaction survey given immediately after the activity. They found the activity to be enjoyable, useful, meaningful, appropriately paced, and appropriately challenging on surveys given immediately after the activity (Figure 1; Multimedia Appendix 2). The qualitative free responses supported the quantitative data (Textbox 1). No correlation was found between any participant characteristics and survey responses (data not shown). A total of 35 (49%) participants responded to the satisfaction survey given 6 months after the activity and found the activity to be useful, enjoyable, and impactful (Figure 2; Multimedia Appendix 2).

Table 1. Background data on first-year residents undergoing educational activity.

Question	Value
Female, n (%)	33 (47)
Had previous ICU[a] experience, n (%)	48 (67)
Had previous experience with our facility's Epic, n (%)	54 (77)
Had previous experience with Cerner, n (%)	34 (49)
Had previous experience with another facility's Epic, n (%)	39 (56)
Had previous experience with Allscripts, n (%)	6 (9)
Had previous experience with VistA[b]/CPRS[c], n (%)	21 (30)
Had previous experience with an EHR[d] not otherwise listed, n (%)	21 (30)
Self-reported ability to efficiently use any EHR[e], mean (SD)	3.0 (0.5)
Self-reported ability to comprehensibly use any EHR[e], mean (SD)	3.0 (0.4)
Self-reported ability to efficiently use facility EHR[e], mean (SD)	2.8 (0.7)
Self-reported ability to comprehensibly use facility EHR[e], mean (SD)	2.9 (0.7)

[a]ICU: intensive care unit.

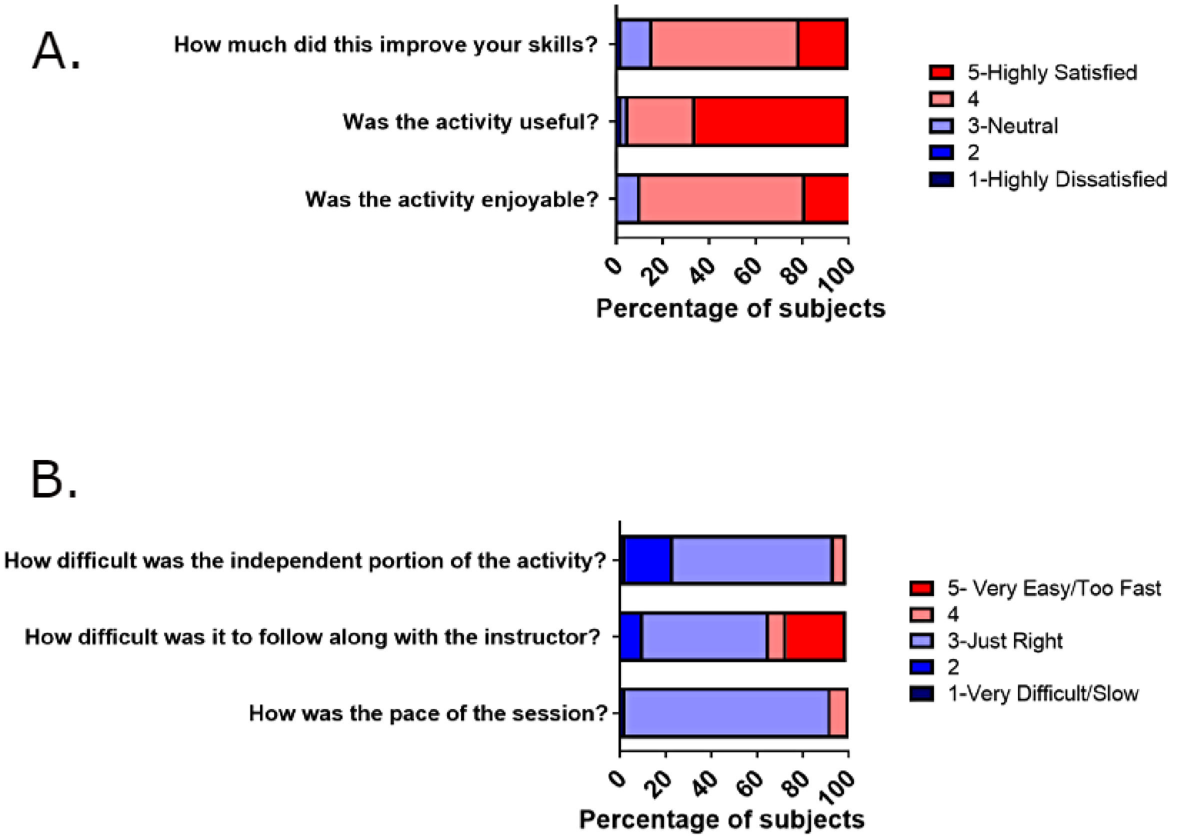
[b]VistA: Veterans Health Information Systems and Technology Architecture.

[c]CPRS: Computerized Patient Record System.

[d]EHR: electronic health record.

[e]Likert scale ranging from 1 (poor) to 5 (excellent).

Figure 1. Postactivity satisfaction survey immediately after the lesson. Intervention interns (N=38) were surveyed on a 5-point Likert scale for their impression of the simulation-based learning activity immediately after the session. Panel A: percentage of participants reporting the activity improved their skills, was useful, and enjoyable. Learners found the activity to be helpful and enjoyable. Panel B: percentage of participants reporting the difficulty of the independent portion, following the instructor, and the session's pacing. Learners found the activity to be appropriately challenging and well-paced.



Textbox 1. Example of free responses to thoughts on the learning activity.

“Fantastic to help us optimize the EHR...Please have more of these sessions throughout residency”

“Second session going through {patient} on our own, then debriefing was great”

“{It was} very valuable. Wish I’d had a session like this in medical school”

“I{t} was a good time to do {the activity} in the year. {The activity} would not have been helpful during orientation”

“{The second case was a} great case to challenge cognitive biases. The {guided first case} was extremely useful”

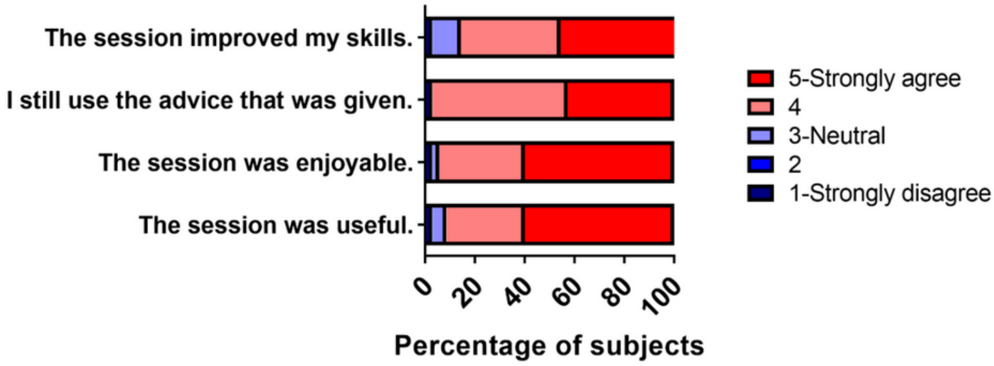
“Applicable tidbits & features. Good class involvement”

“some more test cases/examples”

“Practice case was hard, but great learning experience”

“At times couldn’t follow where instructor was clocking-more of a room issue”

Figure 2. Postactivity satisfaction survey 6 months after the lesson. Intervention interns (n=35, 49%) were surveyed on a 5-point Likert scale for their impression of the simulation-based learning activity 6 months after the session. The graph shows the percentage of participants reporting that the activity was useful and enjoyable, they still use the advice given, and the activity improved their skills. Learners continued to find the activity useful after 6 months of real-world skill use.



We next sought to determine the impact of the program on EHR screen utilization during independent learning activities. Although the average number of total screens viewed by our learners was not significantly different from that of the reference residents (37.8% vs 34.7%; *P*=.17), the average number of unique screens used by our cohort was higher (20.2% vs 17.5%; *P*=.008). As a result, the ratio of total and unique screens tended to be higher in the controls (not shown) and, specifically, the percentage of subjects with a ratio >2, suggesting a high rate of visiting multiple screens multiple times (50% vs 34%; *P*=.06).

Next, we looked at the 10 most commonly used screens for each cohort. Overall, there was a significant increase in the number of individuals using all 10 of these screens in the intervention group compared with the previously established workflow (73% vs 45%; *P*=.001; Figure 3). Interestingly, this was associated with a slight increase in the number of unique screens viewed (20.2% vs 17.5%; *P*=.008), with no difference in the total screens viewed (37.7% vs 34.7%; *P*=.30; Figure 3).

Of the 11 high-yield screens recommended during the guided review, 8 were used statistically significantly more by our intervention interns (Figure 4 and Multimedia Appendix 2). When we assessed the self-reported use of these screens at 6 months, we observed continued high use of these screens. Conversely, when we looked at the ability of the activity to discourage the use of 2 low-yield screens, we observed the use of 2 low-yield screens to be significantly lower in the intervention interns than in the reference. However, discouragement of low-yield screens attenuated over time, with increased self-reported use 6 months after the activity (Figure 5). Finally, when we looked at predictors of high-yield screen use during the simulation, only prior ICU experience predicted the use of graphing functions to review laboratory data (42.8% vs 18.8%; *P*=.03). Otherwise, none of the other variables (sex and prior EHR use and experience) predicted screen use (data not shown).

Figure 3. Parameters of screen use. Reference residents (n=62, 100%) and intervention interns with available data (n=70, 99%) had data gathering navigation patterns during postlesson simulation recorded. Panel A: number of reference residents and intervention interns who used the most common 10 screens among all participants. Intervention interns used these most common screens more frequently than participants using previously established workflow (73% vs 45%; *P*=.001). Panel B: number of total screens and unique screens visualized by reference residents and intervention interns. Although there was no difference in total screens used between groups, intervention interns used more unique screens than the reference (20.2 vs 17.5; *P*=.008).

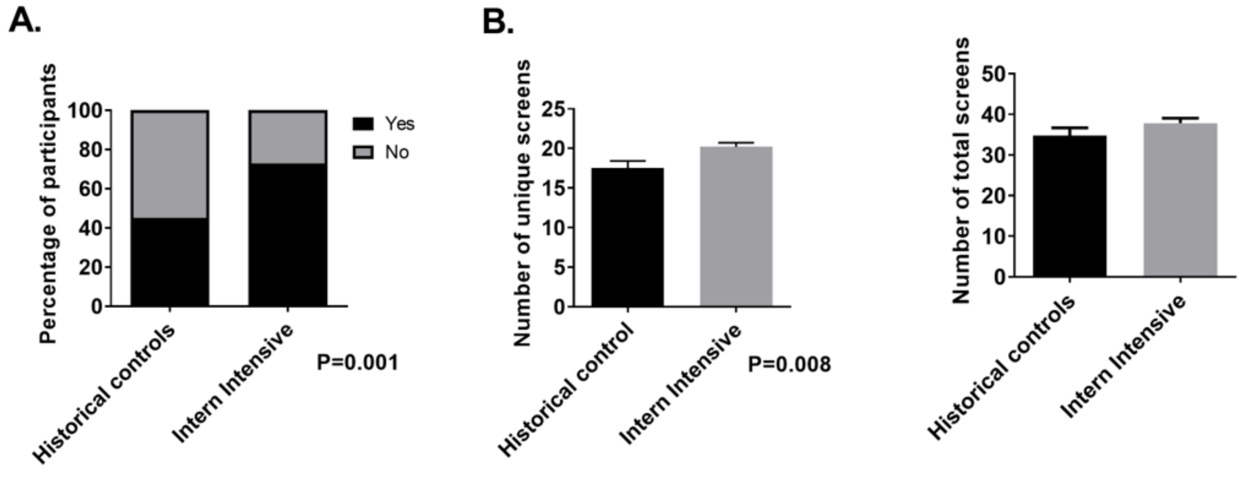


Figure 4. Percentage of reference subjects and intervention interns using high-yield screens and participant self-reported use of high-yield screen 6 months after the intervention. The reference residents (N=62) and intervention interns with available data (n=70, 99%) had data gathering navigation patterns during the independent learning portion of the simulation recorded. Intervention interns used 8 of 13 high-yield screens more frequently by Pearson chi-square as denoted by **P*<.05. Intervention interns responded to a survey querying the continued use of high-yield screens 6 months after the lesson (n=35, 49%), with qualitatively maintained uptake. I/O: Intake/output; ICU: intensive care unit; MAR: Medication Administration Record.

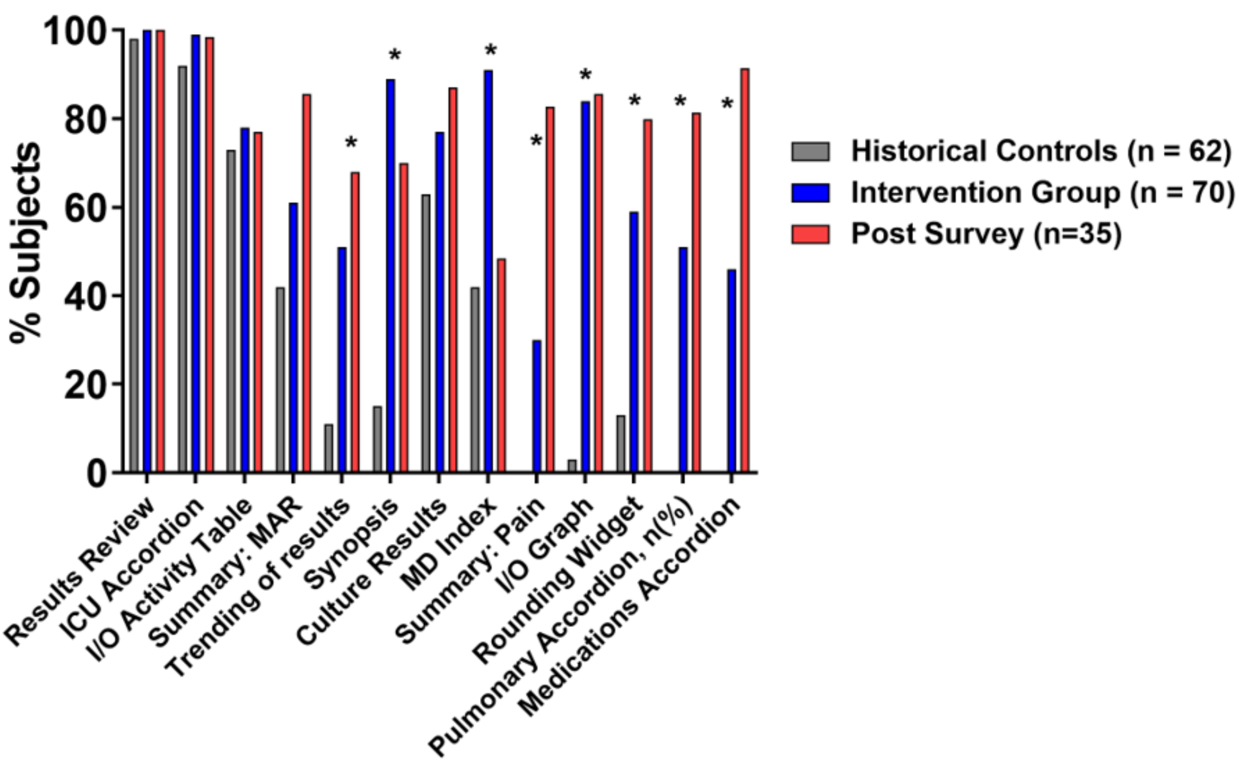
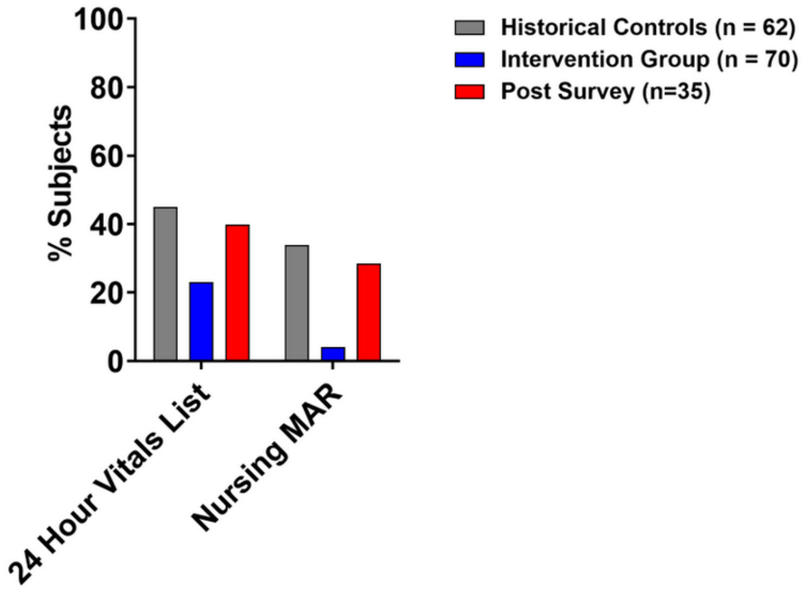


Figure 5. Percentage of reference subjects and intervention interns using low-yield screens and participant self-reported use of low-yield screen 6 months after the intervention. The reference residents (N=62) and intervention interns with available data (n=70, 99%) had data gathering navigation patterns during the independent learning portion of the simulation recorded. Intervention participants used low-yield screens less frequently than historical controls by Pearson chi-square (*P*<.05). Intervention interns responded to a survey querying continued use of high-yield screens 6 months after the lesson (n=35, 50%); decreased use of low-yield screens was not sustained. I/O: Intake/output; ICU: intensive care unit; MAR: Medication Administration Record.



Discussion

In this study, we report the development of a novel, dedicated 2-hour EHR training focused on physician workflow while preparing to evaluate a patient at the beginning of the day (prerounding) using high-fidelity simulation-based learning, with special attention to high-yield and low-yield screens available in the EHR interface. We observed high and sustained learner satisfaction with the activity, which was associated with significant and sustained changes in navigation patterns with respect to the established workflow previously seen in reference residents. Most importantly, these perceptions were sustained 6 months after the activity.

In contrast to previous studies where providers have historically reported low engagement and enjoyment with traditional EHR-based education, our study participants reported high and persistent learner satisfaction; they also perceived usefulness upon immediate postactivity assessment, likely secondary to the use of high-fidelity simulations as the model of instruction [32]. In addition, most EHR education traditionally focuses on the basic functionality of the clinical information system, whereas our lesson focused on practical, systematic approaches to data gathering consistent with learners' realistic workflow. Qualitative comments elicited from participants indicated that the experience was enjoyable and pertinent because of factors such as challenging and realistic cases, layout of the lesson (guided review of a case, solitary review of a case, and then group debrief), learner engagement during the guided review, focus on systematic data extraction, and timing of the lesson a few months after real-world exposure.

Although a number of studies document the impact of EHR-based onboarding on provider satisfaction, few have documented its impact on the way they actually proceed to use the EHR, specifically their EHR screen navigation habits. Simulation has been used for basic EHR education, and a recent study documented the impact of simulation training on the use of a specific data visualization screen and a single information retrieval tool [23,33]. Our study expands on these findings by focusing on changes in the entirety of participant EHR screen navigation patterns after high-fidelity simulation-based learning. Overall, our intervention was associated with an increase in the standardization of EHR use, as evidenced by a near doubling in the number of individuals using the most common screens. Furthermore, the increase in the total number of unique screens employed, with little change in total screens, supports a shift toward data gathering along a scripted progression of different screens within the EHR rather than alternating between a few screens repeatedly. This has potential impacts on information retrieval precision and cognitive processing, as returning to a previously viewed screen within an EHR has been associated with cognitive overload [34,35].

Standardization in screen use was associated with the increased use of high-yield screens and decreased use of low-yield screens during the independent learning portion of the activity. Perhaps more importantly, intervention interns retained these skills 6 months after the session. These results are consistent with a previous study, which demonstrated increased use of a specific EHR-based tool after a simulation-based exercise as assessed through user logs [23]. Unfortunately, EHR user logs were unsuitable for our analysis, as the information collected by audits at our institution does not include the users' contextual activity. Our learning focused on navigation patterns while data gathering prerounding, but user audit logs would be unable to distinguish this activity from that of data entry or documentation. Audit logs also lack information on timing with respect to patient interaction. Although our lesson focused on prerounding on new patients, logs would also capture all of the EHR navigation conducted during the day, including prerounding on known patients, assessing new patients, data gathering to address a change in clinical status, and review during preparation to transfer care (sign-out). However, our follow-up survey suggests that most of the participants continued to find high-yield screens valuable. Thus, overall, the data collected in this study suggests not only that our activity was able to modify participant behavior effectively but also that these changes were sustained long beyond the activity.

Next, we sought to determine whether any participant characteristics impacted either user satisfaction or adoption of EHR best practices. Overall, prior EHR use, sex, and perceived comfort level with EHRs generally and our EHR specifically had no impact on learner satisfaction or performance. However, learners who had already rotated in the ICU showed increased use of the graphing functions of the EHR to visualize laboratory data. This association suggests that although this type of activity is relatively generalizable, some specific EHR skills are still better adopted when placed in the context of actual experience. This is consistent with feedback from learners in the free-text comments of the survey. However, it must be stressed that these studies were specifically conducted after all learners had completed 2 months of internship and thus already had significant experience with the intern workflow in general. It remains to be determined whether this activity would have the same impact if implemented at the very beginning of residency, integrated into their initial EHR onboarding activity.

This study has some important limitations. The first is the use of an established workflow from reference residents for comparators of screen navigation rather than a randomized control. However, as our reference residents participated in simulations using the same simulated charts; were assessed during their ICU rotations; and comprised trainees of all levels with, therefore, greater clinical and EHR exposure, they represent a more expert group of users compared with the intervention interns. Despite a more expert established baseline, we were still able to detect the effect of training. The second is a lack of preactivity assessments. Assessment of navigation patterns before and after the educational activity would have provided stronger support for causality in between-screen navigation pattern change in the intervention. Unfortunately, because of external time constraints, we were unable to perform a preactivity navigation pattern assessment. Similarly, we were limited to self-reporting via a web-based survey to assess retention, as the interns did not have the time to participate in additional simulations, and there was no reliable way to query the EHR to assess real-world screen navigation. Finally, this exercise focused purely on information retrieval. Although this is the most common activity performed by interns in the EHR, there are other important domains of EHR use, including optimization of data entry (eg, note writing) and managing in-basket alerts, that were not addressed [12].

In conclusion, our study presents a novel, short, high-fidelity EHR-based simulation, with special attention to provider-specific workflow during prerounding as opposed to EHR functionality, as an agreeable and effective educational activity. Learners found the activity enjoyable and useful both immediately and on reassessment 6 months after the activity. We found navigation patterns to closely match expert recommendations after the activity. These findings are important given the historical inadequacy of EHR training. The ability to deliver this content in a short time frame allows for the rapid expansion of this methodology not only during onboarding but also throughout the continuum of their training. Future directions may focus on using this technique to optimize other resident interactions with the EHR.

Acknowledgments

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Conflicts of Interest

None declared.

Multimedia Appendix 1

Lesson plan.

[PNG File , 139 KB - mededu_v7i1e25828_app1.png]

Multimedia Appendix 2

Supplementary data tables.

[DOCX File , 15 KB - mededu_v7i1e25828_app2.docx]

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Abbreviations

EHR: electronic health record
ICU: intensive care unit
OHSU: Oregon Health and Science University

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