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Do cognitive, affective and social needs influence mobile learning adoption in emergency remote teaching?

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Abstract

Transitioning to mobile learning or M-Learning in medical education has been challenging due to its subscription to the clinical-based method of knowledge transfer. This shift was accelerated despite the challenges of COVID-19 in what research refers to as Emergency Remote Teaching or ERT. While this modality supported learning continuity, it was evident that online classes have become avenues for students to socially engage with others to meet various psychological needs to buffer pandemic stress. We hypothesized that cognitive, affective, and social needs positively influence learners' attitude towards M-Learning, which leads to its adoption. Given that peers highly influence medical professionals, we further hypothesized that the beliefs of others or social norms have a positive influence on the behavioral intention to use M-Learning. We added psychological needs as influencing factors to Theory of Reasoned Action constructs to develop a structural model, deployed an online survey, and analyzed 219 responses from healthcare students in the Philippines using Partial Least Squares – Structural Equation Modeling or PLS-SEM. We confirm that cognitive, affective, and social needs are psychological factors that influence students' attitude towards mobile learning. While attitude can lead to the behavioral intention to adopt mobile learning, social norms do not exhibit a positive influence at a significant level. We discuss our results from the perspective of a developing economy during a pandemic and provide the implications of its findings to theory, academe, and technology.

Keywords: Emergency remote teaching, Healthcare education, Mobile learning, COVID-19, Theory of reasoned action, Human needs

Introduction

Abrupt disruptions in education due to the Coronavirus of 2019 or COVID-19 forced universities to recalibrate pedagogy to adapt to the evolving challenges of the current pandemic. While the hallmarks of an established online learning environment require careful planning, continuous faculty training, and robust technology infrastructure, emergency remote training or ERT is the abrupt involuntary shift to any available technology-enabled learning modality due to a crisis (Hodges et al., 2020). Prior studies investigated ERT in certain disasters such as ERT delivery due to hurricane Katrina (Johnson et al., 2006; Laprairie & Hinson, 2006) and the earthquakes in New Zealand (Ayebi-Arthur, 2017; Tull, 2017), today's educational response to COVID-19 should be studied given its scale and its impact to various actors including those from developing economies (Hodges et al., 2020).

In recent years, healthcare education transitioned slowly to mobile learning, reflecting students' current needs and maturity of technology-based pedagogy. Traditionally, healthcare education subscribes to face-to-face learning where medical students attend classes physically and learn practical skills within the clinical environment (Eckleberry-Hunt et al., 2018; Li & Bailey, 2020; Li et al., 2021; Remtulla, 2020). As more educators and students learn technology alongside initiatives of universities to innovate, technology has become a core ingredient in healthcare education delivery (Eckleberry-Hunt et al., 2018; Khalil et al., 2020). However, due to the unprecedented challenges brought about by COVID-19, this digital transformation was accelerated through ERT, which proved to be a viable solution in ensuring that healthcare workers continue to learn despite restrictions, lockdowns, and safety concerns (Almoayad et al., 2020; Karim et al., 2022; Nimavat et al., 2021). Universities worldwide relied heavily on their online learning experience, technology prowess, and experienced faculty to quickly transition to deliver their classes fully online (Aivaz & Teodorescu, 2022; Waugh et al., 2022).

While ERT in developed economies ensures that medical education continues, understanding its adoption in a resource-constrained context will ensure its wider adoption beyond COVID-19 and future global emergencies. Evident in research is the wide disparity in how economies tackled COVID-19, with the education sector severely affected (Azionya & Nhedzi, 2021; Kahambing, 2021). With students and faculty experiencing psychological distress in attending ERT, a synthesis of current research in technology adoption advocated for studies beyond the technology factors (Corcuera & Alvarez, 2021; Roberts & Flin, 2019). Given that healthcare professionals must delicately balance their dual roles of serving the healthcare system and attending their classes, COVID-19 negatively affected the mental well-being of this specific cohort of learners, especially at the early stages of the pandemic (Brand, 2020; Wilcha, 2020). Investigating the various psychological motivators behind ERT adoption from the viewpoint of healthcare professionals who continually learn will guide future initiatives of this learning modality closer to a human-centered design for medical education.

In one of the longest and strictest lockdowns, the Philippines suffered the wrath of COVID-19 in both its healthcare systems and education, negatively affecting the mental well-being of medical students when their institutions implemented ERT (Joaquin et al., 2020; Pelmin, 2020). Unskilled faculty and students, poor infrastructure, vague policies, and the absence of a clear direction from the government marked the initial stages of ERT implementation in medical education, which persists up to the present day (Baticulon et al., 2021). In like manner, the healthcare system grappled, given its limited resources and volatile information about COVID-19. Therefore, it is common for healthcare professionals to attend to their profession and attend online classes simultaneously. Despite ERT assuming a valuable role to sustain learning in healthcare, it is timely to understand how unmet psychological needs influence the use of M-Learning (Attalla et al., 2020; Azizi & Khatony, 2019) from the perspective of a developing economy (Barteit et al., 2020) to ensure equal access to education in difficult times.

Adapting to the needs of students in a time of a global crisis and uncertainty, education stakeholders should establish a climate of care online where the needs of students are at the core of every learning opportunity in ERT. We positioned cognitive, affective, and social needs with attitude and social norms of the Theory of Reasoned Action or TRA in a structural model to explore its effects in the behavioral intention to adopt M-Learning during ERT. In conducting this study, we widen current knowledge by investigating the adoption of ERT among adult healthcare students in a developing economy during a crisis to understand the influence of psychological needs in online learning adoption during COVID-19 (Barteit et al., 2020; Freedman & Nicolle, 2020; Karakaya, 2021; Negrescu & Caradaica, 2020). In the next section, we provide an overview of recent literature on the use of ERT in higher education. In the third section, we elucidate our theoretical foundations by discussing TRA and how cognitive, affective, and social needs of learners affect M-Learning; and summarize our hypotheses. This is followed by presenting our structural model and detailing the methodological processes in our fourth section. Our last two sections discuss the results and conclude by charting possible avenues for future research.

Related studies

Although online learning, distance learning, e-Learning, M-Learning, and remote learning have been used interchangeably in prior literature, it refers to a platform that utilizes technology in various facets of education, often requiring resources, time, commitment, and policies. Thus, the sudden shift to ERT, defined by Hodges et al. (2020) as the unplanned and involuntary shift to complete online modality due to a crisis, is a more appropriate term to describe the online environment during COVID-19. In the following sections, we discuss recent studies that shaped ERT literature, present the state of Philippine healthcare education before and during COVID 19 and conclude with a synthesis on how our study can contribute to existing scholarship.

Traditionally, healthcare education is considered a field that is slow to adopt technological innovations. Although with challenges, recent literature emphasizes the value of technology as a complementary tool in sustaining healthcare education, especially during emergencies such as COVID-19 (Aabdien et al., 2022; Almoayad et al., 2020; Doulias et al., 2022). Before COVID-19, it relied heavily on face-to-face, didactic lectures where practical knowledge is gained mainly within the campus or clinical settings (Eckleberry-Hunt et al., 2018; Li & Bailey, 2020). In healthcare education, there is a strong preference to be with peers and mentors where they learn from a stable group of like-minded professionals to advance their field of specialization within and outside the clinical settings (Burgess et al., 2020; Han et al., 2019). This practice is also driven by the preference of healthcare professionals to train within the clinical settings with patients since medical knowledge is best gained through experiential learning (Li & Bailey, 2020).

At the start of COVID-19, healthcare institutions rapidly activated their online learning infrastructure relying heavily on their experience, clear guidelines, and skilled faculty. In the United States, this readiness allowed institutions to innovate ways to engage students, such as virtual practical sessions that allowed healthcare students to acquire clinical knowledge despite learning remotely (Waugh et al., 2022). Likewise, preparations before COVID-19 allowed other medical institutions to sustain healthcare education by adding videoconferencing tools to their existing infrastructure (Li et al., 2021). Along with online learning platforms, technological affordances of telemedicine and teleconsulting applications were integrated as one of the learning modalities in a medicine program (Franklin et al., 2021). A primary component of healthcare education is patient interaction through hospital rounds rendered impossible by restrictions and safety risks of COVID-19. In the United Kingdom, medical institutions participate with their attending faculty in virtual rounds where they interact with patients remotely (Mann et al., 2020; Remtulla, 2020). Factors such as robust technology infrastructure, prior experience, government support, and vast resources supported the sustainability of healthcare education.

Global response to COVID-19 varied in different countries that highlighted disparities in various sectors of the society, including education. Countries with vast resources are quick to apply ERT, leaving behind developing economies that need to balance the interplay of community lockdowns, university closures, and the threats of COVID-19 while sustaining education (Jili et al., 2021; Karakose, 2021). In the Philippines, the pandemic response was unable to cope with the velocity and the scale of COVID-19, resulting in indefinite closures of campuses and involuntarily shifting to online modalities despite the absence of clear guidelines from the government (Arcega et al., 2022; Joaquin et al., 2020; Pelmin, 2020). A study has shown that before the pandemic, the technological readiness of Philippine education to shift to ERT is low in infrastructure, digital literacy, leadership, and digital content (Pouezevara et al., 2020).

Before COVID-19, healthcare education is primarily delivered in physical classrooms or hospitals to impart theoretical and clinical knowledge. Using a sample size of 3,670, Baticulon et al. (2021) attempted to describe healthcare education during COVID-19, where three-fourths of the respondents had difficulty adapting to online learning. This challenge is echoed by the study of Cedeño et al. (2021), which identified that adjustments in students' learning styles to acquire clinical knowledge online were a primary concern due to the university's unpreparedness and the lack of digital learning content. While difficult for others, Baquiran and Plata (2020) proved that uncertainty can be addressed by institutionalized online learning strategy, management support, a sense of community, and commitment to reskilling faculty. However, this may not necessarily reflect the current state of Philippine healthcare education during ERT as these factors may partially be present or practically absent in most universities.

ERT necessitated the involuntary shift to mobile learning, where students were forced to use any available mobile device to learn. Research has long argued that non-adoption of technology can be traced to behavioral factors that may not be necessarily attributable to the features of the technology artifact being studied. Prior research has argued that non-technological factors of attitude and social norms predict the behavioral intention to use technology. The Theory of Reasoned Action, or TRA, posits that a positive attitude towards technology and the influence of significant others will facilitate eventual technology adoption (Alshurafat et al., 2021; Fishbein & Ajzen, 1975). In this study, we used attitude and social norms of TRA as factors that influence behavioral intention to use M-Learning.

Research objective and hypotheses development

While M-Learning literature have been growing, research it its adoption among healthcare students remain unclear, technology-centered and based on developed economies necessitating further scholarly inquiry (Barteit et al., 2020; Freedman & Nicolle, 2020; Karakaya, 2021; Negrescu & Caradaica, 2020; Zhang et al., 2021). Therefore, it is the aim of this study to investigate the impact of human needs in the adoption M-Learning by healthcare students enrolled in a continuing medical education during the COVID-19 pandemic. We contribute to the body of work in M-Learning in medical education in three avenues. First, we widen the understanding of M-Learning use by providing empirical evidence that human needs are drivers of technology adoption in the learning process of medical students. Second, we further the scholarship of M-Learning by understanding its adoption in a resource-constrained setting conducted during a pandemic. Lastly, we broaden M-Learning literature by testing our structural model in a cohort of adult learners experiencing a high level of stress due to their profession as healthcare workers.

To accomplish this objective, we positioned cognitive, affective, and social needs with attitude and social norms of the Theory of Reasoned Action or TRA in a structural model to explore its effects in the behavioral intention to adopt M-Learning during ERT. The decision to use TRA is guided by prior information systems research that found TRA flexible to integrate external variables and its applicability to ERT during a pandemic (Alshurafat et al., 2021; Attalla et al., 2020; Long & Khoi, 2020). We discuss our proposed hypotheses in the next sections along with similar studies that motivated this research.

Attitude and social norms

Attitude is a psychological factor that describes an individual's positive perception of performing an act and has influenced technology adoption. In ERT, learners must use available devices to support the learning process. Given that mobile learning allows remote education, the health threats of the pandemic and psychological effects of community restrictions are mitigated. This is best understood by healthcare workers and may influence how they perceive mobile learning. In studies involving university students, attitude is a dominant predictor of the behavioral intention to adopt M-Learning (Buabeng-Andoh, 2018; Qashou, 2021). Likewise, during COVID-19, studies support that attitude influenced mobile learning adoption (Alshurafat et al., 2021; Long & Khoi, 2020).

Like attitude, social norms are also a strong predictor of technology adoption. Peers or significant others highly influence the likelihood of adopting technology. Healthcare professionals learn from their professional circles where exchanges of new knowledge are highly valued (Burgess et al., 2020). Social norms exert a certain level of social pressure when deciding whether to perform a specific behavior (Sugandini et al., 2022). In the context of technology adoption in education, this social pressure may come from classmates and is a strong determinant in the behavioral intention to adopt technology (Raza et al., 2018). Given that a favorable attitude towards M-Learning and those social norms are strong predictors of the behavioral intention in its adoption, we propose the following hypotheses as our H1 and H2:

H1: Attitude positively influence behavioral intention to adopt mobile learning

H2: Social norms positively influence behavioral intention to adopt mobile learning

Cognitive needs

Healthcare professionals are lifelong learners by default. This can be attributed to the constant requirement to acquire new medical knowledge, clinical techniques, and scientific discoveries. COVID-19 further accelerates the need to learn, and mobile learning is an appropriate tool (Samara & Monzon, 2021). In addition, as adult learners, healthcare professionals have cognitive needs to grow in their profession, and mobile learning allows them to capitalize on learning opportunities remotely despite various levels of restrictions (Pokhrel & Chhetri, 2021; Wayne et al., 2020). Given that learners have cognitive needs and can directly influence the way they perceive mobile learning, we propose the following hypothesis as our H3:

H3: Cognitive needs positively influence attitude towards mobile learning

Social and affective needs

Online learning spaces have transitioned from knowledge transfer avenues to havens of social interactions where learners acquire emotional and social support. Online learners experienced heightened psychological stress and increased social isolation, impacting the way they learn online, especially healthcare students (Alblihed et al., 2022; Brand, 2020; Rasmussen et al., 2022). Participating in learning activities with peers fosters a sense of community, a practice to which medical education heavily subscribes. Community lockdowns heightened social isolation, and physical interactions were practically reduced. The human need to interact with others to share emotions, experiences, and informal discussions are virtually transferred online, thereby meeting their affective needs (van der Meer et al., 2021). Learning is beyond just a cognitive engagement, and in an online learning environment during emergencies, it serves as a platform to build connections to meet social and affective needs (Shin & Hickey, 2021). With this premise, we propose the following hypotheses as our H4 and H5:

H4: Social needs positively influence attitude towards mobile learning

H5: Affective needs positively influence attitude towards mobile learning

To summarize, attitude or the way healthcare students perceive mobile technologies for remote learning positively influences the behavioral intention to adopt mobile learning (H1). Likewise, social norms or significant others' beliefs about mobile technologies will lead to its adoption (H2). In the context of this study, we argued that learners are driven not only by their thirst to learn but also to socialize and build meaningful connections during COVID-19 to meet their social and affective needs. When these psychological needs are addressed, it can positively influence what they think about mobile learning. As such, cognitive (H3), emotional (H4), and affective (H5) can positively impact the attitude of healthcare students towards mobile learning. We illustrate our propositions in Figure 1 – Structural Model.

Methodology

This study utilized a cross-sectional, quantitative research design using partial least squares – structural equation modeling or PLS-SEM technique (Hair et al., 2014). Since this study looks beyond technology design concepts and focuses on psychological factors, the research objective of testing the relationships of theoretical concepts for a scholarly explanation using PLS-SEM is deemed an appropriate approach (Benitez et al., 2020).

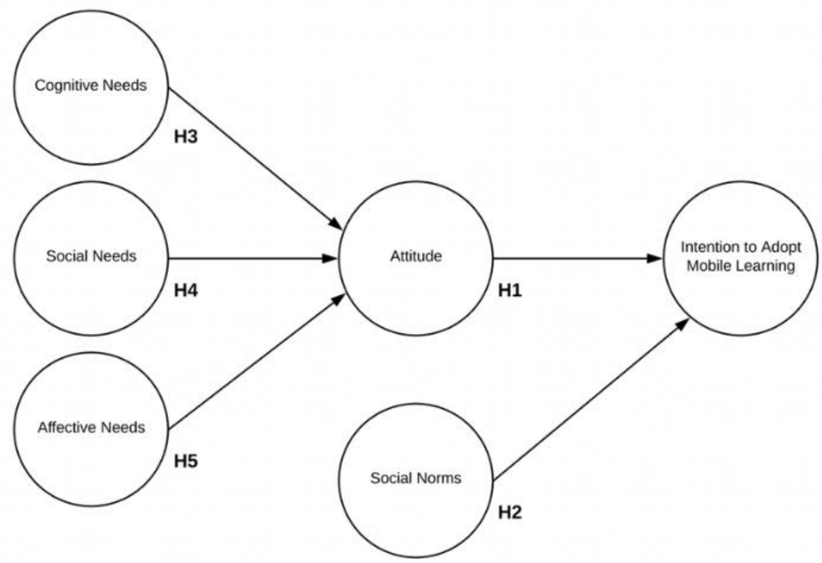

Fig. 1 Structural model

Prior literature also recommends using PLS-SEM in studies where the sample population is small, and there is uncertainty if the data set is normalized (Bayonne et al., 2020).

Participating higher educational institutions

We approached three universities offering a healthcare management postgraduate degree program in Metro Manila. The program is an intensive 2-year program administered in partnership with a professional healthcare management society established in 2011. Faculty members are practicing healthcare executives who are considered experts in establishing and operating various functions of healthcare management. In addition, most of the faculty members are practicing medical professionals such as doctors, surgeons, laboratory managers, and finance executives. Early in the pandemic, these universities were overwhelmed by the requirements of the rapid transition to online learning. There were no online learning platforms, many of the faculty members were untrained, and course materials were lacking. Administrators were forced to postpone the semester's opening for months as enrollment was low and the government had no clear direction.

Students enrolled in the program are employed healthcare professionals who are physicians, healthcare administrators, nurses, laboratory staff, and other allied professionals in private and government hospitals. These healthcare professionals will usually work regularly and attend their online classes on Sundays. Synchronous courses are conducted via popular videoconferencing tools such as Zoom and Google Meet. Lecture materials are distributed through email or via instant messaging groups. While there were attempts to establish a learning management system during the pandemic, the initiative did not flourish because students and faculty preferred to communicate through online groups and mobile devices.

Instrument development

To operationalize the constructs of our structural model, we adopted questions for cognitive needs (4), social needs (4), and affective needs (4) from the instrument of Hashim et al. (2014) in their study on adult learners' adoption of M-Learning. Likewise, to represent attitude (3), social norms (3), and intention to adopt mobile learning (3), we utilized questions from Huang (2016) in their study investigating social factors in the continuous intention to use technology-based learning. We added demographics such as gender, age, area of practice, and devices used for mobile learning. An explanation of the study's objectives, the definition of mobile learning, and sample activities were stated at the beginning of the survey so respondents could understand the study's objectives. Permission to conduct the study was obtained from the partner professional society, and the participants gave informed consent. We invited four students (4) to answer the survey to get their initial feedback to correct errors. The final version of the instrument consists of twenty-six (26) questions with twenty-one (21) questions to represent our structural model, as shown in Table 1 – Survey Instrument.

Table 1 Survey instrument

Construct	Question
Cognitive needs	I use my mobile device to help me know many things
	I use internet on my mobile device to search for new information
	I carry out internet search through my mobile device to answer questions coming from class discussions
	I use internet on my mobile device to explore topics of interest, beyond my normal school assignment
Affective needs	I like to talk to others about mobile technologies
	I like showing my friends how to use mobile device in different ways
	Mobile based courseware layout, animation and illustrations are good to look at
	I enjoy learning using a mobile device
Social needs	Using e-mail on mobile device gives me the feedback I need from others
	I use e-mail on mobile device to interact with my friends
	Mobile internet prepares me to join the extended learning community outside the class
	Using mobile device improves my ability to communicate with other people
Attitude	I like the idea of using mobile device for learning
	Using mobile device for learning is a wise idea
	Using mobile devices give me a pleasant experience
Social norms	Classmates who influence my behavior think that I should use mobile devices for learning
	Classmates who are important to me think that I should use mobile devices for learning
	Classmates around me who have good performance have benefited by using mobile devices for learning
Intention	I intend to use mobile device for learning in the future
	I will use the mobile device for learning in the future
	I will regularly use mobile device for learning in the future

Table 2 Instrument validation

Construct	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
Cognitive needs	0.830	0.872	0.657
Social needs	0.789	0.862	0.610
Affective needs	0.811	0.886	0.631
Attitude	0.870	0.921	0.795
Social norms	0.928	0.954	0.874
Intention	0.941	0.962	0.894

Analysis of results

We purposively selected thirty-one (31) students to answer the survey as a pilot test to validate the instrument. A Partial Least Squares or PLS algorithm was applied to the initial results using SmartPLS. Specifically, this test will ensure that the questions or indicators accurately represent the constructs in our structural model. The validity and reliability tests using the PLS algorithm are shown in Table 2 – Instrument Validation. The lowest scores for the Cronbach's Alpha and Composite Reliability or CR measures are 0.789 and 0.862. Given that these scores meet the minimum threshold of 0.70, the instrument demonstrates satisfactory internal consistency. On the other hand, the lowest score for the AVEs is 0.610, which meets the minimum threshold of 0.50, thereby exhibiting adequate convergent validity.

Discriminant validity

The discriminant validity scores check the presence of a high correlation among the constructs of a structural model. It ensures that a specific construct has a unique explanatory power (Hair et al., 2014; Henseler et al., 2014). We extracted the Fornell-Larcker criterion test scores from the PLS algorithm to test discriminant validity, as shown in Table 3 – Fornell-Larcker Discriminant Validity Test. Diagonal values highlighted in bold indicate the square root of AVEs from observed variables while the off-diagonal values represent inter-correlations with other constructs. For example, the value of 0.892 for attitude is higher than the other values in the same column which means that its indicators have the highest correlation within attitude compared to other constructs

Table 3 Fornell-Larcker Discriminant Validity Test

Construct	Affective needs	Attitude	Cognitive needs	Intention	Social needs	Social norms
Affective needs	**0.794**					
Attitude	0.574	**0.892**				
Cognitive needs	0.556	0.299	**0.810**			
Intention	0.547	0.792	0.417	**0.945**		
Social needs	0.665	0.662	0.559	0.616	**0.781**	
Social norms	0.626	0.694	0.367	0.627	0.547	**0.935**

Table 4 Heterotrait-Monotrait Validity Test

Construct	Affective needs	Attitude	Cognitive needs	Intention	Social needs	Social norms
Affective needs						
Attitude	0.640					
Cognitive needs	0.661	0.332				
Intention	0.577	0.874	0.490			
Social needs	0.801	0.778	0.695	0.700		
Social norms	0.721	0.771	0.426	0.665	0.623	

(Ab Hamid et al., 2017; Buabeng-Andoh, 2018; Henseler et al., 2014). Given that the diagonal values are the highest in the five constructs of the instrument, indicators assigned to each of them can demonstrate distinctiveness.

The results of the Fornell-Larcker test demonstrates strong evidence that the constructs can represent the variables of our structural model for path analysis. While the Fornell-Larcker discriminant validity test has been used in prior information systems research, recent literature proposed a more rigorous assessment through Heterotrait-Monotrait or HTMT test (Ab Hamid et al., 2017; Benitez et al., 2020; Hair et al., 2016). We extracted the HTMT criterion scores from the PLS algorithm in Table 4 – Heterotrait-Monotrait Validity Test. All values are below 0.85 except for the HTMT score of attitude and intention, 0.874. Traditionally, HTMT scores of 0.85 indicate a lack of discriminant validity. However, recent updates to the PLS method as applied in IS research have deemed values below 0.90 acceptable (Benitez et al., 2020).

Structural model test

We deployed our online survey from March to May of 2021. All respondents are currently affiliated with a healthcare institution and enrolled in a postgraduate degree in healthcare management. Of the 219 respondents, 123 or 56% are female, and 96 or 44% are male. 15 or 7% are between 20 and 29 years old, while 72 or 33% are between 30 and 39 years old. Additionally, 38 or 17% belong to the age group of 40-49 years old, while 68 or 31% fall into the 50-59 age group. Of the sample, 26 or 12% are considered older adults. Most of the participants, 146 or 67%, practice their profession within Metro Manila, while 73 or 33% work in the provinces. A Bootstrapping technique using SmartPLS, a structural analysis software best suited for studies with small sample sizes, was used (Benitez et al., 2020; Schmidheiny, 2021).

Common method bias or CMB is an ongoing concern, especially in self-reported scales deployed online. It measures the bias in the way respondents answer a survey, the social desirability to finish a survey, or how the words are chosen to gather similar results. To test whether CMB is present in our study, we extracted the inner Variance Inflation Factors since our structural model utilized reflective constructs. These values represent collinearity problems between constructs in the inner model. As shown in Table 5 – Structural Model

Table 5 Structural model test

Hypothesis	VIF Inner Values	R^2	T Statistics	P Values	Decision
H1: Attitude positively influence behavioral intention to adopt mobile learning	1.928	0.687	5.910	0.000	Supported
H2: Social norms positively influence behavioral intention to adopt mobile learning	1.928	0.151	1.228	0.220	Not Supported
H3: Cognitive needs positively influence attitude towards mobile learning	1.595	0.214	2.171	0.030	Supported
H4: Social needs positively influence attitude towards mobile learning	1.978	0.564	4.697	0.000	Supported
H5: Affective needs positively influence attitude towards mobile learning	1.968	0.300	2.372	0.018	Supported

Test there are no VIF inner value greater than 3.3, indicating the absence of CMB (Heale & Forbes, 2013; Kock, 2015).

The bootstrapping process also revealed the T-Statistics values for each path that served as our basis to support a specific hypothesis. The results of the path analysis are presented in Table 5 – Structural Model Test. T-Statistics values above 1.96 mean that the relationship is significant (Hair et al., 2014). We discuss our path analysis based on the structural model test in the next section.

Discussion

Consistent with prior findings, a positive attitude towards M-Learning leads to the behavior intention of its adoption (Azizi & Khatony, 2019; Raza et al., 2018). The T-Statistics value of 5.910 (H1) infers that it has a direct and positive influence on the intention to use mobile learning among healthcare students (Hair et al., 2014). Although the participants of this study are used to traditional learning as healthcare professionals, their medical background may have added value in the way they view mobile learning as a practical solution to movement restrictions and risks brought about by COVID-19. A study conducted in the Philippines during the shift to ERT observed that attitude towards online learning improved with flexibility and sensitivity (Baquiran & Plata, 2020). In the context of this study, learners were given the flexibility to choose their preferred technology device, academic breaks, and considerations.

The T-Statistics value of 1.228 for the relationship of social norms and intention to adopt M-Learning (H2) is not supported, contradicting prior studies (Gómez-Ramirez et al., 2019; Kucuk et al., 2020) but confirms the study of Azizi and Khatony (2019). Among adult learners, social norms may not necessarily come from classmates but may come from other social networks such as professional communities of practice, family members, and superiors (Hadadgar et al., 2016). In addition, while we find the influence to be positive but not significant, social norms may not necessarily influence students to use mobile learning as it is the only modality that the participating universities currently adopted for ERT. Lastly, in exploring subjective norms construct, others weakly influence adult learners if they have a solid positive attitude towards M-Learning and a high level of cognitive needs (Hossain et al., 2020). Given that attitude and cognitive needs were found to have positive associations to behavioral intention to adopt mobile learning, social norms from peers may not necessarily apply in the context of this research.

The psychological factors of cognitive needs (H3), social needs (H4), and affective needs (H5) have a direct and positive influence on the attitude of frontline learners towards M-Learning based on the T-Statistics values of 2.171, 4.697, and 2.372, respectively. These values are above the minimum threshold of 1.96, demonstrating significant relationships between these human factors and attitude, resulting in the acceptance of H3, H4, and H5 (Hair et al., 2014). Like the findings of prior studies in adopting mobile learning, the factors of cognitive needs, social needs, and affective needs affect how learners view this learning modality (Hashim et al., 2014; Lin & Su, 2020). Although investigations in the adoption and usage behaviors of learners in the medical field established a strong preference for knowledge delivery via classroom or clinical settings to meet their cognitive needs (Lall et al., 2019), the restrictions and safety concerns imposed by COVID-19 highlighted the benefits and affordances of mobile learning in healthcare education (Alsoufi et al., 2020; Rose, 2020). Given that the COVID-19 situation is unprecedented, its impact on patient care, hospital operations, and clinical procedures will need to adjust, and information is best delivered through an online learning modality due to its speed, flexibility, and convenience. A massive shift towards M-Learning has been observed where urgent findings of COVID-19, best practices, and government policies are delivered via webinars to medical students (Al-Ahmari et al., 2021).

Like the influence of cognitive needs on attitude, social and affective needs shape the perceptions of healthcare student towards M-Learning. In fact, the strengths of the paths for social and affective needs towards attitude are stronger than cognitive needs. These findings suggest that the participants of this study view M-Learning sessions as opportunities to interact with fellow healthcare professionals. The psychosocial needs to socialize and acquire affection are heightened among learners during COVID-19, mainly due to social isolation, stress, and fear (Joaquin et al., 2020; Pokhrel & Chhetri, 2021). Evidence from prior pandemics has stressed that healthcare workers are most vulnerable to the adverse psychological effects of a health crisis and will disrupt the continuity of learning (Brand, 2020). Synchronous classes delivered via mobile learning allow breakout rooms where students can freely interact with classmates facilitating lost physical social connections and acquire peer to peer support (Chandler, 2016; Sneddon et al., 2021). Opportunities to discuss and socialize with peers and fellow healthcare professionals on the various topics related to COVID-19 can meet their psychological needs and cushion the negative impact of this pandemic (Brand, 2020; Wilcha, 2020).

The findings of this study reveal that in ERT, learning continuity should be approached beyond addressing the technological needs of learners. While M-Learning offers the ubiquity and flexibility to sustain the learning process, technology implementation should be complemented with support interventions to promote the psychological well-being of learners. The study of Donham et al. (2022) found that the M-Learning environment during ERT provided more challenges than benefits to learners including cognitive, affective and social issues. These human needs influence how learners perceive M-Learning thereby influencing their adoption behavior. In medical education, the transition to ERT through mobile learning emphasized the role of support mechanisms that may come from peers, teachers and institutions to buffer the stress from performing their dual roles of being a healthcare professional and as lifelong learners (Gaur et al., 2020; Hendriksen et al., 2021).

Summary, limitations and conclusions

The sudden shift to ERT is a consequence of COVID-19, accelerating various social processes, including learning. Our structural analysis revealed that cognitive needs, social needs, and affective needs positively influence the attitude towards M-Learning, which in turn, leads to the behavioral intention to adopt M-Learning. In the context of this study, we also found that social norms have no influence on the behavioral intention to adopt M-Learning, and influence may come from other sources, given that the participants of the study are adult learners.

In presenting our findings, we acknowledge methodological constraints. An important consideration in interpreting our results is the small sample size which can be addressed by replicating our study design in a larger population. Our participants are enrolled in 3 private universities that implemented ERT in the capital; conditions might differ in rural communities where technology and economic progress are slow to diffuse. In the future, it will be interesting to know how our findings will apply to public medical schools and those situated in rural areas where resources are scarce, and connectivity is low. Due to the research objective of this study and theoretical underpinnings, we did not test the relationship between social norms and attitude. It will be noteworthy to investigate whether this influence can shape the perception in the use of M-Learning among healthcare professionals given the changing landscape of education in the new normal. Lastly, our study was conducted during the time when science is more informed about COVID-19 and governments have gained momentum to rebuild economies. Comparing our findings when participants start their hybrid semester where they attend both online and physical learning modalities will be noteworthy for future scholarly inquiries.

The results of this study have several implications. The study widens the theoretical applicability of TRA in technology adoption and confirms its flexibility to integrate human needs as applied in a cohort of healthcare students from a developing economy. Another contribution of this study is our finding that social norms may not necessarily apply to all learners but are possibly context-driven, as supported by the nuances in the literature. While mobile learning has been widely investigated, knowledge on the involuntary shift to online platforms due to the pandemic referred to in this research as ERT is still unfolding. From the policy perspective, regulators and administrators can be informed that in recalibrating institutional online pedagogy, universities should look at ERT beyond a convenient substitute to physical learning but a possible avenue where students can gain emotional and social support that can buffer the adverse effects of a crisis. This will support recent calls for a "pedagogy of care" during the pandemic, where well-being and learning new things are equally valued (Karakaya, 2021). Lastly, our research provides empirical evidence for technology designers of online learning technologies to develop technology artifacts that will foster the social presence of the faculty but, more importantly, establish social connections among students. The findings and the future directions of this study can help various stakeholders of healthcare education navigate through the intricacies of ERT as we slowly go back to where we were before this pandemic, mindful of the lessons learned in an unprecedented situation such as COVID-19.

Abbreviations

COVID-19: Coronavirus of 2019; M-Leaning: Mobile learning; ERT: Emergency remote training; TRA: Theory of Reasoned Action; PLS-SEM: Partial least squares - structural equation modeling; CR: Composite Reliability; AVE: Average Variance Extracted; HTMT: Heterotrait-Monotrait; CMB: Common method bias; VIF: Variance Inflation Factors.

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Authors' contributions

Both authors equally contributed to the study.

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Availability of data and materials

Data can be requested from the corresponding author subject to the approval of the affiliated university.

Declarations

Competing interests
The authors declare that they have no competing interests.

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