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Human Factors in the Adoption of M-Learning by COVID-19 Frontline Learners

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Abstract: Mobile Learning is crucial to the continuity of healthcare education during COVID-19. Despite its penchant for the traditional delivery of course content through classroom and clinical settings, M-Learning proved to be a viable solution in a pandemic due to social isolation, community restrictions, and safety concerns. We invited 219 frontline learners from 3 universities, active healthcare professionals who are currently enrolled, to test a structural model based on the Theory of Reason Action. We positioned the human factors of cognitive, social, and affective needs as determinants of attitude in the behavioral intention to adopt M-Learning. We further hypothesize that social norms positively influence the behavioral intention to adopt M-Learning among healthcare frontliners. We applied PLS-SEM to analyze the survey data and revealed that human factors positively influence attitude, leading to the behavioral intention to adopt M-Learning. Social norms and their influence on the behavioral intention to adopt this technology are not supported. We discuss the implications of our study, acknowledge its limitations while mapping out directions for future works to understand M-Learning adoption further.

Keywords: M-Learning, human factors, COVID-19, medical education, healthcare education

1. Introduction

Mobile learning or the use of mobile devices to acquire new knowledge revolutionized 21st-century education. Improvements in mobile technologies and more comprehensive Internet connectivity allowed learners to acquire new knowledge anytime and anywhere through Mobile learning or M-Learning, a benefit that prior research identified as a primary motivation in its increased adoption (Baghcheghi et al., 2020; Maharsi, 2018). The ubiquity of mobile devices, along with a better understanding of the scholarship in its integration with various learning processes, brought forward significant improvements in M-Learning such as context-sensitivity, improved interaction features, and personalization (Lall et al., 2019; Senaratne & Samarasinghe, 2019).

While research on the diffusion of M-Learning in higher education abounds, its adoption in healthcare professional education appears lacking. Prior research has focused primarily on the contexts of university students revealing that today's generation of university learners prefer acquiring new knowledge in the mobile environment (Baghcheghi et al., 2020; Gómez-Ramirez et al., 2019; Qashou, 2021). The quality of healthcare is heavily anchored on what our medical professionals know from their experiences, practices, and formal education; therefore, M-Learning has become an essential vehicle in balancing their profession and the need to acquire new knowledge (Qureshi et al., 2020). Despite the potential of M-Learning to the improvement of the healthcare profession, some opportunities are ripe for further scrutinies such as studies from developing economies (Barteit et al., 2020) and the effects of its adoption beyond technology factors (Attalla et al., 2020; Azizi & Khatony, 2019).

The onset of the novel coronavirus 2019 or COVID-19 disrupted the way we deliver education due to challenges imposed by community lockdowns, social distancing, and campus closures (Pokhrel & Chhetri, 2021). In the Philippines, higher educational institutions or HEIs recalibrated their strategies to ensure continuous learning through a mix of blended and online learning delivery modes (Joaquin et al., 2020; Pelmin, 2020). At the forefront of the battle against COVID-19 are the healthcare professionals who risk their lives to ensure that humanity's battle against the current pandemic is sustained. In fulfilling their roles as frontliners in this battle, learning continues, and the challenge to balance their psychological, cognitive, and social needs can be addressed by M-Learning (Cedeño et al., 2021).

In this study, we approached frontliners – medical doctors and allied professionals – who are currently enrolled in a graduate healthcare management program in three (3) universities in the Philippines. We developed a quantitative model based on the Theory of Reasoned Action with the addition of human factors of cognitive, affective, and social aspects to investigate their influence in the behavioral intention to adopt M-Learning. Given that studies in technology-enabled learning are context-driven, we contribute to current literature in three areas: adoption of M-Learning among adult healthcare students in a developing economy, effects of non-technology factors in M-Learning adoption, and understanding M-Learning during COVID-19 adoption from the perspective of frontline healthcare professionals (Barteit et al., 2020; Freedman & Nicolle, 2020; Heinze & Hu, 2009; Negrescu & Caradaica, 2021). In the following sections, we provide an overview of recent literature in the use of M-Learning in healthcare education, discuss the theoretical underpinnings of our study, present our methodology, highlight the results of our study and conclude by mapping out our recommendations for future research.

2. Related Studies and Theoretical Foundations

Healthcare education has long been viewed as a discipline heavily reliant on the traditional delivery of education. Before COVID-19, medical education relies heavily on practical knowledge application where lessons are delivered mainly within a classroom or a hospital. This practice is also driven by the preference of attending physicians who practice within the clinical settings as there is a need for students to interact, a challenge to which M-Learning is still grappling to address (Li & Bailey, 2020). However, recent literature has reflected the value of disruptive technologies in education demonstrating the viability of M-Learning in healthcare education (Qureshi et al., 2020).

In the literature of technology adoption, attitude and social norms play an essential role in the behavioral intention in using a specific technology. The Theory of Reasoned Action, or TRA, posits that a positive attitude towards technology will facilitate eventual adoption (Ajzen, 1975). The decision to use this theory is guided by prior information system research that found TRA flexible to incorporate external variables and its applicability to the M-Learning adoption domain (Attalla et al., 2020; Buabeng-Andoh, 2018). Like attitude, social norms are also a strong predictor of technology adoption. The likelihood of adopting technology is highly influenced by social pressure. In M-Learning, these two factors have been proven to predict its adoption effectively. For example, studies among university students found that attitude is a dominant predictor of the behavioral intention to adopt M-Learning (Buabeng-Andoh, 2018; Qashou, 2021). Social pressure exerts a certain level of influence when deciding whether to perform a specific behavior. 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, within the context of TRA, we propose the following hypotheses:

H1: ***Attitude has a positive and significant influence on the behavioral intention to adopt M-Learning***

H2: ***Social norms have a positive and significant influence on the behavioral intention to adopt M-Learning***

COVID-19 fostered renewed attention to M-Learning as it has become a tool to sustain learning, especially in healthcare education (Cruz-Cunha & Mateus-Coelho, 2021; Rose, 2020). In prior literature, the experiences of medical students were found to be positive towards technology-supported learning during the pandemic (Alsoufi et al., 2020). During COVID-19, M-Learning proved to be a viable solution to learning disruptions due to its various strengths, such as flexibility, asynchronous features, automated class management, and speed (Cedeño et al., 2021; Juan et al., 2020). While research viewed healthcare learners as a cohort who learns best within the clinical settings, the sudden shift to the M-Learning environment may pose challenges in its adoption and requires further inquiry.

COVID-19 may present a unique context where online learners experience heightened psychological stress and increased social isolation, impacting the way they learn online (Brand, 2020). While technology factors in innovation adoption inspired prior literature, human factors and their effects on technology adoption are equally important (Attalla et al., 2020; Roberts & Flin, 2019). In adult learning, several factors drive M-Learning adoption. Adult learners have cognitive needs to grow professionally, and during the COVID-19 pandemic, opportunities paved the way for healthcare professionals to learn new skills through M-Learning (Pokhrel & Chhetri, 2021; Wayne et al., 2020). Aside from cognitive needs, adult learners are driven by the need to interact and socialize, whether within their professional networks or their significant others (Huang, 2016). Current platforms of M-Learning improved their features to integrate ways for better interactivity to achieve social presence. While cognitive and social needs can influence the way adult learners adopt M-learning, the psychological impact of COVID-19 can influence the learning process, especially among healthcare professionals (Brand, 2020; Cedeño et al., 2021). Adults learn best through experiential learning, which is prominent in medical education (Jin et al., 2019). Through M-Learning, adult learners participate in a group where they can disclose, share and discuss emotional distress that can potentially address their affective needs (Tang & Hew, 2018). Given that cognitive, social, and affective needs are factors that can positively influence the attitude of frontline learners towards M-Learning during COVID-19, in the context of our study, we propose the following hypotheses:

H3: ***Cognitive needs has a positive and significant influence on the attitude towards M-Learning***
H4: ***Social needs has a positive and significant influence on the attitude towards M-Learning***
H5: ***Affective needs has a positive and significant influence on the attitude towards M-Learning***

In recent literature on M-Learning in healthcare education, studies have shown that TRA constructs are established predictors of the behavioral intention in its adoption. Attitude or the positive feelings about M-Learning (H1) and social norms, or the perceived influence of significant others (H2), can influence healthcare students' adoption of M-Learning. COVID-19 presents a unique context, and in the adoption of, M-Learning we hypothesized that cognitive (H3), social (H4), and affective needs (H5) are salient considerations in technology. While a few studies have integrated these factors in the behavioral intention to adopt M-Learning, these studies are mostly limited before COVID 19 and using a cohort of medical students at the university level. We summarize our five (5) hypotheses in Figure 1 – Structural Model.

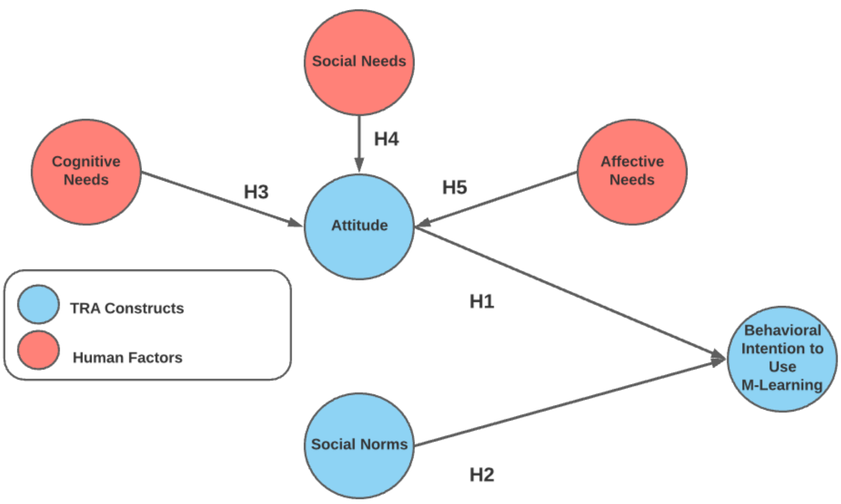

Figure 1. Structural Model.

3. Methodology

We approached three (3) HEIs currently offering a hospital management graduate degree in partnership with a healthcare professional management society to test the structural model. Students enrolled in the program are employed healthcare professionals who are physicians, healthcare administrators, nurses, laboratory staff, and other allied professionals. A total of two hundred nineteen (219) respondents provided their informed consent and answered an online survey through Google Forms.

3.1 Instrument Development

To operationalize the constructs of our structural model, we combined questions from the instrument of Hashim et al. (2014) in their study on adult learners' adoption of M-Learning and the instrument of Huang (2016) in a study investigating social factors in the continuous intention to use technology-based learning. We added questions related to demographics such as gender, age, area of practice, and devices used for M-Learning. An explanation of the study's objectives, the definition of M-Learning, and sample activities were stated at the beginning of the survey for further contextualization. The final version of the instrument consists of twenty-six (26) questions. We invited four students (4) to answer the survey to get their initial feedback. Minor modifications were made, such as the addition of Instant Messaging apps as an example of a communication tool in the social need construct and reframing questions in the social norms construct to mobile devices for further contextualization.

3.2 Validity and Reliability Tests

To further validate the instrument, we purposively selected thirty-one (31) students from the three participating HEIs to answer the survey as a pilot test. 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 1 – 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.

Table 1. *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

3.3 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. We extracted the Fornell-Larcker criterion test score from the PLS algorithm in the prior section to test discriminant validity, as shown in Table 2 – Fornell-Larcker Discriminant Validity Test. The diagonal values highlighted in bold text indicate the highest scores compared to non-diagonal values for each construct, demonstrating the absence of inter-correlation and establishing strong discriminant validity for each variable.

Table 2. *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

While the Fornell-Larcker discriminant validity test has been used in prior information systems research and found to be sufficient, recent literature highlighted its reliance on factor loading estimates necessitating a further test using Heterotrait-Monotrait or HTMT test (Hamid et al., 2017; Hair et al., 2017). We extracted the HTMT criterion scores from the PLS algorithm as shown in Table 3 - Heterotrait-Monotrait Validity Test. All values are below 0.85 except for the HTMT score of attitude and intention, which is 0.874. Traditionally, HTMT scores of 0.85 indicate 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). The results of the Fornell-Larcker and HTMT tests demonstrate strong evidence that the constructs can represent the dimensions of our structural model and are sufficient to accept or reject our given hypotheses.

Table 3. *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	

3.4 Participants and Test for Common Method Bias

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. In terms of age groups, 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 falls into the 50-59 age group. Of the sample, 26 or 12% are considered older adults. Most of the participants, 146 or 67%, are employed within Metro Manila, while 73 or 33% practice their profession in the provinces.

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 as shown in Table 4 – Test for Common Method Bias. There are no VIF values that are greater than 3.3, indicating the absence of CMB.

Table 4. *Test for Common Method Bias*

Construct	Affective Needs	Attitude	Cognitive Needs	Intention	Social Needs	Social Norms
Affective Needs		1.968				
Attitude				1.928		
Cognitive Needs		1.595				
Intention						
Social Needs		1.978				

Social Norms	1.928

4. Discussion of Results

After collecting the survey responses, a Bootstrapping technique using SmartPLS, a structural analysis technique best suited for studies with small sample sizes, was applied (Benitez et al., 2020; Schmidheiny, 2014). Specifically, we were interested in the T-Statistics values for each path to accept or reject a specific hypothesis. The results of this test are presented in Table 5 – Structural Model Test. A T-Statistics value of above 1.96 means that the relationship is significant (Hair et al., 2014).

Table 5. *Structural Model Test*

HYPOTHESIS	SD	T STATISTICS	P Values	DECISION
H1: Attitude has a positive and significant influence on the behavioral intention to adopt M-Learning	0.126	2.372	0.018	Accept
H2: Social norms have a positive and significant influence on the behavioral intention to adopt M-Learning	0.123	1.228	0.220	Reject
H3: Cognitive needs has a positive and significant influence on the attitude towards M-Learning	0.085	2.171	0.030	Accept
H4: Social needs has a positive and significant influence on the attitude towards M-Learning	0.120	4.697	0.000	Accept
H5: Affective needs has a positive and significant influence on the attitude towards M-Learning	0.126	2.372	0.018	Accept

The human factors of cognitive needs (H1), social needs (H2), and affective needs (H3) 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 H1, H2, and H3 (Hair et al., 2014). Like the findings of prior studies in adopting M-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 M-Learning in healthcare education (Alsoufi et al., 2020; Cedeño et al., 2021; 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 the M-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 frontliners (Al-Ahmari et al., 2021; Nepal, 2020).

Like the influence of cognitive needs on attitude, social and affective needs shape the perceptions of frontline learners towards M-Learning. 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). Among frontline learners, 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). Additionally, synchronous classes delivered via M-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).

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 2.372 (H1) infers that it has a direct and positive influence on the intention to use M-Learning among frontline learners (Hair et al., 2014). As discussed in the prior section, aside from meeting the cognitive needs of learners, M-Learning can facilitate social interactions and provide social support, valuable human needs that are important during this pandemic. In the context of this study, the Philippines experienced one of the most prolonged closures of academic institutions, and M-Learning supported the continuity of medical education (Cedeño et al., 2021; Pelmin, 2020). On the other hand, the T-Statistics value of 1.228 for the relationship of social norms and intention to adopt M-Learning (H2) is not supported as it does not meet the minimum value to establish significance (Hair et al., 2014). While it contradicts the other studies (Gómez-Ramirez et al., 2019; Kucuk et al., 2020), it aligns with 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; Park et al., 2021). In addition, while we find the influence to be positive but not significant, social norms may not necessarily influence students to use M-Learning as it is the only modality that the participating universities currently offer during the COVID-19 crisis. Lastly, a possible explanation is the recent exploration of subjective norms, which argue that 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).

5. Conclusion

In summary, the results of our SEM analysis confirm that the human factors of cognitive needs, social needs, and affective needs are positively related to the attitude, 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 direct influence on attitude, and influence may come from other sources, given that the participants of the study are adult learners. The study further established the applicability of TRA in IS research and confirms its flexibility to integrate external variables. M-Learning is well-researched, but COVID -19 and the involuntary shift to online modalities renewed calls to synthesize further how education can be best delivered. Given that prior studies emphasized culture and context in IS research, we contribute to the unfolding scholarship on M-Learning adoption during a pandemic through investigating the influence of human factors in its adoption, using participants from the healthcare sector, and presenting a perspective from a developing economy.

The COVID-19 situation presents a dichotomy of a threat and an opportunity for healthcare education (Brand, 2020). The unknown in medical education is always balanced by scientific curiosity. While the ongoing pandemic disrupted how healthcare professionals learn in physical classrooms and clinical settings, it is an opportune time to embrace innovative technologies as a complementary tool in healthcare education. Integrating advances in educational technologies such as virtual reality to address the lack of clinical practice and the use of telemedicine platforms to interact with patients may be a way to move forward (Remtulla, 2020). Another revelation in this study is the importance of humanizing M-Learning. Although there is an urgent need to continue medical education, universities should balance this with empathy where the well-being of learners is also considered and the pedagogical and curricular implications of M-Learning. Possible ways to further humanize M-Learning are using breakout rooms to encourage free and intimate discussions, utilizing interactive discussion boards, integrating social technologies, and implementing self-care academic breaks (Chandler, 2016; Qureshi et al., 2020; Rapanta et al., 2020).

Our study is limited by several research constraints but can guide future scholarly undertakings to understand M-Learning further. Foremost among these limitations is the small sample size. Future research can replicate our study to a randomized, nationally representative sample size to aid policymakers in deploying M-Learning. Second, we focused our attention on healthcare professionals in the Philippines; comparative studies with other countries can further contextualize our study and understand the role of culture in adopting M-Learning in medical education. Third, the quantitative results can be further explained by qualitative inquiries such as interviews or focused group discussions to shed light on the constructs of human factors and how universities can integrate our findings in deploying M-Learning platforms and crafting their academic policies. Lastly, we conducted our study during the COVID-19 pandemic; another study can be conducted after this crisis to verify whether the results are still applicable once universities revert to normalcy. The findings and the future directions of this study can help various stakeholders of healthcare education navigate through the intricacies of M-Learning as we slowly go back to where we are before this pandemic, mindful of the lessons learned in an unprecedented situation such as COVID-19.

References

Ab Hamid, M. R., Sami, W., & Mohmad Sidek, M. H. (2017). Discriminant Validity Assessment: Use of Fornell & Larcker criterion versus HTMT Criterion. Journal of Physics: Conference Series, 890(1), 3–7. https://doi.org/10.1088/1742-6596/890/1/012163

Ajzen, I. (1975). Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research. 6(2), 244. https://doi.org/10.2307/2065853

Al-Ahmari, A. N., Ajlan, A. M., Bajunaid, K., Alotaibi, N. M., Al-Habib, H., Sabbagh, A. J., Al-Habib, A. F., & Baeesa, S. S. (2021). Perception of Neurosurgery Residents and Attendings on Online Webinars During COVID-19 Pandemic and Implications on Future Education. World Neurosurgery, 146, e811–e816. https://doi.org/10.1016/j.wneu.2020.11.015

Alsoufi, A., Alsuyihili, A., Msherghi, A., Elhadi, A., Atiyah, H., Ashini, A., Ashwieb, A., Ghula, M., Ben Hasan, H., Abudabuos, S., Alameen, H., Abokhdhir, T., Anaiba, M., Nagib, T., Shuwayyah, A., Benothman, R., Arrefae, G., Alkhwayildi, A., Alhadi, A., … Elhadi, M. (2020). Impact of the COVID-19 pandemic on medical education: Medical students' knowledge, attitudes, and practices regarding electronic learning. PLoS ONE, 15(11 November), 1–20. https://doi.org/10.1371/journal.pone.0242905

Attalla, S. M., Hanafy, N. A., Akter, M., & Ruhi, S. (2020). Screening of medical students' intention to practice mobile-learning in malaysia. Malaysian Journal of Medicine and Health Sciences, 16(10), 40–45.

Azizi, S. M., & Khatony, A. (2019). Investigating factors affecting on medical sciences students' intention to adopt mobile learning. BMC Medical Education, 19(1), 1–10. https://doi.org/10.1186/s12909-019-1831-4

Baghcheghi, N., Koohestani, H. R., Karimy, M., & Alizadeh, S. (2020). Factors affecting mobile learning adoption in healthcare professional students based on technology acceptance model. Acta Facultatis Medicae Naissensis, 37(2), 191–200. https://doi.org/10.5937/afmnai2002191b

Barteit, S., Guzek, D., Jahn, A., Bärnighausen, T., Jorge, M. M., & Neuhann, F. (2020). Evaluation of e-learning for medical education in low- and middle-income countries: A systematic review. Computers and Education, 145(October 2019). https://doi.org/10.1016/j.compedu.2019.103726

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2020). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. Information and Management, 57(2), 103168. https://doi.org/10.1016/j.im.2019.05.003

Brand, P. L. P. (2020). COVID-19: a unique learning opportunity if the well-being of learners and frontline workers is adequately supported. Perspectives on Medical Education, 9(3), 129–131. https://doi.org/10.1007/s40037-020-00596-y

Buabeng-Andoh, C. (2018). Predicting students' intention to adopt mobile learning. Journal of Research in Innovative Teaching & Learning, 11(2), 178–191. https://doi.org/10.1108/jrit-03-2017-0004

Cedeño, T. D., Rocha, I. C., Ramos, K., & Uy, N. M. (2021). Learning Strategies and Innovations among Medical Students in the Philippines during the COVID-19 Pandemic. International Journal of Medical Students, 77–79. https://doi.org/10.5195/ijms.2021.908

Chandler, K. (2016). Using Breakout Rooms in Synchronous Online Tutorials. Journal of Perspectives in Applied Academic Practice, 4(3). https://doi.org/10.14297/jpaap.v4i3.216

Cruz-Cunha, M. M., & Mateus-Coelho, N. (2021). m-Learning and m-Health education applications in SARS-Cov2 Pandemic. Proceedings of 2100 Projects Association Joint Conferences – Vol.X (2020), March.

Freedman, A., & Nicolle, J. (2020). Social isolation and loneliness: the new geriatric giants. Canadian Family Physician, 66, 176–182.

Gómez-Ramirez, I., Valencia-Arias, A., & Duque, L. (2019). Approach to M-learning acceptance among university students: An integrated model of TPB and TAM. International Review of Research in Open and Distance Learning, 20(3), 141–164. https://doi.org/10.19173/irrodl.v20i4.4061

Hadadgar, A., Changiz, T., Masiello, I., Dehghani, Z., Mirshahzadeh, N., & Zary, N. (2016). Applicability of the theory of planned behavior in explaining the general practitioners eLearning use in continuing medical education. BMC Medical Education, 16(1), 1–8. https://doi.org/10.1186/s12909-016-0738-6

Hair, J. F., Hult, G., Ringle, C., & Sarstedt, M. (2014). Partial least squares structural equation modeling (PLS-SEM). In Sage Publisher. https://doi.org/10.1108/EBR-10-2013-0128

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. Industrial Management and Data Systems, 117(3), 442–458. https://doi.org/10.1108/IMDS-04-2016-0130

Hashim, K. F., Tan, F. B., & Rashid, A. (2014). Adult learners' intention to adopt mobile learning: A motivational perspective. British Journal of Educational Technology, 46(2), 381–390. https://doi.org/10.1111/bjet.12148

Heinze, N., & Hu, Q. (2009). Why college undergraduates choose IT: A multi-theoretical perspective. European Journal of Information Systems, 18(5), 462–475. https://doi.org/10.1057/ejis.2009.30

Hossain, M. N., Talukder, M. S., Khayer, A., & Bao, Y. (2020). Investigating the factors driving adult learners' continuous intention to use M-learning application: a fuzzy-set analysis. Journal of Research in Innovative Teaching & Learning, ahead-of-p(ahead-of-print). https://doi.org/10.1108/jrit-09-2019-0071

Huang, Y. M. (2016). The factors that predispose students to continuously use cloud services: Social and technological perspectives. Computers and Education, 97, 86–96. https://doi.org/10.1016/j.compedu.2016.02.016

Jin, B., Kim, J., & Baumgartner, L. M. (2019). Informal Learning of Older Adults in Using Mobile Devices: A Review of the Literature. Adult Education Quarterly, 69(2), 120–141. https://doi.org/10.1177/0741713619834726

Joaquin, J. J. B., Biana, H. T., & Dacela, M. A. (2020). The Philippine Higher Education Sector in the Time of COVID-19. Frontiers in Education, 5(October), 1–6. https://doi.org/10.3389/feduc.2020.576371

Juan, A., Frontera, G., Ap, C., Ros, I., Narváez, J., Marí, B., & Jm, N. (2020). MEDITERRANEAN JOURNAL elderly. 31(1), 42–49.

Kucuk, S., Baydas Onlu, O., & Kapakin, S. (2020). A Model for Medical Students' Behavioral Intention to Use Mobile Learning. Journal of Medical Education and Curricular Development, 7, 238212052097322. https://doi.org/10.1177/2382120520973222

Lall, P., Rees, R., Yi Law, G. C., Dunleavy, G., Cotič, Ž., & Car, J. (2019). Influences on the implementation of mobile learning for medical and nursing education: Qualitative systematic review by the digital health education collaboration. Journal of Medical Internet Research, 21(2). https://doi.org/10.2196/12895

Li, H. O. Y., & Bailey, A. M. J. (2020). Medical Education Amid the COVID-19 Pandemic: New Perspectives for the Future. Academic Medicine, E11–E12. https://doi.org/10.1097/ACM.0000000000003594

Lin, X., & Su, S. (2020). Chinese College Students' Attitude and Intention of Adopting Mobile Learning. International Journal of Education and Development Using Information and Communication Technology, 16(2), 6–21.

Maharsi, I. (2018). Developing EFL Students' Learning Reflection and Self-Regulated Learning through Google Classroom. ACM International Conference Proceeding Series, 62–66. https://doi.org/10.1145/3234825.3234841

Negrescu, V., & Caradaica, M. (2021). M-Learning and Security Issues in the Coronavirus Era. Ceeol.Com, March, 6–25. https://www.ceeol.com/search/article-detail?id=928130

Nepal, P. (2020). Eastern Green Neurosurgery. 02(01), 52–55.

Park, S., Kim, B., & Kim, K. A. (2021). Preventive behavioral insights for emerging adults: A survey during the covid-19 pandemic. International Journal of Environmental Research and Public Health, 18(5), 1–10. https://doi.org/10.3390/ijerph18052569

Pelmin, M. (2020). Readings on Coronavirus Disease (COVID-19) and the Higher Education Institution (HEIs) Emergency Preparedness in the Philippines. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3573896

Pokhrel, S., & Chhetri, R. (2021). A Literature Review on Impact of COVID-19 Pandemic on Teaching and Learning. Higher Education for the Future, 8(1), 133–141. https://doi.org/10.1177/2347631120983481

Qashou, A. (2021). Influencing factors in M-learning adoption in higher education. In Education and Information Technologies (Vol. 26, Issue 2). Education and Information Technologies. https://doi.org/10.1007/s10639-020-10323-z

Qureshi, M. I., Khan, N., Ahmad Hassan Gillani, S. M., & Raza, H. (2020). A systematic review of past decade of mobile learning: What we learned and where to go. International Journal of Interactive Mobile Technologies, 14(6), 67–81. https://doi.org/10.3991/IJIM.V14I06.13479

Rapanta, C., Botturi, L., Goodyear, P., Guàrdia, L., & Koole, M. (2020). Online University Teaching During and After the Covid-19 Crisis: Refocusing Teacher Presence and Learning Activity. Postdigital Science and Education, 2(3), 923–945. https://doi.org/10.1007/s42438-020-00155-y

Raza, S. A., Umer, A., Qazi, W., & Makhdoom, M. (2018). The Effects of Attitudinal, Normative, and Control Beliefs on M-Learning Adoption Among the Students of Higher Education in Pakistan. Journal of Educational Computing Research, 56(4), 563–588. https://doi.org/10.1177/0735633117715941

Remtulla, R. (2020). The present and future applications of technology in adapting medical education amidst the COVID-19 pandemic. JMIR Medical Education, 6(2). https://doi.org/10.2196/20190

Roberts, R., & Flin, R. (2019). The psychological factors that influence successful technology adoption in the oil and gas industry. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 63(1), 1183–1187. https://doi.org/10.1177/1071181319631105

Rose, S. (2020). Medical Student Education in the Time of COVID-19. JAMA - Journal of the American Medical Association, 323(21), 2131–2132. https://doi.org/10.1001/jama.2020.5227

Schmidheiny, K. (2014). Clustering in the Linear Model. Short Guideds to Microeconometrics - Universitaet Basel, 1–11. https://doi.org/10.1016/j.genhosppsych.2011.03.015

Senaratne, S. I., & Samarasinghe, S. M. (2019). Factors Affecting the Intention to Adopt M-Learning. International Business Research, 12(2), 150. https://doi.org/10.5539/ibr.v12n2p150

Sneddon, S., Stapleton, G., & Huser, C. (2021). Twelve tips for online synchronous small group learning in medical education. MedEdPublish, 10(1), 1–10. https://doi.org/10.15694/mep.2021.000076.1

Tang, Y., & Hew, K. F. (2018). Examining the utility and usability of mobile instant messaging in a graduate-level course: A usefulness theoretical perspective. Australasian Journal of Educational Technology, 35(4), 128–143. https://doi.org/10.14742/ajet.4571

Wayne, D. B., Green, M., & Neilson, E. G. (2020). Medical education in the time of COVID-19. Science Advances, 6(31), 4–6. https://doi.org/10.1126/sciadv.abc7110

Wilcha, R. J. (2020). Effectiveness of virtual medical teaching during the COVID-19 crisis: Systematic review. JMIR Medical Education, 6(2), 1–16. https://doi.org/10.2196/20963