Original Research Article

Novel Impact Model for Mobile Learning Adoption in Higher Education

An Assessment of Novel Impact Model for Learning adoption in Higher Education

Abstract

In successful mobile learning (ML) integration, factors associated with live-ware, software, and infrastructure are important. When the developments of the earlier ML adoption models. the researchers considered the learner and the teacher separately. The main objective of this study is to investigate and model the influencing factors for learners and teachers at once to adopt ML in higher education. The proposed model consists of five impact factors: teacher, learner, mobile devices, ML tools, ML contents, communication technologies, and higher education institutes. Then the proposed model was implemented using a modified Moodle mobile application and evaluated using 60 teachers and 60 learners attached to the University of Kelaniya, Sri Lanka in 2021. The proposed impact model was assessed as pre-test and post-test surveys using seven questionnaires. According to the Pearson correlation coefficient test, the most significant factor for learners and teachers to adopt ML is the mobile device. Learning content and communication technology were elected as the second most significant adoption factors for teachers and learners consecutively. However, higher correlation values were obtained for all factors denoting that they are greatly influenced the participant to adopt ML. The significant influencing factor of each impact factor was also investigated. In conclusion, it was discovered that featured smart devices, quality learning content, user-satisfied communication technology, academic enriched ML tools and higher education institutes with sound educational facilities are crucial for the university community to adopt ML in higher education. These findings help design academic community acceptable ML environments for higher education context.

The author should state the research design employed and also add at least one of the recommendations made as an aspect of the abstract.

Keywords: mobile learning, teacher, learner, higher education, impact model, influencing factors.

1. Introduction

Expeditious advancements in technologies affect mobile device-based technologies such as computing power of mobile devices, connectivity, storage, memory, and many more. On the other hand, nowadays, various reasons demand mobile learning (ML) such as learning while working, on the way learning, situated learning, self-learnability, independent and flexible learning, ability to use augmented learning, and public health requirement classroom-based learning. ML is a subset of electronic learning, and it more effective than conventional personal computer-based electronic learning when considering mobility, portability, and technology evolution. Mobile learners can carry on academic activities through portable devices such as smartphones, tablet computers, and other portable computing devices (Sönmez, et al., 2018). In ML, learner pursue academic activities through mobile devices by studying contents in multimedia, taking assignments and exams, involving group chats and forum posts with colleagues, plying games integrated academic tasks, doing mobile devices enable situated learning activities, and etc. (Miglani & Awadhiya, 2017) On the other hand, teacher or instructor able to provide teaching services through mobile devices by developing learning content integrating study materials in multimedia, setting exams and assignments, collaborating learners via chats and forums, and etc. (El-Sofany & El-Haggar, 2020) However, in ML learner and teacher should have several qualities for successful ML such as acceptance, readiness, device ownership, affordability, eagerness, affordability, trustworthy, attitude, behavioral intention, self-efficacy, technology self-efficacy, and etc. (Chao, 2019), (Hamidi & Chavoshi, 2018) According to the past studies, teachers and learners ML involvement decides several other factors such as mobile device (Dolawattha, et al., 2020), learning tools (Dolawattha, et al., 2021), ML content, communication technology, and hosting higher education institute (Dolawattha, et al., 2020). Previous researchers conduct a significant amount of studies to investigate learners' and teachers' requirements, improve attitudes, and other factors in the successful implementation of ML in education. They have developed several ML models that can be used to utilize ML productively. This study's primary purpose is to create a ML adoption impact model that intends to develop an applicable and sustainable ML framework for higher education. As the study's contribution, the authors proposed a ML adoption model for learners and teachers in an applicable and sustainable ML environment in higher education using impact factors mobile device, ML tools, ML content, communication technology, higher education institute. The paper organization as follows: The literature review section describes previous research related to ML and ML-associated models. Also, it accumulates the artifacts for formulating the proposed model. The following impact model and hypothesis section represent the model creation and hypothesis generation. The system used in this study is described under the section system function and architecture. The subsequent sections are methodology, results, discussion, and conclusion and implication. (**Expunge as they are not necessary**)

2. Literature review

Learners' and teachers' ML adoption depends on several impact factors. The mobile device is one of the dominant factors for ML adoption. Researches highlighted that the device features such as screen size (Naylor & Sanchez, 2018), (Park, et al., 2018), supportive software (Patel, 2018), (Dibbari & Dangata, 2018), (Arnold, et al., 2016), device's hardware functionalities (Farhad & MacKenzie, 2018), (Jo, et al., 2018), (Aiyoshizawa & Komuro, 2017), etc. are essential for ML adoption. Learners and teachers facilitate and influence for adopting ML with various ML tools such as mobile applications (Pappas, et al., 2017), push notifications (Wang, et al., 2017), chat applications (Calvo, et al., 2017), forum interactivity (Sebbowa & Muyinda, 2018), SMS (Ziden, et al., 2017), and gamification (Brull, et al., 2017). ML content impacts for learner and teacher to adopt ML, because ML content has facilities helpful learner and teacher (Baldwin & Ching, 2020) with, easy to use (Zhonggen, et al., 2019), interactive (Kukulska-Hulme & Lee, 2019), authenticate (Almaiah & Mulhem, 2019), and device independence (Baldwin & Ching, 2020). Also, various factors in communication technology services such as cost (Yusufu & Nathan, 2016), connectivity (Budiman, et al., 2017), and facilities (Arun & Prabu, 2017) impact for adopting ML. Finally, higher education institute's ML policy (West & Vosloo, 2013), facilities (Kaliisa, et al., 2019), and decision for using technologies (Osakwe, et al., 2017) impact ML adoption.

Various ML models developed in previous studies can be identified. Influencing factors for learners to adopt ML were determined using the Unified theory of acceptance and use of technology (UTAUT) model. The learners' intention to use ML is influenced by their expectance of enactment and exertion and communal impression (Alshraideh & Al-Shrida, 2017). A complete ML model was developed to support the implementation of the technology-based learning environment. The model was implemented through the national e-learning strategy and helped rectify several local m-learning challenges (Al-Hunaiyyan, et al., 2017). Cultural variances in a country affect ML adoption. A UTAUT based model was developed to estimate the level of ML adoption. Performance and effort of users, facilities, device features, and activities affect learner's attitude to using ML. While their performance and effort, social factors, and facilities positively influence adopting ML (Mosunmola, et al., 2018). Instant technology learning in the Science museum environment was tested using the UTAUT model. It revealed that the relationships in UTAUT original constructs were moderate according to the age and gender of the research sample of selected 118 staff personals. While self-directedness does not help adopt ML technology in the museum (Welch, et al., 2020). Another research was carried out with 820 higher education students through TAM to find practical factors for adopting ML. It revealed that easiness and cognitive satisfaction are the highest controlling impact factors for adopting ML in the considered domain. Mobile learners prefer to carry out academic activities in social network-enabled, enjoyable, and collaborative learning environments (Aburub & Alnawas, 2019). Effective factors and their relationship in adopting ML for undergraduate students in health studies were researched. Technology acceptance model (TAM) based study was carried out using 310 learners. The results revealed that the target learners accepted ML satisfactory and original TAM constructs were major causes for ML acceptance (Baghcheghi, et al., 2019). Innovation diffusion theory (IDT) was joined to model of innovation resistance (MIR) to develop an intergraded model for investigating learners struggling to adopt ML. The research was conducted using 493 university students revealed that Learners' resistance reflects their intention to use ML and intervenes benefit, difficulty, and will to use ML (Kim, et al., 2017). A requirement model for teaching and learning through ML was developed. This was considered various pedagogical and education requirements when using ML stream in a higher educational environment.

Moodle, Schoology, and Blackboard were used as sample applications for this model, and the proposed model can be used to evaluate ML applications for testing user satisfaction, teaching, and learning needs (Sarrab, et al., 2018). A country in the middle east region was researched for ML adoption utilizing academic knowledge dissemination via the Concern Based Adoption Model (CBAM). Two hundred thirty-eight users participated in the evaluation, and they confirmed mobile learning-based training is crucial for obtaining academic achievement using mobile technology (Al Masarweh, 2019). Different research is carried to develop a model for ML adoption in a non-state higher education institute. The model is developed by integrating the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and Theory of Planned Behavior. Six hundred forty students who participated in the evaluation emphasized the ML applications with better standard digital learning content (Rataj & Wójcik, 2020). A study was conducted to investigate and model the influence of mobile phone utilization in education. Also, evaluate critical factors for adopting and applying a self-developed ML system. The evaluation was done using 300 students to confirm that context should be easy to use and valuable. Further, its easiness depends on the usefulness. However, ML behavioral intention is not depending on personal characteristics, with ease of use and usefulness. But individual trust is vital for intent to use ML (Hamidi & Chavoshi, 2018).

As shown in table 1, in previous ML models, researchers consider only learners' or teachers' ML adoption. Also, they have not been implemented through the learning system all the time. They were also evaluated using only learners or teachers and not done parallel evaluation using both categories simultaneously. Moreover, these models are developed based on well-known technology acceptance models and theories. Therefore, an exciting research gap has been set in previous studies in ML model developments' research. In this study, to address this research gap, the researchers consider both learner's and teacher's ML adoption with other impact factors such as mobile device, ML tools, ML content, communication technology, higher education institute. The proposed ML adoption model is also implemented via Moodle ML application and evaluated using both learners and teachers concurrently.

Table 1: Comparison for similarities and differences of the proposed model with some previous ML adoption models

Description	Implementation	Tools or models used	Sample size
Influencing factors for adopting ML for learners and teachers (Proposed model)	Modified Moodle mobile app	Results of previous studies	60 teachers and 60 students at the University
Influencing factors for adopting ML (Alshraideh & Al-Shrida, 2017)	No	UTAUT model	70 University students
Estimating effects of cultural variances in ML adoption (Mosunmola, et al., 2018)	No	UTAUT model	700 Undergraduate students
Investigating factors of Science Museum group staff to adopt ML (Welch, et al., 2020)	No	UTAUT model	118 staff personals
Testing the intention to adopt ML in higher education (Aburub & Alnawas, 2019)	No	TAM model	820 university students
Investigating learner's resistance to adopt ML (Kim, et al., 2017)	No	IDT, MIR	493 university student
A requirement model for teaching and learning in higher education through ML (Sarrab, et al., 2018)	No	DeLone and McLean, frameworks for content design	
Staff members ML adoption were researched (Al Masarweh, 2019)	No	Concern Based Adoption Model (CBAM)	238 higher education staff members
ML adoption in non-state higher education institute (Rataj & Wójcik, 2020)	No	TAM, UTAUT, and TPB	640 higher education students.
Modeling the influence of mobile phone utilization in education (Hamidi & Chavoshi, 2018)	No	TAM model with other several theories	300 university students

3. Impact model and hypothesis

In this article, the model was developed to describe the factors that depend on learners' and teachers' ML adoption in the applicable and sustainable ML framework. Mainly five observed variables are identified with the ML adoption to elaborate the proposed model by literature. These observed variables (influencing factors or impact factors) are mobile devices, ML tools, ML contents, Communication technologies, and Higher education institutes (see Figure 1).

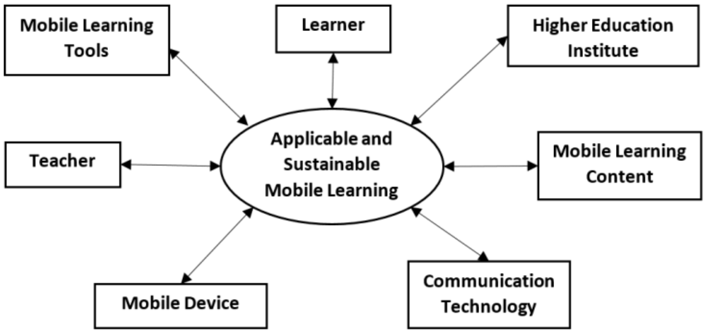

Figure 1: The proposed model with main impact factors

3.1. Learner and teacher in mobile learning

Mobile learners connect to learning systems using mobile apps in mobile devices anytime from anywhere to use educational resources and collaborate with peer learners and teachers inside or outside the classrooms. They can follow digital content and pursue learning activities at their own pace, durations, and learning styles. On the other hand, a teacher attached to ML facilitates learners by creating mobile device enable digital learning materials. In this medium, the teacher empowers various ML tools to utilize academic services to learners (Hoi & Mu, 2020). This study used the results of our research was conducted to develop an impact model for influencing factors of learners and teachers to adopt ML in applicable and sustainable ML (Dolawattha, et al., 2018), (Dolawattha, et al., 2019) (see Figure 2).

3.2. Mobile devices

The mobile device is an essential factor for adopting ML in higher education. Because its various features support learners and teachers for academic activities. Screen size is an important feature that decides the usability of devices for adopting ML (Chae & Kim, 2004) and the lowest screen size for better persuasion in academic transactions is 4.3 inches (Raptis, et al., 2013). Support software is another feature in mobile devices that bear creative utilization, security, and authentication of the device for learning (Khaddage, et al., 2011). Another exciting feature is screen zooming direct involve for device usability by enhancing readability and visibility (Garcia-Lopez, et al., 2015). The video playback control feature helps users by switching facilities of the video and data usage in ML (Pan, et al., 2012). Another device feature controls usability is the touch screen keyboard, and it evolves day by day (Yatani & Truong, 2009). One of the useful features for learning associated with the device is language predictive tools. It speeds up the text inputs in touch screen keyboards by providing typing aids (Rădescu & Pupezescu, 2016). This study used the results of our research was conducted to develop an impact model for influencing factors of learners and teachers to adopt mobile devices in applicable and sustainable ML (Dolawattha, et al., 2020) (see Figure 2).

H_{1a}: Mobile devices positively affect teacher to adopt applicable and sustainable mobile learning system.

H_{1b}: Mobile devices positively affect learner to adopt applicable and sustainable mobile learning system.

3.3. Mobile learning tools

When developing content for ML and pursuing academic activities ML tools also essential. Hence ML tools are significant for adopting ML. The mobile application is a vital ML tool as it holds all the background utilities and necessities for ML. Push notification helps alert learners to provide dissimilar information inside the current learning surroundings (Gan & Balakrishnan, 2016). Chat and forum are valuable tools that can be used in ML. Chat is a synchronous communication medium, while a forum is an asynchronous communication for mobile learners. Learners and teachers can chat and forum for academic activities collaboratively as well as interactively. A short message service (SMS) is another tool that enables learning purposes via mobile devices. Around 160-character length text message can send and recipient capable of getting voice conversion as audio (Premadasa & Meegama, 2016). Mobile gamification is an influential learning tool that helps teachers to prepare learning materials integrating games. These learning materials influence learners to study enthusiastically (Wu, 2018). This study used the results of our research was carried out to develop an impact model for influencing factors of learners and teachers to adopt ML tools in applicable and sustainable ML (Dolawattha, et al., 2021) (see Figure 2).

H_{2a}: Mobile learning tools positively affect teacher to adopt applicable and sustainable mobile learning system

H_{2b}: Mobile learning tools positively affect learner to adopt applicable and sustainable mobile learning system

3.4. Mobile learning contents

Learning content is a significant factor for pursuing teaching and learning activities in ML. Facilitating conditions such as availability of multimedia content creation (Moldovan, et al., 2017), edutainment content creation (Barrena, et al., 2016), navigations with simple menus, and video guides are helpful. Also, limited clicks for navigating, manageable fragments of content with limited words, highlighted keywords, light images are recommended for past information retrieval in mobile interfaces. Ease of use content influence learner to use ML in learning. It depends on flexibility and collaborative peer connectivity (Alrasheedi & Capretz, 2015). Ease of use ML content leads to learner satisfaction, performance, lower cognitive loads (Zhonggen, et al., 2019). Interactivity in learning content makes better use of devices for collaboration. Interactive learning content, especially video-based learning advantages learners lower cognitive learning, high productivity, and learning enthusiasm (Kazanidis, et al., 2018). Authenticate features of ML content ensure accuracy, security, and ownership of the ML content. Proper authentic ML content leads to enhance learners' trust and usage of ML (Almaiah & Mulhem, 2019). Device independence is a ML content feature that enables devices to function with different device specifications. Device-independent content supports devices with varying screen sizes, functionalities for device holding style, platforms, operating system, etc., for steady and stable learning performance (Baldwin & Ching, 2020). This study used the results of our research was conducted to develop an impact model for influencing factors of learners and teachers to adopt ML content in applicable and sustainable ML (Dolawattha, et al., 2020) (see Figure 2).

H_{3a}: Mobile learning contents positively affect teacher to adopt applicable and sustainable mobile learning system

H_{3b}: Mobile learning contents positively affect learner to adopt applicable and sustainable mobile learning system

3.5. Communication technology

Communication technology is a significant factor for mobile learning adoption. Cost is a considerable aspect for learners and teachers to utilize communication technology in ML. Latest technologies such as cloud computing are the best solution for reducing costs for communication technology and infrastructure in ML (Yusufu & Nathan, 2016). For better ML adoption, institutional policy should address the cost-related issues such as cost for devices, infrastructure, and data (Parajuli, 2016). Connectivity has a higher priority in communication technology for ML. Connectivity properties such as upload and download speed, stableness, packet loss, etc., are required to match the standard for better ML transactions (Budiman, et al., 2017). Facilitating conditions associate with communication technology such as assistance when needed, awareness, sharing (Parajuli, 2016), and storage facilities in cloud computing are very useful for uninterrupted teaching-learning services in ML. This study used the results of our research was conducted to develop an impact model for influencing factors of learners and teachers to adopt ML using communication technology in applicable and sustainable ML (Dolawattha, et al., 2020) (see Figure 2).

H_{4a}: Communication technology positively affects teachers to adopt applicable and sustainable mobile learning systems.

H_{4b}: Communication technology positively affects teachers and learners to adopt applicable and sustainable mobile learning systems.

3.6. Higher Education Institute

The ML hosting higher education institute is a significant factor for learning through mobile devices. Because in ML the hosting institute is responsible for the skill or the qualification obtained by the learner via mobile devices. Also, higher education institute enables ML is different than conventional learning institutes as it needs to facilitate technology for learners to obtain certifications and teachers to provide services. The institutional policy needs to be prioritized teacher development, content development, optimized connectivity, personalized device usages, promoting health factors, and awareness (West & Vosloo, 2013). For superior ML, HEIs need to be enhanced by facilitating better technical facilities (Kaliisa, et al., 2019). Stakeholders' acceptance to change is a key requirement in ML adoption. Especially administrators' positive attitude for ML is significant than the better institutional ML policy. Therefore, the learning system expects staff's most full support to have ML integration (Osakwe, et al., 2017), (Adresi, et al., 2020). This study used the results of our research was conducted to develop an impact model for influencing factors of learners and teachers to adopt ML using higher education institutes in applicable and sustainable ML (Dolawattha, et al., 2020) (see Figure 2).

H_{5a}: Higher Education Institute positively affects teacher to adopt applicable and sustainable mobile learning system.

H_{5b}: Higher Education Institute positively affects learner to adopt applicable and sustainable mobile learning system.

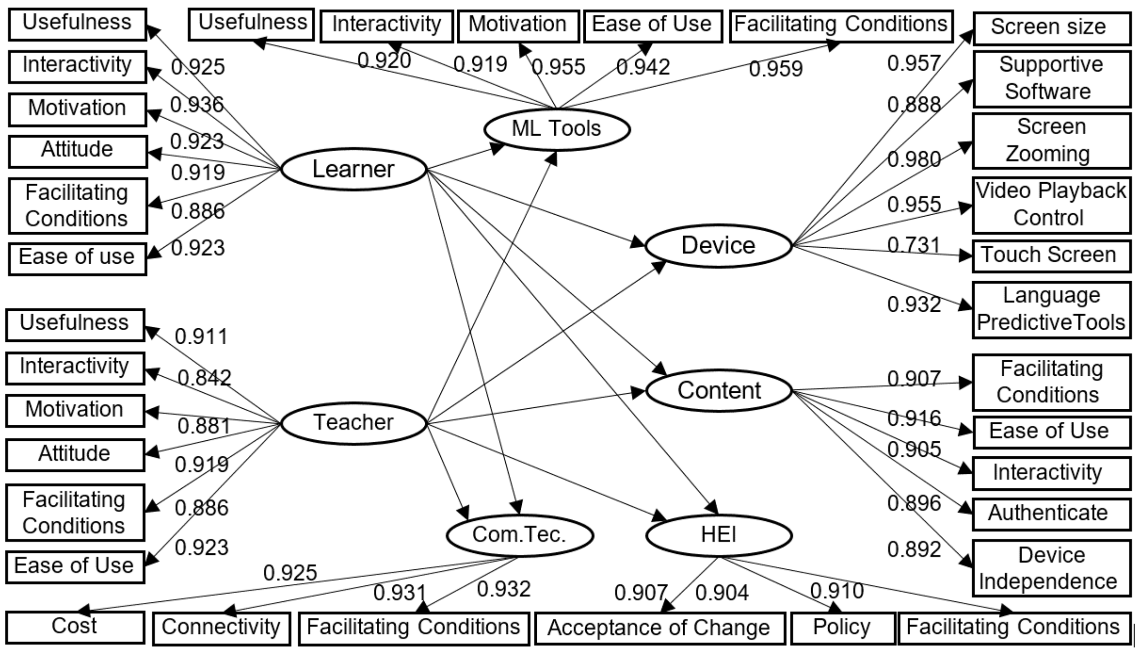

Figure 2: Proposed impact model for learner and teacher to adopt ML in higher education

4. System function and architecture

In this study, Moodle mobile app (MMA) was used by modifying and integrating various functionalities. MMA is the mobile version of the Moodle open-source learning management system (MLMS). HTML, PHP, JavaScript, ionic, MySQL, and Cordova/PhoneGap mobile application development framework are the technologies used to develop the MMA. New functionalities can be integrated into MMA through a plugin (Dougiamas, 2019). For that, the plugin should be designed to MLMS, and then it requires to enable MMA by creating support files using PHP. Existing Moodle plugins also can allow MMA to by using the same approach. In this study, few plugins were enabled by developing support files such as annotate PDF, Checklist, Hot question, Games (i.e., Millionaire, Hangman, Quizventure), etc. (Dolawattha, et al., 2019)

5. Methodology

Sixty learners and sixty teachers participated in the research. All participants represent faculties of Science, Social Sciences, Humanities, and commerce and management at a state university. Five different questionnaires were developed for evaluating five impact factors of the proposed impact model, i.e., Mobile Devices, ML Tools, ML Contents, Communication Technologies, and Higher Education Institute. The same questionnaire in each impact factor was used for both learners and teachers. When developing questionnaires, different influencing factors of each impact factor were considered. 6 influencing factors were considered to the mobile device impact factor, i.e., Screen size, Supportive Software, Screen Zooming, Video playback control, Touch screen keyboard, and Language Predictive Tools. The questionnaire for the impact factor mobile device consists of 24 questions. Each influence factor consists of 4 questions. 5 influencing factors were considered to the ML tools impact factor, i.e., usefulness, interactivity, motivation, facilitating conditions, and ease of use. The questionnaire for the impact factor ML tools consists of 20 questions. Each influence factor consists of 4 questions. 5 influencing factors were considered to the ML content impact factor, i.e., facilitating conditions, ease of use, interactivity, authentication, and device independence. The questionnaire for the impact factor ML content consists of 20 questions, with each influence factor consists four questions. Three influencing factors were considered to the higher education institute impact factor, i.e., policy, facilitating conditions, and acceptance of the change. The questionnaire for the impact factor higher education institute consists of 12 questions, with each influence factor consists four questions. Three influencing factors were considered to the communication technology impact factor, i.e., cost, connectivity, and facilitating conditions. The questionnaire for the impact communication technology consists of 6 questions, with each influence factor consists 2 questions. First of all, each questionnaire was given to both learners and teachers as a pre-test survey. Then they were allowed to use the modified Moodle mobile app. Finally, they were asked to respond to the questionnaire again as the post-test survey.

Another two separate questionnaires were developed for evaluating influencing factors of learner and teacher. When creating a questionnaire for the learner, six influencing factors were considered, i.e., usefulness, interactivity, motivation, attitude, facilitating condition, and ease of use. Each influencing factor consists of 4 questions, and the questionnaire for the learner contains 24 questions. The teacher impact factor was described using six influencing factors, i.e., usefulness, interactivity, motivation, attitude, facilitating conditions, and ease of use. The teacher questionnaire was used 24 questions with four questions for each influencing factor. Next, two separate surveys were also conducted for learners and teachers. First, learners and teachers were given two particular questionnaires separately to respond as a pre-test survey. Then they were allowed to use the modified Moodle mobile app. Finally, they were asked to respond to the individual questionnaires as a post-test survey. The five-point Likert scale ranging from -10 – strongly disagree, -5 – disagree, 0 – neutral, 5 – agree, and 10 – strongly agree was used in these questionnaires.

In this study, 60 valid pairs of pre-test and post-test questionnaires were selected for each impact factor in the proposed ML adoption model. i.e., Teacher, Learner, Mobile Devices, ML Tools, ML Contents, Communication Technologies, and Higher Education Institute. The primary data analysis was done using mean values of bar charts and the Anderson-Darling Normality Test. The paired sample *t*-test and the correlation model with the Pearson correlation coefficient were developed as advanced data analysis.

The author should state the type of research design employed in this study

6. Results and discussion

Anderson-Darling Normality (ADN) test was employed on overall post-test survey responses with Likert scales as shown in Table 2 as primary data analysis.

Table 2. Likert scale data conversion

Questionnaire Answers	Value
Strongly Disagreed	-10
Disagreed	-5
Neutral	0
Agree	5
Strongly Agree	10

Table 3. Likert mean interpretation

Likert Mean	Interpretation

Less than -5	The proposed system strongly rejected by the university education community
Between -5 and 0	The proposed system normally rejected by the university education community
0	Neutral
Between 0 and 5	The Proposed system normally accepted by the university education community
Greater than 5	The proposed system strongly accepted by the university education community

The overall post responses mean is equal to 6.9707, P-value <0.005, and the confidence interval is (6.8978, 7.2310). According to the Table 3, this implies that the university teachers and learners have firmly accepted the ML system developed based on the proposed model. The data set is normally distributed and can apply a parametric test on the data set. Mean is within the Confident interval and mean accepted under 0.05 significant level. As shown in Table 4, the means of each attribute of post responses, i.e., Mobile Devices, ML Tools, ML Contents, Communication Technologies, and Higher Education Institute, were calculated.

Table 4. Means of each attribute in the post-test survey

Attribute	Mean for teacher	Mean for learner
Mobile Devices	6.234	7.514
ML Tools	6.123	6.208
ML Contents	7.113	6.945
Communication Technologies	7.024	7.360
Higher Education Institute	6.911	6.417

As shown in Table 4, each attribute's mean values are greater than 5 for both teacher and learner. This denotes that the university community accepted the proposed ML adoption factors with the modified MMA. Likewise, impact factors of the proposed model in ML adoption for teachers and learners were accepted. As the data set is normally distributed (ADN test results) and the number of data sets exceeds 30, the paired sample *t*-test (parametric test) was applied to pre-test and post-test data sets as an advance analysis. The hypothesis was set as follows in this test.

$H_{0x} : \mu = 0$ VS $H_0 : \mu > 0$ Where, x= 'a' or 'b',

H_{0a}=Mobile Devices/ML Tools/ML Contents/Communication Technologies/Higher Education Institute does not affect teacher to adopt an applicable and sustainable ML system.

H_{0b}=Mobile Devices/ML Tools/ML Contents/Communication Technologies/Higher Education Institute does not affect learner to adopt an applicable and sustainable ML system.

Table 5. Paired sample *t*-test results

Factor	Teacher		Learner	
	Mean value	P-value	Mean value	P-value
Mobile Devices	6.234	0.000	7.514	0.000
ML Tools	6.123	0.000	6.208	0.000
ML Contents	7.113	0.000	6.945	0.000
Communication Technologies	7.024	0.000	7.360	0.000
Higher Education Institute	6.911	0.000	6.417	0.000

As shown in Table 5, the paired sample *t*-test results in a p-value of each factor equal to 0.000 (<0.005). This implies that the H_{0x} is rejected and H_{1x} is accepted. Also, the mean value greater than zero. Therefore, the result of the paired sample *t*-test denotes that the Mobile Devices, ML Tools, ML Contents, Communication Technologies, and Higher Education Institute affect teachers and learners to adopt applicable and sustainable ML.

Finally, the Pearson correlation coefficient was calculated to describe the correlation in the proposed impact model. The weight and counts are used for students' responses and the rules shown in Table 6. are used to interpret the correlation coefficients.

Table 6. Correlation coefficient interpretation rules

Correlation coefficient	Positive	Negative
0.0 – 0.3	No correlation	No correlation
0.3 – 0.5	Week positive correlation	Week negative correlation
0.5 – 1.0	Strong positive correlation	Strong negative correlation

$H_{0x}: \rho = 0$ VS $H_{1x}: \rho \neq 0$ where x='a' or 'b'

The above hypotheses tests were applied with p-values, and these hypotheses were rejected at 0.05 significant levels when the test p-values are less than 0.05. The Pearson correlation coefficient test between student response weight and counts calculated using the MINITAB computer application for Windows, and the results were summarized as shown in Table 7.

Table 7. Pearson correlation coefficient test results

Variable	Teacher		Learner	
	Correlation	p-value	Correlation	p-value
Mobile Devices	0.931	0.011	0.941	0.010
ML Tools	0.859	0.017	0.856	0.017
ML Contents	0.901	0.014	0.913	0.012
Communication Technologies	0.842	0.018	0.915	0.012
Higher Education Institute	0.834	0.020	0.851	0.017

According to the test results, each p-value is less than 0.05 denotes that the H_0 is rejected and - H_1 is accepted. Therefore, it implies that the Mobile Devices, ML Tools, ML Contents, Communication Technologies, and Higher Education Institute positively affect teachers and learners to adopt applicable and sustainable ML. Also, each variable's correlation greater than 0.5 and close to 1. According to the correlation interpretation rules shown in Table 6, each observed variable of the proposed impact model is strongly correlated with the learner and teacher to adopt ML. Finally proposed impact model with correlations is shown in Figure 3. The results reveal that teachers' and learners' most significant factors in adopting ML are mobile devices.

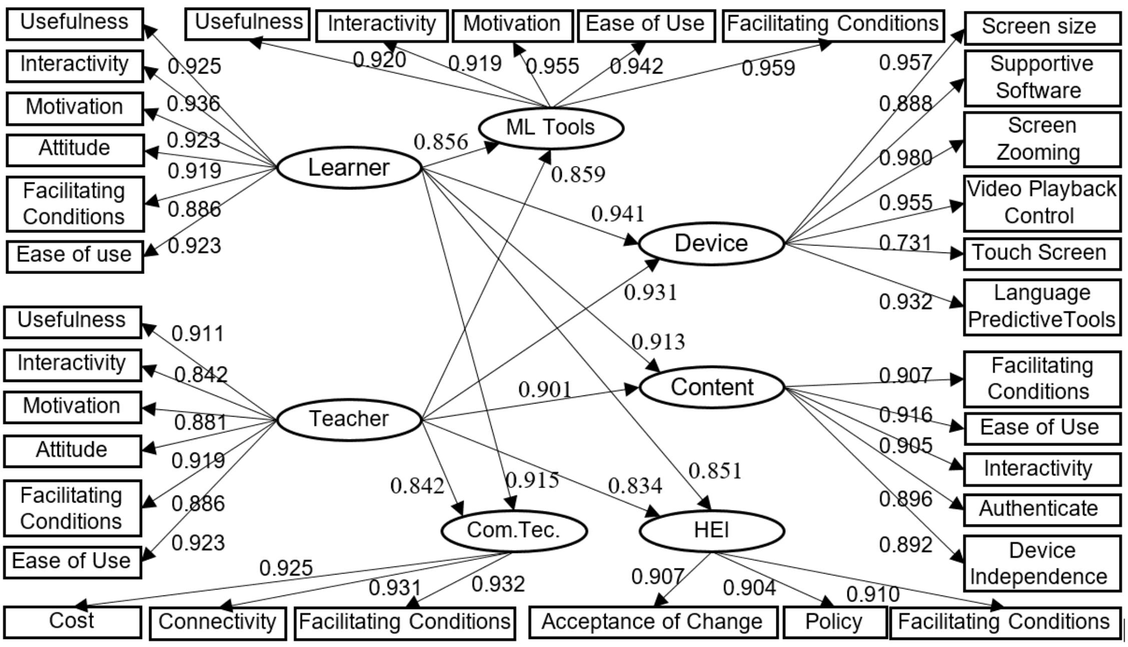

Figure 3: Influencing factors on ML adoption for learner and teacher in the proposed model with correlations

According to the Pearson correlation coefficient test results, though the mobile device is the most significant factor for both learner and teacher to adopt ML, the learner has a better correlation value than the teacher (0.941>0.931). This implies that the learner has more significant interaction with mobile devices when adopting ML. The reason for this may be the younger generation, like learners, prefer to use cutting-edge mobile devices than teachers. The teacher's next most correlated factor is ML content, while communication technology is the second most correlated for the learner. However, ML content almost similar value is showing for learners compared to communication technology. This situation can be clarified as both learners' and teachers' ML involvement heavily depend on ML content. Also, learners concern more about communication technology-related factors such as connectivity and cost for data and other infrastructure. However, teachers do not worry much about communication technology because institute they involved bears facilitating communication technology for teaching via mobile devices. When considering the overall results of this study, each influencing factor reported similar and higher correlation values. This can be interpreted as learners' and teachers' better engagement in ML ensured significance of impact factors selected, i.e., Mobile Devices, ML Tools, ML Contents, Communication Technologies, and Higher Education Institute. These results partially confirm the results obtained by Hamidi & Chavoshi (2018). They revealed that mobile learning contents' easy-to-use and usefulness features significantly affect a leaner's mobile learning adoption.

7. Conclusion and implication

Today mobile learning is an important learning mechanism as it ensures successful learning under social health issues and busy lifestyles of learners and teachers. This study's primary purpose is to investigate influencing factors and develop an impact model for learners and teachers to adopt mobile learning in higher education. The proposed model consists of 7 impact factors, i.e., Teacher, Learner, Mobile Devices, Mobile Learning Tools, Mobile Learning Contents, Communication Technologies, and Higher Education institutes. The proposed model was implemented using a modified Moodle mobile app. The implemented model was evaluated with 60 university learners and 60 university teachers with seven different questionnaires. According to the Pearson correlation coefficient test, the most significant factor for learners and teachers to adopt mobile learning in higher education is the mobile device. Teachers consider the mobile learning content as the second-best factor for mobile learning adoption, while learners decide communication technology is influenced more for adopting mobile learning. Finally, it can be concluded that featured smartphones, user satisfied and reached learning content, user satisfied communication technology are significant for mobile learning adoption of the university community. Besides, other factors considered, such as Mobile learning tools and higher education institutes, are also significant for learners and teachers to adopt mobile learning in higher education as they received higher and similar correlation values compared to other factors. The mobile learning systems developers, designers, and administrators can use these outputs to develop productive mobile learning systems because such systems adhere to the educational preferences of both academic communities: learners and teachers.

8. Future prospects

The model needs to evaluate using more samples to represent other higher educations as this mobile learning framework was developed for entire higher education on the Island.

References

Aburub, F. & Alnawas, I., 2019. A new integrated model to explore factors that influence adoption of mobile learning in higher education: An empirical investigation. *Education and Information Technologies,* 24(3), pp. 2145-2158.

Aiyoshizawa, T. & Komuro, T., 2017. *Comparative study on text entry methods for mobile devices with a hover function.* Stuttgart, ACM, pp. 355-361.

Al Masarweh, M., 2019. Evaluating m-learning system adoption by faculty members in saudi arabia using concern based adoption model (cbam) stages of concern. *International Journal of Emerging Technologies in Learning (iJET),* 14(5), pp. 153-164.

Al-Hunaiyyan, A., Al-Sharhan, S. & Alhajri, R., 2017. A new mobile learning model in the context of the smart classrooms environment: a holistic approach. *International Journal of Interactive Mobile Technologies (iJIM),* 11(3), pp. 39-56.

Almaiah, M. . A. & Mulhem, A. A., 2019. Analysis of the essential factors affecting of intention to use of mobile learning applications: A comparison between universities adopters and non-adopters. *Education and Information Technologies,* 24(2), pp. 1433-1468.

Alrasheedi, M. & Capretz, L. F., 2015. Determination of critical success factors affecting mobile learning: a meta-analysis approach. *Turkish Online Journal of Educational Technology,* 14(2), pp. 41-51.

Alshraideh, R. S. & Al-Shrida, R. S., 2017. Factors Affecting the Adoption of Mobile Learning by Jordanian University Students Based on UTAUT Model. *NG-Journal of Social Development,* 417(5806), pp. 72-80.

Arnold, K. C., Gajos, K. Z. & Kalai, A. T., 2016. *On suggesting phrases vs. predicting words for mobile text composition.* Tokyo,, ACM, pp. 603-608.

Arun, C. & Prabu, K., 2017. *Applications of Mobile Cloud Computing: A Survey.* Madurai, International Conference on Intelligent Computing and Control Systems (ICICCS) 2017.

Baghcheghi, N., H. . R., Mahmood , K. & Alizadeh, S., 2019. Factors affecting mobile learning adoption in healthcare professional students based on technology acceptance model. *Acta facultatis medicae Naissensis,* 32(2), pp. 191-200.

Baldwin, S. J. & Ching, Y.-H., 2020. Guidelines for Designing Online Courses for Mobile Devices. *TechTrends,* 64(3), pp. 413-422.

Barrena, N., Navarro, A. & Oyarzun, D., 2016. *A Flexible and Easy-to-Use Platform to Create Advanced Edutainment Applications.* s.l., s.n., p. 291–300.

Brull, S. et al., 2017. Using Gamification to Improve Productivity and Increase Knowledge Retention During Orientation. *The Journal of nursing administration,* 47(9), pp. 448-453.

Budiman, E., Haryaka, . U., Watulingas, J. R. & Alameka, F., 2017. *Performance Rate for Implementation of Mobile Learning in Network.* Yogyakarta, Indonesia, Proc. EECSI 2017.

Calvo, R., Iglesias, A. & L. C., 2017. Evaluation of accessibility barriers and learning features in m-learning chat applications for users with disabilities. *Universal Access in the Information Society,* 16(3), pp. 593-607.

Chae, M. & Kim, J., 2004. Do size and structure matter to mobile users? An empirical study of the effects of screen size, information structure, and task complexity on user activities with standard web phones. *Behaviour & information technology,* 23(3), pp. 165-181.

Chao, C.-M., 2019. Factors Determining the Behavioral Intention to Use Mobile Learning: An Application and Extension of the UTAUT Model. *Frontiers in psychology,* Volume 10, p. 1652.

Church, K. & Oliveira, R. d., 2013. *What's up with WhatsApp?: comparing mobile instant messaging behaviors with traditional SMS.* Munich, Germany, s.n., pp. 352-361.

Dibbari, C. J. & Dangata, J. N., 2018. The impact of Microsoft word on office technology and managements. *Knowledge Review,* 37(2), pp. 82-87.

Dolawattha, D., Pramadasa, H. S. & Jayaweera, P. M., 2019. The Impact Model: Teachers' Mobile Learning Adoption in Higher Education. *International Journal of Education and Development using Information and Communication Technology (IJEDICT),* 15(4), pp. 71-88.

Dolawattha, D., Premadasa, H. S. & Jayaweera, P. M., 2018. *Modelling the Learner's Perspectives on Mobile Learning in Higher Education.* Colombo, IEEE, pp. 133-141.

Dolawattha, D., Premadasa, S. & Jayaweera, P. M., 2020. *Mobile Learning: Modelling the Influencing Factors on Mobile Devices.* Colombo, IEEE, pp. 1-2.

Dolawattha, D., Premadasa, S. & Jayaweera, P. M., 2020. *The Influence on Mobile Learning: Mobile Learning Contents, Higher Education Institutes, and Communication Technology.* Colombo, s.n.

Dolawattha, D., Premadasa, S. & Jayaweera, P. M., 2021. Modelling the Influencing Factors on Mobile Learning Tools. *International Journal of Information and Communication Technology Education (IJICTE),* 17(4).

Dougiamas, M., 2019. *Moodle mobile customization.* [Online]
Available at: https://docs.moodle.org/dev/Moodle_Mobile_Customization
[Accessed 18 12 2019].

El-Sofany, H. F. & El-Haggar, N., 2020. The effectiveness of using mobile learning techniques to improve learning outcomes in higher education. *International Journal of Interactive Mobile Technologies (iJIM),* 14(8), pp. 4-18.

Farhad, M. & MacKenzie, I. S., 2018. *Evaluating Tap-and-Drag: A Single-Handed Zooming Method.* s.l., Springer, pp. 233-246.

Gan, C. L. & Balakrishnan, V., 2016. An empirical study of factors affecting mobile wireless technology adoption for promoting interactive lectures in Higher Education. *Internal review of research in open and distributed learning,* 17(1).

Garcia-Lopez, E., de-Marcos, L., Garcia-Cabot, A. & Martinez-Herraiz, J.-J., 2015. Comparing zooming methods in mobile devices: effectiveness, efficiency, and user satisfaction in touch and nontouch smartphones. *International Journal of Human-Computer Interaction,* Volume 31, p. 777–789.

Hamidi, H. & Chavoshi, A., 2018. Analysis of the essential factors for the adoption of mobile learning in higher education: A case study of students of the University of Technology. *Telematics and Informatics,* 35(4), p. 1053–1070.

Hoi, V. N. & Mu, G. M., 2020. Perceived teacher support and students' acceptance of mobile-assisted language learning: Evidence from Vietnamese higher education context. *British Journal of Educational Technology,* 52(1), p. e13044.

J. A. T., Adresi, A. A. & Mahmud, F., 2020. Impact of Information System and Blockchain on Organizational Learning Effectiveness. *International Journal of Emerging Technologies in Learning (iJET),* 15(11), pp. 89-101.

Jo, S.-W., Yoo, W. & Chung, J.-M., 2018. Video Quality Adaptation for Extended Playback Time on Mobile Devices With Limited Energy. *IEEE Communications Letters*, 22(6), pp. 1260-1263.

Kaliisa, R., Palmer, E. & Miller, J., 2019. Mobile learning in higher education: A comparative analysis of developed and developing country contexts. *British Journal of Educational Technology,* 50(2), pp. 546-561.

Kazanidis, I., Palaigeorgiou, G., Papadopoulou, A. & Tsinakos, A., 2018. Augmented Interactive Video: Enhancing Video Interactivity for the School Classroom. *Journal of Engineering Science and Technology Review,* 11(2), pp. 174 - 181.

Khaddage, F., Lattemann, C. & Bray, E., 2011. *Mobile apps integration for teaching and learning. Are teachers ready to re-blend?.* s.l., Association for the Advancement of Computing in Education (AACE), pp. 2545--2552.

Kim, H.-J., Lee, J.-M. & Rha, J.-Y., 2017. Understanding the role of user resistance on mobile learning usage among university students. *Computers & Education,* p. 108e118.

Kukulska-Hulme, A. & Lee, H., 2019. Mobile Collaboration for Language Learning and Cultural Learning. In: *The Handbook of Informal Language Learning.* s.l.:Wiley Online Library, pp. 169-180..

Miglani, A. & Awadhiya, A. K., 2017. Mobile learning: readiness and perceptions of teachers of Open Universities of Commonwealth Asia. *Journal of learning for development-JL4D,* 4(1), pp. 58-71.

Moldovan, A.-N., Ghergulescu, I. & Muntean, C. H., 2017. *Analysis of Learner Interest, QoE and EEG-based Affective States in Multimedia Mobile Learning.* Timisoara, Romania, s.n.

Mosunmola, A., Mayowa, A., Okuboyejo, S. & Adeniji, C., 2018. *Adoption and use of mobile learning in higher education: the UTAUT model.* s.l., s.n., pp. 20-25.

Naylor, J. S. & Sanchez, C. A., 2018. Smartphone Display Size Influences Attitudes Toward Information Consumed on Small Devices. *Social Science Computer Review,* 36(2), pp. 251-260.

Osakwe, J., Dlodlo, N. & Jere, N., 2017. Where learners' and teachers' perceptions on mobile learning meet: A case of Namibian secondary schools in the Khomas region. *Technology in Society,* Volume 49, pp. 16-30.

Pan, J. (., Li, L. & Chou, W., 2012. *Real-time collaborative video watching on mobile devices with rest services.* s.l., IEEE, pp. 29-34.

Pappas, I. O., Cetusic, L., Giannakos, M. N. & Jaccheri, L., 2017. *Mobile learning adoption through the lens of complexity theory and fsQCA.* s.l., IEEE.

Parajuli, K. P., 2016. Mobile Learning Practice in Higher Education in Nepal. *Open Praxis,* 8(1), p. 41–54.

Park, E. et al., 2018. *Effects of Screen Size in Mobile Learning Over Time.* New York, ACM.

Patel, Z. D., 2018. *Malware Detection in Android Operating System.* s.l., IEEE, pp. 366-370.

Premadasa, H. S. & Meegama, R., 2016. Two-way text messaging: an interactive mobile learning environment in higher education. *Research in Learning Technology,* Volume 24.

Rădescu, R. & Pupezescu, V., 2016. *Text prediction techniques based on the study of constraints and their applications for intelligent virtual keyboards in learning systems.* s.l., IEEE, pp. 1-8.

Raptis, D., Tselios, N., Kjeldskov, J. & Skov, M., 2013. *Does size matter?: investigating the impact of mobile phone screen size on users' perceived usability, effectiveness and efficiency.* s.l., s.n., pp. 127-136.

Rataj, M. & Wójcik, J., 2020. The mobile learning adoption model tailored to the needs of a private university. *Electronic Journal of E-Learning,* 18(4), pp. 310-322.

Sarrab, M., Al-Shihi, H., Al-Manthari, B. & Bourdoucen, H., 2018. Toward educational requirements model for Mobile learning development and adoption in higher education. *TechTrends,* 62(6), pp. 635-646.

Sebbowa, D. K. & Muyinda, P. B., 2018. Sebbowa, D.K. and Muyinda, P.B., 2018. The utilisation of a Mobile Phone Forum on the Winksite application in the teaching and learning of History: a case study of Pre-service Teachers at Makerere University. *Yesterday and Today,* Volume 20, pp. 124-147.

Seraj, M. & Wong, C. Y., 2014. Lecturers and Students' Perception on Learning Dijkstra's Shortest Path Algorithm Through Mobile Devices. *International Journal of Interactive Mobile Technologies,* 8(3), pp. 19-24.

Sönmez, A., Göçmez, L., Uygun, D. & Ataizi, M., 2018. A Review of Current Studies of Mobile Learning. *Journal of Educational Technology & Online Learning,* 1(1), pp. 13-27.

Wang, J. et al., 2017. The usability of WeChat as a mobile and interactive medium in student-centered medical teaching. *Biochemistry and Molecular Biology Education,* 45(5), pp. 421-425.

Welch, R., Alade, T. & Nichol, L., 2020. Using the unified theory of acceptance and use of technology (utaut) model to determine factors affecting mobile learning adoption in the workplace: a study of the science museum group. *IADIS International Journal on Computer Science & Information Systems,* 15(1), pp. 85-98.

West, M. & Vosloo, S., 2013. *UNESCO policy guidelines for mobile learning,* s.l.: UNESCO .

Wu, Y.-L., 2018. Gamification design: A comparison of four mlearning courses. *Innovations in Education and Teaching International,* 55(4), pp. 470-478.

Yatani, K. & Truong, K. N., 2009. *SemFeel: a user interface with semantic tactile feedback for mobile touch-screen devices.* s.l., ACM, pp. 111-120.

Yusufu, G. & Nathan, N., 2016. Cloud-Based Mobile Learning for Higher Education in Nigeria: A Review. *Adamawa State University Journal of Scientific Research,* 4(1), pp. 13-22.

Zhonggen, Y., Ying, Z., Zhichun, Y. & Wentao, C., 2019. Student satisfaction, learning outcomes, and cognitive loads with a mobile learning platform. *Computer Assisted Language Learning,* 32(4), pp. 323-341.

Ziden, A. A., Rosli, M., Gunasegaran, T. & Azizan, S. N., 2017. Perceptions and Experience in Mobile Learning via SMS. *International Journal of Interactive Mobile Technologies,* 11(1).