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Factors Influencing Students' Acceptance of M-Learning in Higher Education: An Application and Extension of the UTAUT Model

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Abstract: The goal of this study was to develop a new model and conduct confirmatory factor analysis to learn more about how students use M-learning in higher education. The study is theoretically based on the unified theory of acceptance and use of technology (UTAUT) theory and the technology acceptance model (TAM). Theoretically, the factors related to the adoption of M-learning in higher education, identified as contributory to perceived ease of use, perceived usefulness, and attitudes towards M-learning and actual use of M-learning, were analyzed. A questionnaire survey was distributed to 362 university students who were randomly selected. Structural Equation Modeling (SEM)-AMOS was used for data analysis. Based on the findings, M-learning appears to be one of the most promising educational technologies for development in educational environments. Perceived facilitating conditions, performance expectancy, effort expectancy, social influence, and perceived enjoyment have a significant positive effect on the perceived ease of use and perceived usefulness, while performance expectancy has a negative effect on the perceived ease of use. Perceived ease of use and perceived usefulness have a positive and significant effect on attitudes towards using M-learning and actual use of M-learning. Therefore, we recommend lecturers encourage students to utilize M-learning for educational purposes in higher education.

Keywords: M-learning; unified theory of acceptance and use of technology; technology acceptance model; structural equation modeling (SEM)

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1. Introduction

In recent years, M-learning systems have become an essential instrument for students and educators alike [1]. In any case, anywhere and in any way, an M-learning platform can provide quick access to learning resources and learner knowledge, thereby opening up pioneering and novel options for the management and delivery of creative learning services [2,3]. M-learning is an essential element of higher learning and education. As one of the most recent technologies used to improve learning and teaching performance, M-learning is a key tool for students and instructors. By using M-learning, such as smartphones, students can be provided with real-time learning and university services [4,5]. Through the development of internet technology, M-learning enables students to learn how to cooperate and communicate their ideas. On the other hand, M-learning is important for the M-learning developed by students and tutors. The determination of students and educators is an important factor in accepting or refusing M-learning [6,7]. While the delivery of learning facilities is now predictable for M-learning, many of the universities' initiatives have been a key step in M-learning [8–10]. However, technical and non-technical hurdles remain, especially for students' utilization and adoption of M-learning [11]. Several studies have shown that the issues of M-learning continue to exist [12–14]. In addition, existing researchers and mobile providers do not clearly understand the needs and requirements of M-learning users. In fact, acceptance of M-learning by students is a critical step towards ensuring the effective adoption of the system in higher education [15,16]. The necessary determinants affecting students' adoption of M-learning systems are, therefore, understanding and identification. In addition, the required time and effort are costly for the implementation and deployment of any information system. Scholars of information systems are always working to discover the factors that influence a system's adoption in order to assure its sustainability [17,18]. In order to achieve this goal, several information system models were developed. These criteria are usually combined into one model to effectively analyze the use and acceptance. Among these, the technology acceptance model, which was developed by [19] as mentioned by [17,20], has been one of the most widely adopted models for evaluating the acceptability of information technologies so far due to its versatility. The technology acceptance model has proven to have undergone many changes and developments in terms of M-learning, which has resulted in increased M-learning adoption. A technology acceptance model with a unified theory of acceptance and use of technology [19,21], which was developed to investigate the acceptance of computers in a workplace context, incorporates a unified theory of acceptance and use of technology factors with the technology acceptance model as key constructs in this model. Some of these factors are facilitating conditions (FC), performance expectancy (PEX), effort expectancy (EEX), social influence (SI), perceived enjoyment (PE), perceived usefulness (PU), perceived ease of use (PEOU), attitude towards using (ATM), and actual use of M-learning (AUML). These studies did not identify all the main factors that can impact students" M-learning adoption. Shin and Kang [22] stated that in the last decades, M-learning was frequently confined to the use of M-learning, but today in this field, students' mobility is dominant. According to Koole et al. [23], M-learning strengthens and increases the capability of learners to engage and obtain knowledge over mobile or smart wireless devices. Mobile phones are the best and most common technology for learning. Multi-tasking is potentially the principal reason since mobile phones are equipped with functionalities such as video recording, photography, and SMS, etc. [24]. This appears to be the most complete description of M-learning, which is defined as the achievement of information, assertiveness, and skills via the use of mobile devices at any time and anywhere that will cause fluctuations in the actual use of M-learning. Park [25] investigated the use of M-learning in traditional schooling in Singapore in 2001 and discovered that the information-quick response technique was beneficial. In this instance, learning information is shown on a device, and students' behavioral reactions form a loop called "Sense and respond". In addition, Thornton and Houser [26] state that the essential support for M-learning environments demonstrates the influence of M-learning in enhancing knowledge transfer and feedback systems. A smart classroom is positioned in the center of the surrounding area and can assist conventional classroom activities through computers and mobile phones [27,28]. This technique contains a suggestive structure that allows the instructors to adapt and improve their teaching methods in response to the system's instructions. Students found interactive learning to be both entertaining and informative, and academics agreed that the use and execution of the learning background are appropriate for academic purposes [28]. However, as smartphone devices and M-learning became more common, institutions began to create M-learning apps to provide students with immediate access to learning resources. Moreover, the adoption rate of M-learning applications among students is very high in schools, but the students' acceptability level of M-learning is still quite low [29]. The digitalization of university education has transformed the conventional picture of universities and shaped the demand for higher institutions and learning [30]. According to Yeap et al. [31], the use of higher education M-learning can offer a range of basic apps based on traditional instruction to complicated systems that are specially constructed for M-learning. Miloevi et al. [32] argue that the development of higher education methods is becoming increasingly important and crucial in M-learning. As mentioned by [33], M-learning is effective for the academic environment as there are no limitations on schedulability and location that facilitate the process of learning for students in multiple contexts. Despite previous research demonstrating several benefits of M-learning, M-learning has not been successful in all universities due to differences in student attitudes and institutional culture.

In addition, Raza et al. [34] studied the variables affecting M-learning for higher learning in Jordan and determined that the use of M-learning for students is positive due to the facilitation conditions, perceived ease of use and perceived usefulness. A recent study by Al-Adwan et al. [35] found that M-learning adoption is acceptable in Jordan as a developing country in terms of facilitating conditions and social influence factors.

M-learning is the most recent trend in educational technology. It makes learning elastic, ambulant, unrestricted, distinctive, and inspirational by utilizing mobile gadgets such as tablets, smart phones, iPads, and other portable devices [36,37]. Mobile devices are employed to acquire a flexible, accessible, and superior learning environment, which researchers have classified as an extension of Electronic Learning (E-learning) [38]. M-learning, according to Abu-Al-Aish and Love [39], is "any learning that takes place via wireless mobile devices such as smart phones and tablet PCs that can travel with the learners to allow learning anytime, anywhere". There are several advantages to utilizing M-learning. Wireless contact between students and their peers, on the one hand, and between students and their lecturers, on the other hand, is one of these advantages [39]. Students can also use M-learning to access learning resources, share ideas with others, and engage actively in a collaborative learning environment. It also aids them in acquiring feedback, value, and direction from teachers [40]. There are a plethora of qualities associated with M-learning. The most significant qualities of M-learning are ubiquity, which allows learners to access technology from any location at any time, and mobility, which refers to learning while on the move [40]. Today, M-learning is becoming increasingly popular. It is used by students and teachers to complete their everyday activities in a flexible and comfortable manner. Many universities across the world have reacted to current technology by implementing it in order to give and assist learning at all times and in a variety of ways [41]. M-learning has a number of definitions. M-learning, according to [2], is a new learning technology that allows learners to conduct their educational tasks more simply by using mobile devices to access learning resources (lectures, courses, duties, quizzes and exams). M-learning is defined by [42] as a learning technique in which objects and materials essential for learning are supplied utilizing mobile devices, allowing anybody to access them from anywhere. M-learning, as a technical effort, has shown a number of promising advantages in the sphere of higher education. It has aided in the creation of an educational environment free of time and space constraints, hence increasing the efficiency and efficacy of learning [43]. This research highlighted the unified theory of acceptance and use of technology and technology acceptance model factors while also providing new information on user acceptance and the usage of M-learning. M-learning plays a crucial role in increasing the quality of learning and study activities for university students in the twenty-first century, not just for high-school students but also for school students. However, no previous research has examined students' attitudes towards M-learning and their plans to use it for digital learning in Saudi Arabian higher education. As a result, this research aimed to develop a new model and conduct confirmatory factor analysis to learn more about how students use M-learning in Saudi Arabia's higher education.

2. Theoretical Background

2.1. M-Learning Acceptance

User adoption of the system is essential to guarantee the achievement of any system in Information Systems (IS). Therefore, the factors influencing students' adoption of M-learning systems are important to recognize and assess. Several studies have found that M-learning systems are currently being adopted and that contemporary researchers and mobile service providers understand the needs and requirements of M-learning in a comprehensive way [14,44]. Adoption of a new technology or system is the first step towards its successful application [19,45]. Although there are numerous theoretical frameworks and models associated with technology acceptance, M-learning acceptance by students can be achieved, such as the technology acceptance model, unified theory of acceptance and use of technology and the Theory of Planned Behaviour (TPB). In order to examine the students' adoption of M-learning in the Jordan region, Almaiah et al. [3] empirically evaluated the technology acceptance model with the addition of factors, which are quality of learning, interaction, functionality, user interface design, convenience, customization, and quality of content design. The study showed that the acceptance of M-learning applications by learners has a positive influence on quality.

Huang et al. [46] proposed the technology acceptance model to study the determinants promoting the use of M-learning among students. Resistance to change and attachment have been shown by empirical results to have an important influence on the behavior of M-learning apps. The technology acceptance model has been used by Aburub and Alnawas [4] in Jordan to explore the acceptance of M-learning. They found that the primary considerations for M-learning among students are cognitive gratification and ease of use. While the adoption of M-learning does not include determinants such as personal integrative gratification, hedonic gratification, and perceived usefulness, although several studies have evaluated M-learning acceptance and adoption, less research has looked at the major aspects that influence the acceptance of M-learning from the point of view of students. Moreover, there is no comprehensive model of existing literature about the important factors that allow university students to accept an M-learning system.

2.2. Unified Theory of Acceptance and Use of Technology

Consistent with the literature, numerous models and theories have been established to study the acceptance of new technology by users and their intentions to use it, for example, Davis et al. [19] created a technology acceptance model [21,47], while the theory of planned behavior (TBP) was created by [48]. Other researchers have adopted, amended, and validated every model and theory to gain insight into the acceptability and use of technology and predict it [21]. Many researchers have looked into these models in a similar way [21]. In comparison with other related models and theories of information system and information technology (IS/IT) acceptance, researchers revealed that the unified theory of acceptance and use of technology has the greatest capacity for explanation. Almaiah et al. [2] claimed the unified theory of acceptance and use of technology to be the widely used model for technology acceptance and to concentrate on the technology factors that help implement information systems successfully. Several studies have reported the same idea. For example, Jawad and Hassan [49] found that the unified theory of acceptance and use of technology is among the most extensively adopted research models for users to anticipate and accept data systems and technologies based on certain factors. Finally, a meta-analysis conducted by Walldén et al. [50] found the unified theory of acceptance and use of technology to be an effective model grounded on considerable empirical evidence. The researchers therefore chose the unified theory of acceptance and use of technology for this study and developed a conceptual model to establish a strong foundation to describe why students accept or reject M-learning. Hence, the unified theory of acceptance and use of technology supports this study theoretically, and thus we develop a research framework.

3. Research Model

As already stated, factors such as acceptability, intent to be used, and adoption must be taken into account so as to ensure the effective execution of M-learning applications in higher education [51]. Acceptance evaluations for students are regarded as a critical issue for success in M-learning, including student requirements, system requirements, and student service qualities and observations [52]. Several determinants studied by researchers and found effective can prevent M-learning from being accepted by students in M-learning perspectives. This study has developed a research model, incorporating eight factors derived from the technology acceptance model and unified theory of acceptance and use of technology model analysis. The model proposed as displayed in Figure 1 seeks to examine how different elements can contribute to the acceptance and usage of M-learning by learners. The study results showed [53,54] that the students' attitude to the use of M-learning affects their PE, SI, and facilitating conditions. Furthermore, Nasuora [55] extended the unified theory of acceptance and use of technology to examine the acceptance of M-learning in higher education. In general, M-learning has been significantly influenced by effort expectations, performance expectancy, and social influence. Moreover, Alasmari and Zhang [56] extended unified theory of acceptance and use of technology to look at the acceptability of M-learning in various Saudi universities, in line with the above research. The results showed that the student's behavioral intent on M-learning was decisively determined by effort expectancy, performance expectancy, and the characteristics of the social influence of M-learning. In addition, earlier literature studies examined the effects of several factors on M-learning acceptance by students. These studies do not cover every factor contributing to the acceptability of M-learning for students, despite these findings. The study findings encourage the authors to conduct this study and to look at eight elements associated with facilitating conditions, perceived enjoyment, effort expectancy, social influence, perceived usefulness, perceived ease of use, perceived enjoyment, and the attitudes towards the predictions of acceptance towards M-learning. The sections below provide a thorough review of the proposed hypotheses for this study.

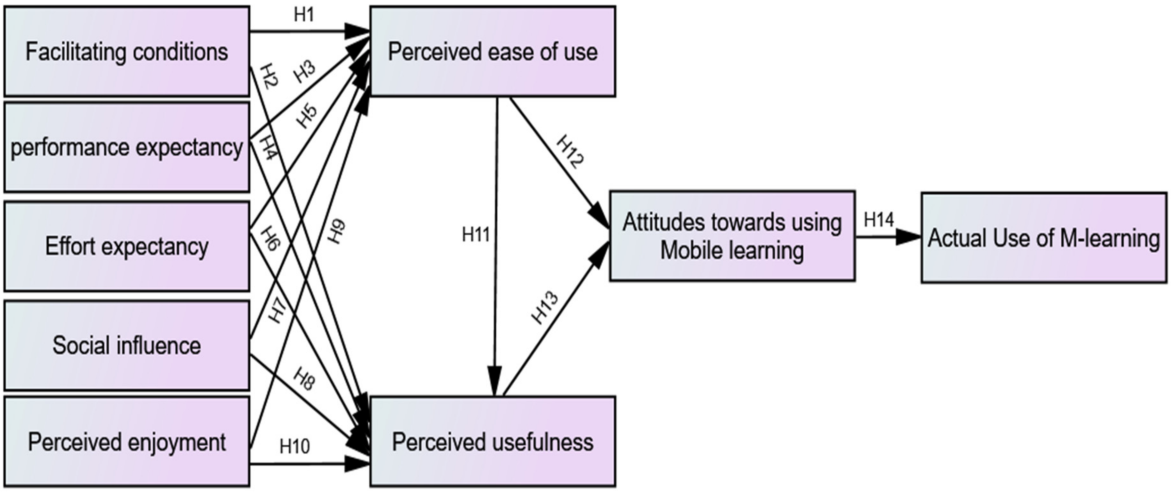

Figure 1. Research model.

3.1. Facilitating Conditions (FC)

Facilitating conditions tend to mean "a user's perception of the resources and support that can be used to perform a task" [57]. The unified theory of acceptance and use of technology model was significantly affected by these facilitating conditions [21,58]. Studies have found a relationship between facilitating conditions and online public services. For instance, in a study on the adoption of M-learning [59,60], they adopted the unified theory of acceptance and use of technology and confirmed that perceived usefulness and perceived ease of use in the adoption of M-learning were useful to facilitating conditions. The authors thus develop the hypothesis that:

Hypothesis H1. *Facilitating conditions have a significant influence on the perceived usefulness of M-learning.*

Hypothesis H2. *Facilitating conditions have a significant influence on the perceived ease of use of M-learning.*

3.2. Performance Expectancy (PEX)

Performance expectancy (PE) is "the extent to which a technology benefits the user in a particular activity" [21]. In order to anticipate the intention to use information and communications technology systems, the variable perceived enjoyment is commonly integrated with the unified theory of acceptance and use of technology [55]. In order to investigate the use of M-learning in South Korea, Sung et al. [59] used the unified theory of acceptance and use of technology and the results show that performance expectancy is associated with behavioral intention. The same trend was found in [61,62]. The unified theory of acceptance and use of technology model has been implemented by other researchers [63,64], which supports the idea that perceived enjoyment, perceived usefulness, and perceived ease of use are interlinked. Consequently, it is hypothesized that:

Hypothesis H3. *Performance expectancy has a significant influence on the perceived usefulness of M-learning.*

Hypothesis H4. *Performance expectancy has a significant influence on the perceived ease of use of M-learning.*

3.3. Effort Expectancy (EEX)

Effort expectancy is the "level of effort that a student believes they have for a certain task" [57]. It is an essential component of the unified theory of acceptance and use of technology theory and is extensively used to investigate users' intentions to adopt new technologies [46,47]. Sung et al. [59] found that M-learning acceptability was influenced by effort expectancy in South Korea. Constantly, Kaliisa et al. [61] revealed that the effort expectancy is associated with perceived usefulness and perceived ease of use. Several studies [63,65] adopted the unified theory of acceptance and use of technology and found the idea that effort expectancy, perceived usefulness, and perceived ease of use are closely related. As a result, for this study, the following hypothesis is proposed:

Hypothesis H5. *Effort expectancy has a significant influence on the perceived usefulness of M-learning.*

Hypothesis H6. *Effort expectancy has a significant influence on the perceived ease of use of M-learning.*

3.4. Social Influence (SI)

Social influence is "the degree to which consumers feel other people should use a particular technology" [57]. Social influence is the third component of the unified theory of acceptance and use of technology model, and several studies have found it very useful. In others, the results indicate that the relationship is not significant. According to Kaliisa et al. [61], social influence was found as a significant factor for M-learning acceptance. However, we did not find any good indication of South Korean users' M-learning acceptability [66]. The influence may vary from time to time and country to country and is also culturally dependent. Thus, the authors proposed the hypothesis that:

Hypothesis H7. *Social influence has a significant influence on the perceived usefulness of M-learning.*

Hypothesis H8. *Social influence has a significant influence on the perceived ease of use of M-learning.*

3.5. Perceived Enjoyment (PE)

Perceived enjoyment is an essential motivation to indicate how much fun IT, or an IS, can bring. According to Park, Son, and Kim [67], perceived enjoyment is defined as "the extent that, in addition to any performance effect caused by system use, the activity of utilizing a particular system is evaluated as pleasurable by itself." Therefore, in this study, we investigated the positive and negative effects of perceived enjoyment on M-learning. As previous research has demonstrated the impact of perceived enjoyment on system use [68–70], the external factor most commonly used in the technology acceptance model is perceived enjoyment. Perceived enjoyment is a key external element influencing the perceived usefulness, perceived ease of use, and users' intentions toward an IS. Nevertheless, few studies have investigated whether perceived enjoyment is an important outer element in the unified theory of acceptance and use of technology model. Perceived usefulness and perceived ease of use were presented in the technology acceptance model in the unified theory of acceptance and use of technology as the two most appropriate predictors derived from perceived usefulness and ease of use. We, therefore, maintain that a significant positive impact on perceived enjoyment and effort expectancy is perceived to be enjoyed with the use of M-learning. Thus, the hypotheses are suggested on the basis of this discussion:

Hypothesis H9. *Perceived enjoyment has a significant influence on perceived usefulness of M-learning.*

Hypothesis H10. *Perceived enjoyment has a significant influence on perceived ease of use of M-learning.*

3.6. Perceived Usefulness (PU)

Perceived usefulness is "one of the most common and well-accepted factors for accepting a technology acceptance model-based technology and is used in many acceptance and adjustment models for new technology" [19,71]. Perceived usefulness is "defined as a level of belief in the use and improvement of the performance of a particular system" [22,72]. According to Althunibat [33], defining the degree to which the system is dependent on an individual's performance improvements in a specific field is difficult. Perceived usefulness signifies a level of confidence regarding M-learning that this will result in improved individual outcomes or learning consequences [73]. Perceived usefulness is also defined as the degree to which a student believes that a mobile phone will help them accomplish educational goals [66,74,75]. The benefits for students of M-learning are many, and they can control their learning environment better [75]. Students think M-learning is useful because it improves their studies and facilitates cooperation with teachers and classmates, leads to improved productivity and quality of learning, and helps them achieve their learning goals anytime, anywhere, and without delay [76]. According to [57], perceived ease of use is similar to perceived usefulness in the technology acceptance model and is defined as a certain level of individual belief that using the system will help them achieve the objectives. The perceived usefulness of M-learning demonstrates that M-learning benefits from the opportunity provided by M-learning for users to quickly access information at any time and place [32]. Students will adopt M-learning technology if they believe it will improve their performance [77]. Many similar studies [14,63] have been carried out on the technology acceptance model that support the idea that there is a strong connection between perceived utility and convenience and attitudes to use. The hypothesis is therefore suggested:

Hypothesis H11. *Perceived usefulness has a significant influence on the perceived ease of use of M-learning.*

Hypothesis H12. *Perceived usefulness has a significant influence on attitudes towards using M-learning.*

3.7. Perceived Ease of Use (PEOU)

Perceived ease of use is one of the major and repeating factors in technology acceptance [19,71]. In the technology acceptance model, this factor was raised and widely used. Perceived ease of use "is defined as a degree of confidence in the fact that it does not take effort to use a specific system" [19]. Furthermore, Joo et al. [66] pointed out that the perceived ease of use is a student's belief that a device can be used without particular difficulty. In the context of M-learning, the perceived ease of use combines ease of use, flexibility, and the M-learning system interface with ease of access to information [76] and concentrates on the ability of users to learn how to utilize a system [73]. According to Venkatesh et al. [57], the effort expectancy has a degree of system easiness, similar to the perceived ease of use in the technology acceptance model. Students should consider that M-learning satisfies their requirements and aims to improve the system's efficiency [32]. Indeed, if students find it easy to use the technology, they will accept it [77]. Furthermore, technology that is simpler to use is more useful for users under the same conditions [74]. We, therefore, maintain that the perceived easiness of M-learning has significant and positive effects on M-learning attitudes. The following hypotheses were suggested on the basis of this discussion:

Hypothesis H13. *Perceived ease of use has a significant influence on the attitudes towards using M-learning.*

3.8. Attitudes towards Using (ATM)

An attitude is an emotional and psychological entity describing the beliefs and state of mind of a person formed by experience. The behavior of a person is primarily the good or bad feelings of an individual about the effects of certain behaviors [34]. It is a person's socially conditioned attitude regarding a value that is the consequence of a sensitive action directed at a person, position, issue, or event (the object of an attitude). Some studies suggest that the attitude of a learner toward M-learning affects his behavior with regard to using the system [78,79]. The individual's attitude to a particular behavior is equal to the overall view of the person's actions [80]. The following hypothesis is therefore proposed by this study:

Hypothesis H14. *Attitudes towards using M-learning have a significant influence on actual use of M-learning.*

4. Research Methodology

The study's analysis was grouped into two parts to effectively achieve the research objectives. The first step included the collection of data via a questionnaire from university students. The study examined how M-learning can affect M-learning in higher education, together with attitudes towards using M-learning and its actual usage. In this study, the students in higher education were undergraduates and graduates from universities. The respondents were from various IT school departments such as information systems and management, engineering, and social science. Those who are currently using the M-learning system are included. In this regard, the study's participants may be able to assist us in responding to the survey's questions. The survey used a five-point Likert scale, and this Likert scale is supposed to be more perfect than the five-point Likert scale [66]. Our research has moved on to the next stage. The collected data were evaluated with AMOS Structural Equation Modeling and SPSS. Construct validity, convergent validity, and discriminant validity were tested in the structural model that was suggested for this form [81].

4.1. Participants

Gender, age, specialization, and M-learning application usage were all included in the demographic profile section of the survey. The demographic profile of respondents is shown in Table 1.

Table 1. Demographic profile.

Items	Description	N	%	Cumulative %
Gender	Male	257	71.0	71.0
	Female	105	29.0	100.0
Age	18–22	40	11.0	11.0
	23–28	108	29.8	40.9
	29–34	146	40.3	81.2
	35–40	56	15.5	96.7
	41 and above	12	3.3	100.0
Specialization	Social Science	36	9.9	9.9
	Engineering	541	14.9	74.6
	Science and Technology	80	49.7	59.7
	Management	80	22.1	96.7
	Others	12	3.3	100.0
Use _ AUML	Several times a day	273	75.4	75.4
	Once a day	52	14.4	89.8
	Several times in a month	30	8.3	98.1
	Once a month	7	1.9	100.0

4.2. Data Collection Method

A questionnaire survey was used in this study as part of a quantitative strategy. Data collection was accomplished through an online survey of university students; see the Appendix A. A total of 370 questionnaires were sent to the students; however, owing to the huge number of missing values, eight questionnaires were deleted. As a result, 362 valid questionnaires were chosen, with a response rate of 97.5 percent. The sample size of the study is N = 361 and is satisfactory as recommended by [81], in that the quantitative research should be the least number of samples (N = 354). Table 1 demonstrates the respondents' information.

4.3. Measurement Instruments

This portion provides the measurement scales for all variables of the study adopted from past M-learning and information systems and information technology expert opinion studies. As we can see from Table 2, for example, effort expectancy, social influence, perceived enjoyment and facilitating conditions items were adopted from [21], while measuring perceived usefulness, perceived ease of use, and perceived enjoyment, items from [57,82,83] were used. Finally, the attitude toward M-learning and actual use of M-learning were adapted from [21], as shown in Table 2—constructs, items, and outer loading.

4.4. Evaluation of The Research Model

In this study, we employed structural equation modeling to evaluate the relationships between eight constructs and the actual use of M-learning. First, we conducted a reliability test using Cronbach's Alpha. After that, we assessed the measurement validity using convergent and discriminant validity analysis. For the model-fit test, we used confirmatory factor analysis (CFA). Lastly, path analysis was assessed to observe the proposed hypotheses and path coefficients among the constructs.

Table 2. Constructs, items, and outer loading.

Construct	Items	Outer Loading	References
Facilitating Conditions (FC)	FC 1	0.84	[84,85]
	FC 2	0.70	
	FC 3	0.83	
	FC 4	0.85	
	FC 5	0.85	
Performance Expectancy (PEX)	PEX 1	0.84	[84,86]
	PEX 2	0.83	
	PEX 3	0.86	
	PEX 4	0.81	
	PEX 5	0.78	
Effort Expectancy (EEX)	EEX 1	0.77	[84,85]
	EEX 2	0.82	
	EEX 3	0.82	
	EEX 4	0.82	
	EEX 5	0.79	
Social Influence (SI)	SI 1	0.49	[84,86]
	SI 2	0.86	
	SI 3	0.87	
	SI 4	0.88	
	SI 5	0.84	
Perceived Enjoyment (PE)	PE 1	0.82	[82,83]
	PE 2	0.85	
	PE 3	0.84	
	PE 4	0.84	
	PE 5	0.78	
Perceived Usefulness (PU)	PU 1	0.82	[76,82]
	PU 2	0.83	
	PU 3	0.84	
	PU 4	0.84	
	PU 5	0.80	
Perceived Ease of Use (PEOU)	PEOU 1	0.55	[76,85]
	PEOU 2	0.85	
	PEOU 3	0.85	
	PEOU 4	0.89	
	PEOU 5	0.80	
Attitude towards Using Mobile Learning (ATM)	ATT 1	0.87	[76,84]
	ATT 2	0.90	
	ATT 3	0.87	
	ATT 4	0.81	
	ATT 5	0.85	
Actual Use of M-learning (AUML)	AUML 1	0.71	[64,85]
	AUML 2	0.67	
	AUML 3	0.82	
	AUML 4	0.82	
	AUML 5	0.79	

5. Result and Analysis

5.1. Measurement Model Analysis

As mentioned earlier, we applied the structural equation modeling using AMOS version 23 to assess the results based on confirmatory factor analysis (CFA). This model was used to investigate overconvergence [82]. Furthermore, Hair et al. [81] as well as, [86–88] recommended that the score model be measured using goodness-of-fit strategies, such as chi-square, standard chi-square, the Normed Fit Index (NFI), Incremental Fit Index (IFI) and Relative Fit Index (RFI), and Tucker Lewis Index (TLI). The model fits well when the

Comparative Fit Index (CFI) is equal to or greater than 0.90. In addition, the root means that the RMSEA satisfies the proposed criterion as suggested by [81,89], that is, less than or equal to 0.08 to support the required suit, and the RMR is accepted as shown in Table 3.

Table 3. Goodness fit indices for the measurement model.

Type of Measure	Acceptable Level of Fit	Values
"Root-Mean Residual" (RMR)	Near to 0 (perfect fit)	0.036
"Normed Fit Index" (NFI)	= or >0.90.	0.899
"Relative Fit Index" (RFI)	= or >0.90.	0.911
"Incremental Fit Index" (IFI)	= or >0.90.	0.926
"Tucker Lewis Index" (TLI)	= or >0.90.	0.922
"Comparative Fit Index" (CFI)	= or >0.90.	0.930
"Root-Mean Square Error of Approximation" (RMSEA)	<0.05 indicates a good fit.	0.049

5.2. Reliability Analysis

Before carrying out basic analysis, the research instrument was confirmed using a reliability test. The Cronbach's Alpha test evaluates the reliability between items in the same construct using Cronbach's Alpha. Hair et al. [81] proposed that Cronbach's Alpha should be greater than 0.7 (>0.7) to be considered very reliable. Table 3 shows that the Cronbach's Alpha values for all variables are greater than 0.7, and thus, the research instrument is considered reliable.

5.3. Discriminant Validity Analysis and Convergent Validity

The validity of the constructs was evaluated for convergent validity and discriminant validity in this study. For the convergent validity, the results in Figure 4 show that the average variance extracted (AVE) was higher than 0.5. Hair et al. [81] state that a degree of variance greater than 0.5 is considered acceptable. The square root of the AVE was used to correlate the latent components for the discriminant validity analysis. This means that the entire loading factors are not insignificant and pass the value of 0.50, thereby satisfying the presented correlations [81,90], as shown in Table 4. Figure 2 displays the unified theory of acceptance and use of technology theory of measurement. The dependent variables and measurement of the mediator are mentioned in Figure 3.

Table 4. Summary of validity and reliability for students (male and female).

	FC	PE	SI	EEX	PEX	PEOU	PU	ATT	AUML	AVE	CR	CA
FC	0.900									0.669	0.910	0.909
PE	0.647	0.830								0.680	0.914	0.913
SI	0.615	0.638	0.858							0.648	0.902	0.900
EEX	0.630	0.644	0.647	0.863						0.642	0.897	0.878
PEX	0.734	0.600	0.613	0.639	0.855					0.687	0.916	0.916
PEOU	0.603	0.618	0.587	0.592	0.581	0.795				0.679	0.914	0.913
PU	0.639	0.623	0.616	0.683	0.612	0.588	0.856			0.633	0.894	0.884
ATT	0.630	0.598	0.551	0.629	0.609	0.659	0.632	0.976		0.742	0.935	0.934
AUML	0.640	0.724	0.617	0.616	0.601	0.591	0.619	0.623	0.746	0.583	0.874	0.870

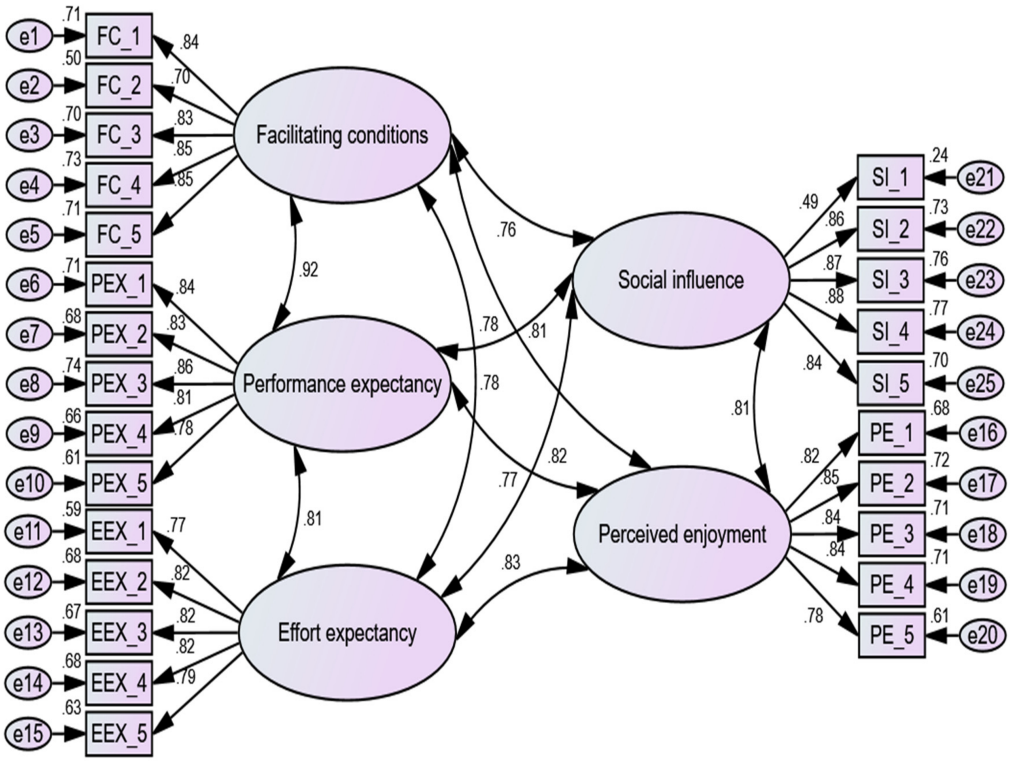

Figure 2. Measurement model of independent factors.

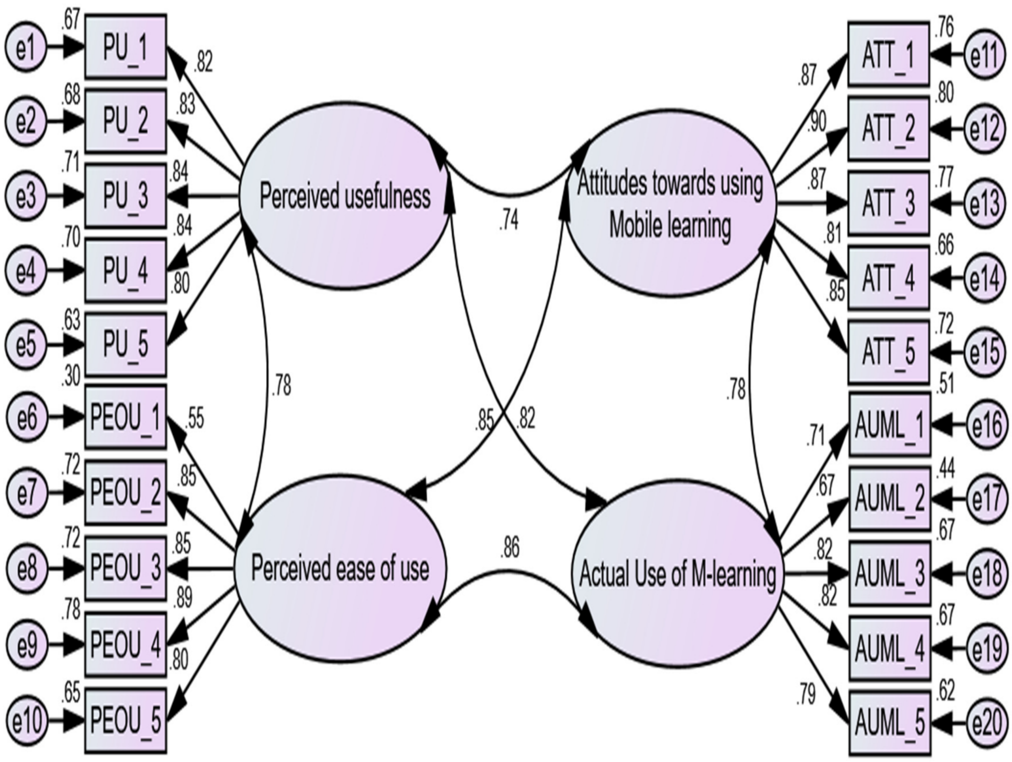

Figure 3. Measurement model of mediator and dependent factors.

5.4. Path Analysis of The Structural Model

Path analysis for structural equation modeling (SEM), as shown in Table 5, was utilized to analyze the research hypothesis in the established framework. A total of 14 hypotheses have been evaluated. All hypotheses were supported, except for H4, which was rejected, as shown in Table 5 and Figure 4.

Table 5. Structural model for hypothesis testing results.

H	Independent	Relationship	Dependent	Estimate	S.E.	C.R.	P	Result
H1	FC	⟶	PEOU	0.136	0.058	2.359	0.018	Supported
H2	FC	⟶	PU	0.166	0.056	2.977	0.003	Supported
H3	PEX	⟶	PEOU	0.118	0.059	1.986	0.047	Supported
H4	PEX	⟶	PU	0.039	0.057	0.684	0.494	Rejected
H5	EEX	⟶	PEOU	0.143	0.053	2.691	0.007	Supported
H6	EEX	⟶	PU	0.390	0.051	7.583	***	Supported
H7	SI	⟶	PEOU	0.154	0.051	3.009	0.003	Supported
H8	SI	⟶	PU	0.105	0.050	2.115	0.034	Supported
H9	PE	⟶	PEOU	0.325	0.055	5.945	***	Supported
H10	PE	⟶	PU	0.113	0.055	2.061	0.039	Supported
H11	PEOU	⟶	PU	0.128	0.051	2.521	0.012	Supported
H12	PEOU	⟶	ATT	0.574	0.052	11.060	***	Supported
H13	PU	⟶	ATT	0.345	0.050	6.898	***	Supported
H14	ATT	⟶	AUML	0.638	0.031	20.306	***	Supported

***: null.

The results in Figure 4 and Table 5 show that facilitating conditions have a significant influence on perceived usefulness and perceived usefulness for adopting M-learning in higher education (β = 0.136, t = 2.359 $p < 0.001$) and (β = 0.166, t = 2.977, $p < 0.001$), thus supporting hypotheses H1 and H2. Moreover, they show that performance expectancy has a significant influence on perceived ease of use for using M-learning (β = 0.118, t = 1.986 $p < 0.001$). Thus, hypothesis H3 is supported. The influence of performance expectancy on perceived usefulness was negative (β = 0.039, $p < 0.684$); hence, H4 was unacceptable. Next, the results confirmed that effort expectancy has a significant effect on perceived ease of use and perceived usefulness for using M-learning (β = 0.143, t = 2.691 $p < 0.001$), and (β = 0.390, t = 7.583 $p < 0.001$), thus supporting hypotheses H5 and H6. Moving on to the seventh and eighth hypotheses, the results show that social influence is positively and significantly associated with perceived ease of use and perceived usefulness for using M-learning (β = 0.154, t = 3.009 $p < 0.001$) and (β = 0.105, t = 2.115 $p < 0.001$). Therefore, hypotheses H7 and H8 are acceptable. In the next step, for the ninth and tenth hypotheses, the outcomes demonstrate that perceived enjoyment is positively and significantly associated with perceived ease of use and perceived usefulness for using M-learning (β = 0.325, t = 5.945, $p < 0.001$) and (β = 0.113, t = 2.061, $p < 0.001$), thus supporting hypotheses H9 and H10. Moreover, the hypotheses 11 and 12 confirmed that perceived ease of use with perceived usefulness is positively and significantly associated with attitudes towards using M-learning (β = 0.128, t = 2.521, $p < 0.001$) and (β = 0.574, t = 11.060, $p < 0.001$).

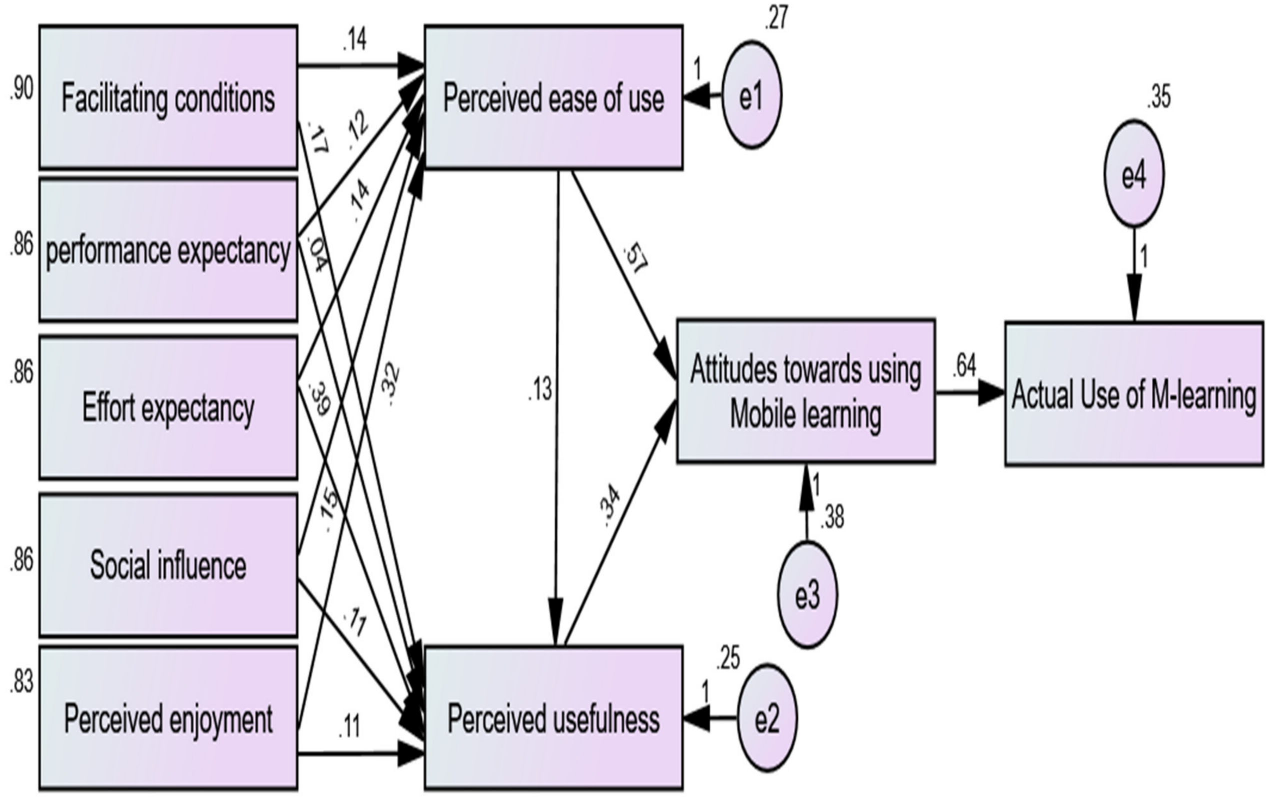

Figure 4. Results of all students group for the proposed model.

Therefore, hypotheses 11 and 12 are supported, indicating that perceived ease of use and attitudes towards using them are useful for the perceived usefulness of M-learning adoption for education. Moving on to the thirteenth hypothesis, perceived usefulness was found to be significant in influencing attitudes toward M-learning ($\beta = 0.345$, $t = 6.898$, $p < 0.001$), supporting hypothesis H13. Finally, hypothesis 14 proposed that attitudes toward M-learning are positively and significantly related to M-learning use ($\beta = 0.638$, $t = 20.306$, $p < 0.001$). Consequently, hypothesis 14 is acceptable, indicating that the impact of attitudes towards using M-learning on the use of M-learning for education, in turn, affects the use of M-learning adoption positively for education.

6. Discussion and Implementation

Though some studies attained significant results by determining the most common factors that influence the acceptance of M-learning (computer anxiety, accessibility self-efficacy, and system quality), in this study, other factors were found to have significant effects on access (effort expectancy, perceived enjoyment, social influence, facilitating conditions, and performance expectancy). We have examined and analyzed the latest studies that have been conducted so as to study the acceptance of M-learning with the objective of our study. Therefore, via the combination of the unified theory of acceptance and use of technology with technology acceptance model factors recognized in this study, a new cohesive structural model has been established. The debate on the results is detailed as follows: First, we examined the relationship between the facilitating conditions and perceived usefulness and perceived ease of use, based on this study's structural model. The results show a strong connection with the perceived ease of use, perceived usefulness of M-learning systems, and facilitating conditions. On this basis, students can infer that the acceptance of the M-learning system relates to this facilitating condition factor.

As shown in Tables 3 and 5, the results of [33] are supported by Hypothesis H3, facilitating conditions with perceived usefulness and perceived ease of use [2,73]. This implies an effect on perceived usefulness and perceived ease of use on facilitating conditions. These results may be because, as indicated in the previous sections, the information and communications technology infrastructure is in a favorable position in higher education. Therefore, it will increase efficacy in facilitating conditions up to a threshold and then stay constant. In such cases, consumers might also notice that they have the maximum M-learning technology requirements (containing internet speed, usage cost, and convenience of appropriate devices, etc.), and increasing these conditions will make a substantial difference in quality, thereby increasing the perceived usefulness and perceived ease of use of the facilitating conditions. The facilitating conditions support the positive impact on perceived usefulness and perceived ease of use [33,73].

Second, we studied the interaction between perceived enjoyment and effort expectancy with perceived usefulness and perceived ease of use on the basis of the structural model of this study. The study results confirmed that attitude towards using M-learning was influenced by perceived enjoyment and effort expectancy, in line with the results of earlier studies such as [57,91–93]. The results of our investigation further underlined the key importance of perceived enjoyment. Our study discovered that perceived enjoyment, along with perceived ease of use and effort expectancy, is positively associated with perceived usefulness and perceived ease of use attitude towards using M-learning. This suggests that perceived enjoyment and effort expectancy had a considerably beneficial effect on perceived usefulness and perceived ease of use attitude toward employing M-learning, which is in line with the study of [94]. Moreover, we revealed that the impact of perceived enjoyment and effort expectancy on perceived usefulness and perceived ease of use with regard to M-learning attitudes was positive and statistically significant, which is consistent with the findings of [82,95]. In conclusion, M-learning is becoming more and more important for students' learning.

Third, using this study's structural model, we investigated the link between perceived enjoyment and perceived usefulness and perceived ease of use. The majority of similar studies [44,69,70] contend that perceived enjoyment is a critical element having a considerable impact on the perceived usefulness and ease of use of M-learning. However, no research has been conducted to our knowledge that has studied the impacts of perceived enjoyment on perceived usefulness and perceived ease of use. Consequently, a theoretical framework has yet to be established. This study's findings revealed that perceived enjoyment has a significant influence on perceived ease of use and perceived usefulness. As a result, subjective enjoyment is a crucial element in the unified theory of acceptance and use of the technology paradigm.

The current study's findings suggest that perceived enjoyment has a significant positive impact on perceived usefulness and perceived ease of use. This study extended the use of perceived enjoyment, perceived usefulness, and perceived ease of use. With the prevalence of the internet and M-learning for enjoyment purposes, university students experience perceived usefulness and perceived ease of use from utilizing their mobile devices. Students' enjoyment of M-learning is projected to grow because it has become a more prevalent mode of learning. M-learning is not just easy to use for students; they also recognize the value of learning.

Fourth, the findings revealed a strong social influence on perceived usefulness and perceived ease of use. The results were supported, and both social influence on the perceived usefulness and perceived ease of use were significant and direct. Social influence on positive perceived usefulness and perceived ease of use effects are in contrast to the results [75,96]. The results show that social influence can affect perceived usefulness and perceived ease of use, which provide positive or negative feedback to users. In addition, the general public can increase and accept the use of M-learning in other cases, and individuals can determine that using such systems is not difficult and influence the perceived usefulness and perceived ease of use. When teachers and experts advise the use of M-learning, the concerns of students will be reduced, and they will be confident in the right support of the system. Support of positive social influence on perceived usefulness, perceived ease of use, mobile learning acceptance, and intention to use mobile learning applications is shown in [75–77,96–100].

The research offers some practical insight into the acceptance of mobile education systems. The study findings provide a more in-depth review of the critical aspects of higher education for M-learning. The study outcomes thus provide helpful information for policymakers, designers, developers, and academics to better understand the main variables in accepting M-learning systems. As noted during previous studies, acceptance of M-learning is not limited to system characteristics, cultural aspects, and individual factors but also includes additional factors including perceived compatibility, quality of information, perceived trust, availability of resources, and self-efficacy.

First, those factors that play an essential role in improving student approval of M-learning, which further affect learners' performance and efficiency, should therefore be a priority of higher education policymakers. Second, technical support for universities is responsible for providing students with successful experience, software, and technical assistance, since students will be able to implement mobile training efficiently if universities constantly update the technological resources they need. Third, the outcomes can guide policymakers in the university through training programs on how the moving learning system is implemented to increase student awareness and knowledge of the benefits of M-learning. Fourth, the results can direct designers and developers to recognize the needs and importance of their students before the system is implemented, avoiding post-implementation failure. Fifth, student awareness and computer skills should be enhanced by teaching courses to guarantee that students are able to effectively implement their M-learning system. The study findings can help stakeholders make effective M-learning acceptance decisions that support the successful implementation of higher education M-learning projects. Finally, in the whole of this study, the model developed determined the main factors that might be beneficial to higher education in terms of M-learning system acceptance.

7. Conclusions and Future Work

In this research, the effects of factors of M-learning acceptance were explored by a complete model based on unified theory of acceptance and use of technology and technology acceptance model factors influencing the use of M-learning. Therefore, the unified theory of acceptance and use of technology and technology acceptance models were validated in terms of using M-learning, and this study included data on student perceptions of using M-learning by university students. This research highlighted the unified theory of acceptance and use of technology and technology acceptance model advantages while also providing new information on user acceptance and the usage of M-learning. M-learning plays a crucial role in increasing the quality of learning and study activities for university students in the twenty-first century. However, no previous research has examined students' attitudes towards M-learning and their plans to use it for digital learning in Saudi Arabian higher education. As a result, the unified theory of acceptance and use of technology and technology acceptance models are demonstrated to be sufficiently robust to provide findings on the studied phenomena, namely, students' attitudes toward M-learning adoption and actual use of M-learning. This research makes a significant contribution by guiding researchers, practitioners, system developers, service providers, and academics in recognizing systematic research approaches for model validation in higher education, particularly when modeling structural equations on the use of M-learning for digital learning at universities. In this study, nine novel unified theory of acceptance and use of technology and technology acceptance model characteristics were used as important predictors of M-learning adoption for digital learning in this study. In addition, the study model focuses on the interactions between the following factors: facilitating conditions, performance expectancy, effort expectancy, social influence, perceived enjoyment, perceived usefulness, perceived ease of use, attitude towards using M-learning, and actual use of M-learning for digital learning. Because of sample constraints, this study cannot take into account all the features of M-learning and determinants that affect user acceptance. Nevertheless, a lack of understanding of M-learning is also effective in the university environment. Moreover, the outcomes of the study cannot be generalized because of the population, which is only limited by the number of universities in higher education. Given the limitations of the study design and the qualitative methodology used, future research should use interview methodologies to learn more about students' and educators' opinions of the use of M-learning. Future studies should delve into these areas by cross-validating them with this model and taking other elements. As a result, a qualitative study might be beneficial in deconstructing these factors in order to analyze the similarities and differences between the various perspectives on M-learning adoption. After the IS Success Model of M-learning Acceptance was established and proved in this study, more work is needed to adapt the findings to various contexts, analyze the model's breadth of applicability, and develop new applications. Our present understanding of IS application use may be increased by extending the research to additional technology-based industries with a larger research sample.

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Appendix A

Facilitating conditions (FC)	
1.	In general, my University campus has support for mobile learning
2.	In general, the country in which my university campus is located has support (infrastructure, policies etc.) for mobile learning
3.	I have the resources necessary to use M-learning
4.	I have the knowledge necessary to use M-learning
5.	Support from an individual or service is available when problems are encountered with M-learning technologies
Performance Expectancy (PEX)	
6.	Mobile Technologies are useful in education in general
7.	Using mobile technologies enable students to accomplish tasks more quickly
8.	Mobile technologies would improve students' performance
9.	Mobile technologies would increase students' productivity
10.	Using mobile learning increases my chances of achieving learning goals that are important to me
Effort Expectancy (EEX)	
11.	Mobile technologies are easy to use
12.	Finding or using features in mobile technologies is easy
13.	Learning to operate mobile technologies is easy
14.	My interaction with the mobile learning would be clear and understandable
15.	It is easy for me to become skillful at using mobile learning
Social influence (SI)	
16.	People who influence my behavior think that I should use mobile technologies
17.	People who are important to me think that I should use mobile technologies for learning
18.	University teachers are supportive of the use of mobile technologies

19.	People whose opinions I value think that I should use mobile for learning
20.	Using mobile for my studies is a status symbol among people whoare important to me
Perceived enjoyment (PE)	
21.	I find using mobile learning enjoyable
22.	The actual process of using the mobile learning is pleasant
23.	I have fun using the mobile learning
24.	Using mobile learning is very entertaining
25.	Using mobile learning is fun
Perceived Usefulness (PU)	
26.	Using mobile learning can save me a lot of time to learn the course materials
27.	Mobile learning helps me get my work done more quickly
28.	Mobile learning is easy to operate
29.	Mobile learning would make me understand the course materials better
30.	Mobile learning would enhance my teamwork with classmates on group assignments
Perceived Ease of Use (PEOU)	
31.	Mobile learning makes it easy to access course material for my learning
32.	I would be willing to make use of a mobile learning tool if someone showed me through tutorial
33.	Mobile learning would help me study my courses anywhere and anytime
34.	Using mobile learning is straightforward
35.	It is easy to become skillful at using M-Learning
Attitude towards Using Mobile learning (ATM)	
36.	I believe it is beneficial to use mobile learning to learn technology management
37.	I feel positive about using mobile learning for learning
38.	My experience with mobile learning to learn technology management will be good
39.	I like my technology-related subjects more when I use mobile learning
40.	Using M-learning to learn technology-related subjects will be a pleasant experience
Actual use mobile learning (AUML)	
41.	I use M-Learning daily
42.	I plan to use M-Learning in my studies
43.	I recommend M-Learning for others to use
44.	I believe that using M-Learning is always a pleasurable experience for me
45.	I spend a lot of time on using mobile learning for academic use

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