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Investigating Factors M-Learning Acceptance and Use for Distance Learning Students in Higher Education

Mohammed Al Masarweh[1*], *Waleed Afandi*[1]

[1]Management Information System Department, College of Business in Rabigh, King Abdulaziz University, Saudi Arabia,
e-mail: malmasarweh@kau.edu.sa; wafndy@kau.edu.sa

Abstract: Many research has been conducted to examine the acceptance factors to use mobile learning (m-learning) for regular students. During the COVID-19 most of the higher education institutions around the world were converted to m-learning especially for regular students, in order to continue supporting the educational stage for these students. This situation, allow researches to tested the use of m-learning for regular students while they are studying in distance learning environment. However, limited researches, especially in developing countries, have been tested the acceptance factors to use m-leaning for distance learning students. In this study the behavioral intention to use mobile learning (m-learning) were examined as well as the m-learning factors that affecting its acceptance amongst the distance learning students were outlined. The study framework was depended on the model of Unified Theory of Acceptance and Use of Technology (UTAUT). A quantitative approach was used to analyze the data that collected from a random sample of 154 male and female participants from Saudi universities. The results indicated that significant factors influencing distance learning students' behavioral intention include quality of service, effort expectancy, facilitating conditions, gender, educational level, and type of device. The regulations governing distance learning programs and the implementation of mobile learning by Saudi universities under the direction of the Ministry of Higher Education are having a good impact and encouraging widespread use of m-learning.

Keywords: distance learning, UTAUT, higher education, m-learning, user acceptance, Saudi Arabia.

Introduction

Nowadays, the necessity for online learning is increasing quickly, and was given a fillip in the pandemic of Covid-19, when regular educational service delivery was prevented in most contexts. This compelled educational institutions to hastily adopt e-learning methods and platforms, with varying degrees of success and challenges. However, the development of online learning capabilities has been underway for decades, accompanied by identification of numerous prerequisites for effective deployment in practice (Colleges, 2017). Advanced digital technologies are increasingly essential in all dimensions of life, but their application in education remains relatively limited (Qashou, A., 2021). However, advanced learning techniques have been developed, including methods of learning through mobile devices, palmtops, laptops, and private media players) as a result of the fast growth of information networks and the Internet (Moya and Camacho, 2021; Tan, G. et al., 2012; Pedro, Barbosa and Santos, 2018). The rapid consumer-driven development of mobile technologies has allowed people to access information on the move, and enabled the potential facilitation of online learning methods (Al Masarweh, 2019; Yu-Lin Jeng. et al., 2010). The appearance of new educational technology helps society to gain experience and knowledge broadly by using mobile technologies, which has mainly been driven by the commercial potential of such technologies, but which offers promise for innovative solutions in education (Vallejo-Correa, Monsalve-Pulido and Tabares-Betancur, 2021).

M-learning is a modern learning model formed by employing technological mobile mechanisms and wireless technology to assist in collaborative and approachable education at all stages, from primary to postgraduate education, which will be the next generation in distance learning and e-learning approaches, since it revolutionizes the capabilities of ubiquitous learning (anytime, anywhere) (Al-Nawayseh, M. et al., 2019; Al Masarweh, 2018; Motiwalla, L.F., 2007; Jouicha, Burgos and Berrada, 2022).

Mobile-based applications for learning as being one of the fastest developing mobile technologies

*Corresponding author: malmasarweh@kau.edu.sa

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in education, with particular advantages in eliminating many barriers to traditional educational service delivery formats (e.g., geographical or financial barriers) (Johnson, L. et al., 2016). Modern revolutions in mobile devices have simplified the exchange of information in mobile applications. This permits mobile students to access a broad diversity of highly expanded learning resources (Tan, G. et al., 2012).

Smartphone use is increasingly universal among university learners, and their use as a supportive-learning technology in the education process can supply and deliver learning between students globally. This wide spread of smart devices on educational institutions offers a new scope to merge traditional learning with m-learning (Anshari, M. et al., 2017). Empirical research attests that smart devices can expedite university learners' access to teaching resources through the Internet, ability to handle group tasks and assignments, and even to interact with instructors (Syafar and Husain, 2017).

The reason behind the particular popularity of mobile/smart devices among other potential e-learning tools is that they are relatively inexpensive in comparison with PCs, and being "mobile" they are easy to handle, as well as being simple to use (Tan, G. et al., 2012; Syafar and Husain, 2017; Syafar, F. et al., 2017). However, mobile devices in themselves, along with any learning technology, are useless without the support of high-quality mobile learning applications and learning resources per se, which can meet user needs with regard to learning objectives (e.g., curriculum content and examination relevance) (Almaiah, Jalil and Man, 2016; Almaiah and Man, 2016; Arain, A. et al., 2019).

In order to bridge the gap between inherently advanced mobile technologies and the practical achievement of learning goals, researchers have studied e-learning phenomena of information technology assumptions by using theoretical models, such as UTAUT model, which is used to categorize mobile learning students' approval on the use and acceptance of technologies in relation to their principles and behavioral purposes of use. Much of this research has considered the elements of mobile learning approval, such as cultural, social, facilitating conditions, and cost (Abu-Al-Aish and Love, 2013; Alahmari, 2017; Althunibat, 2015; Mohammadi, 2015).

UTAUT-based research indicates that the following components affect the interactive purpose and use of conduct to implement online and mobile learning: effort anticipation, performance anticipation, quality of service, the inspiration of lecturers, and personal creativity (Abu-Al-Aish, A. et al., 2013; Al Masarweh, 2018). Building on this consensus, the current study seeks to analyse student acceptance of m-learning for Saudi students in higher educational institutions, a context where such research has hitherto been lacking.

Distance Learning

Distance learning is any shape of teaching and learning assisted by the use of computer networks based on information technology (Daniel, 2020). It can also be known as a method of delivering knowledge electronically, with using suitable computer applications and the Internet for data communication. Recently, distance learning has expanded along two main avenues: the Individual Flexible Teaching Model (IFTM) and the Extended Classroom Model (ECM) (Gabriska and Pribilova, 2021). IFTM permits learners to begin their lessons at any time, choose customized special environments, and interact with their lecturers and colleagues through specific tools. ECM arranges learners into groups, expects them to gather at a local study place, and lets them exploit some interactive technologies like video conferencing to facilitate their mutual interactions (Mergany, Dafalla and Awooda, 2021).

Because of the fast growth of technology, classes can now use different types of media to deliver educational services and content to students in different locations, to meet the educational requirements of larger or more geographically diffuse student populations. Interactive video, print materials, satellite telecommunication, broadcast television, electronic mail, multimedia computer technology, broadcast radio, and computer conferencing have all been used to help teacher-student interactions, albeit mainly in the narrow context of providing feedback to distant learners. Although the methods by which distance learning is applied vary among countries and particular context, distance education programs in general depend on technologies that are currently available, or are considering investment in such technologies, because of their increasing cost-effectiveness (Al-Fahad, 2009). The goals of distance learning as a complementary way of delivering classes include granting degrees to students, tackling illiteracy in developing countries, providing training opportunities for economic growth, and enriching the curriculum in non-traditional schools (Sarrab, Al-Shihi and Rehman, 2013).

Such contexts exist around the world, but became immediate and pressing issues during the Covid-19 pandemic, when latent resources were suddenly shut off for most educational services due to social distancing public health requirements. Montenegro's education system moved through various phases from the beginning of the virus. During the first stage, distance learning started to be used in all schools and universities. At this point, Viber groups were created by lecturers, teachers, and tutors to send students sufficient literature and guidance. After that, the education system was switched to Google Classroom applications. Class teachers were required to organize their classrooms by subject and by class, facilitating distance learning. Additionally, state TV channels offered services to enable students to learn at home, providing video tutorials with material delivered by educators from various subjects (Gabriska and Pribilova, 2021).

Simultaneously, seminars were arranged for all Montenegrin tutors and teachers to train them on how to use Microsoft Teams (Gabriska and Pribilova, 2021), which provides modern, high-quality workspaces, particularly for team environments in virtual work organizations, and this platform outmatched Skype and Viber for such uses in the Covid-19 e-learning context, being available in 181 countries and 18 languages (Alahmari, 2017).

Logically, M-learning is the current method for distance and E-learning technology. The most important features of distance learning are the time and distance shifting between tutor and learners. E-learning proposes new approaches for distance learning which depend on computer and net technologies (Abu-Al-Aish, A. et al., 2013).

Mobile Learning

Several previously deployed M-learning frameworks and models are analysed and compared in this section. The following characteristics are listed in Table 1 as the distinctions between prior frameworks: the method used to develop the model, the presence of deployment stages, the key components used, sustainability reflection, validation and assessment, and link with e-learning (Daniel, 2020; Mostakhdemin-Hosseini, A., 2009).

Table 1
Frameworks Evaluation for M-Learning

Framework	M-learning Framework (Koole, M., 2006)	Framing M-learning Model (FRAME) (Koole, M.L., 2009; Barker, A., Krull, G. and Mallinson, B., 2005)	Proposed a M-learning Theoretical Model in Developing Countries (Ng, W. and Nicholas, H., 2012)	A model of m-learning Sustainability in Schools (Raman, A. and Don, Y., 2013)
Approach used	Depends on the data, which collected from Helsinki University. (Venkatesh, V. et al. 2003)	the outcome of conjunction of human learning capabilities, mobile technologies, and social communication	Literature review	Data gathered using questionnaires, observations, and focus groups
Main elements used	– Education elements – Network and devices resources – Prototyping	M-learning is the interchange between device, learner, and social dimensions	– M-learning procedures – Traditional learning and e-learning systems – Communication infrastructure	– Interrelations between participants and with devices – Trust and support between participants – M-learning community
Model evaluation and validation	The paradigm was evaluated with real users (staff and students)	No	No	Model tested by pre- and post-questionnaires, focus group interviews, and interviews
Sustainable	No	No	No	Some sustainability
Deployment stages	No	No	No	No
e-learning system Relation	e-learning Related	No	e-learning Related	No

The earlier frameworks or models for m-learning are not examined specific stages deployment for m-learning. Moreover, a limited discussion on sustainability issues has been conducted to ensure that m-learning systems would be continuously improved and assessed after deployment. Building a schema that detects the earlier deployment success factors for m-learning and provides assistance for after-deployment sustainability is therefore necessary (Venkatesh, V. et al., 2003).

Unified Theory of Acceptance and Use of Technology

The UTAUT paradigm defines the acceptance of technology depending on eight technology acceptance models, the most widely used of which are use behavior (UB), facilitating conditions (FCs), social factors (SFs), effort expectancy (EE), behavioral intentions (BI), and performance expectancy (PE)

(Venkatesh, 2000). Behavioral intention is affected directly by effort expectancy, Performance expectancy, and social factors, whereas, use behavior is ancillary impacted by facilitating conditions. All of these aspects are fundamentally determined by behavioral intention, which is the main underlying concern of UTAUT (Venkatesh, 2000). Furthermore, other aspects might affect the structure for example age of the user, user experience, voluntariness of use, and gender. The UTAUT paradigm thus interprets technology use behavior based on behavioral intention. The eight factors of technology are established, which related interpreters of behavioral intention, illustrate in Figure 1.

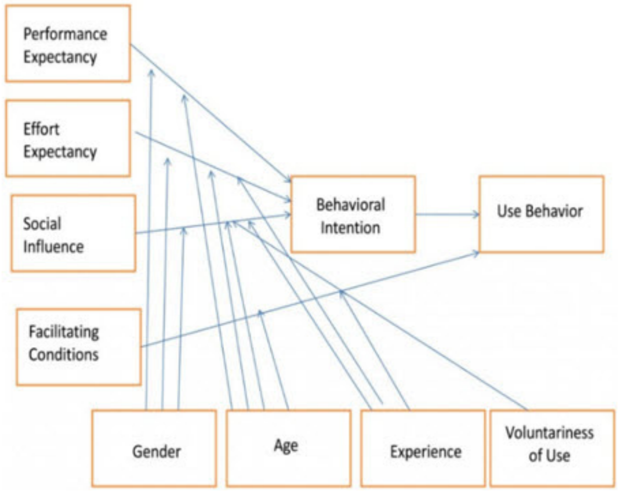


Figure 1. The model of UTAUT (Venkatesh, V. et al., 2003).

Performance Expectancy (PE)

Performance expectancy can be understood as the people think level that they can achieve their tasks with the aid of ICT (Venkatesh, 2000). In terms of PE, e-learning can be a huge support for e-learners, by enabling them to complete learning events more expediently, and novel technological solutions in themselves can inspire learning, educational skills, and production. PE thereby influences behavioral intention to control the E-learning system favourably.

Effort Expectancy (EE)

The level of smoothness that related to the information systems and their administration is referred to as effort expectancy (Alshurideh, 2010). Based on previous research, concepts about EE relate to users' individual objectives and proficiency in relation to the associated tools (Salloum and Shaalan, 2018). Particular e-learning applications (if not the concept in general) are usually relatively new for most learners and educators, because it is believed that EE is behavioral intention key component to use e-learning systems. Individual acceptance of e-learning is influenced by the usability and simplicity of technology, which also has an impact on behavioral intention more broadly. Consequently, EE has a convenient effect on behavioral intent to use an e-learning system.

Social Influence (SI)

Social influence can be described as the impact that the opinions or experiences of others on the way in which an individual understands and conceptualizes how technologies should be handled (Alshurideh, 2010). Empirical studies based on the UTAUT have reported that people's intention to use new e-learning technological solutions is heavily affected by SI, which can be understood as word-of-mouth or peer pressure (Jogezai, N. et al., 2021; Abbad, 2021). Accordingly, SI affects behavioral intention to utilize an e-learning system favourably.

Facilitating Conditions (FC)

Facilitating conditions pertain to the ambience and infrastructure in which technologies are deployed, relating to environmental and behavioral influences that shape user deployment of tools. The designer of the UTAUT paradigm found that FC is a very valuable factor influencing the use of information systems (Yu, 2012). The level of which people think technical and organizational infrastructures are latently accessible to adopt and ongoing usage of novel technologies is what FC refers to; any social, behavioral, and personal factors conducive to e-learning system use do not guarantee successful use without commensurate FC, including materials, individual support, and training for improving knowledge and familiarity, as well as access to the system of e-learning itself. Accordingly, FC will have a major and favourable impact on students' utilization of the e-learning system.

Use Behavior (UB)

Use behavior refers to the pattern or routine of people handling ICT, which is affected by behavioral intention and assisting prerequisites (Yu, 2012). In other words, the behavior of learners to use information technology has been influenced by their intention and interest of it's used, and the accessibility of equipment and facilities to provide this intention.

Behavioral Intention (BI)

Behavioral intention was originally developed as an expansion of the Theory of Reasoned Action (TRA) (Moya, M. et al., 2017). BI is described as a theory to clarify the motivational influences that shape behavior. This theory pertains to the attempts and efforts expected from users seeking to execute specific tasks. It is shaped by personal factors regarding the individual's intention to perform something.

Research Framework and Hypotheses

This research adopts the UTAUT framework in order that explore the main elements of behavioral intention of using m-learning and its challenges for distance learning students in Saudi universities. It investigates the main factors affecting behavioral intention among 154 male and female distance learning students. Many research studies have used a similar approach to study regular students in higher education, but limited research has been conducted on distance learning students, particularly in developing countries. for the reason of customize the main scope of the research intention, participants' demographic information was included in this research to find out if the participants'' demographic have any significant impact between the participants.

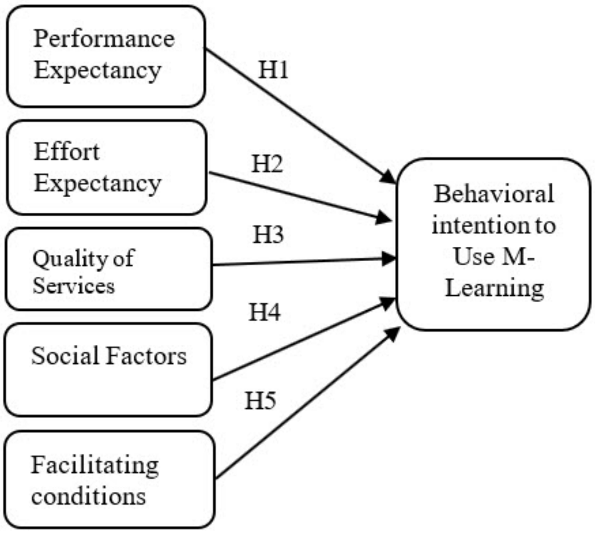


Figure 2. Research framework.

H1: Behavioral intention to use m-learning (BI) is significantly affected by performance expectancy (PE).

H2: Behavioral intention to use m-learning (BI) is significantly affected by effort expectancy (EE).

H3: Behavioral intention to use m-learning (BI) is significantly affected by quality of services (QoS).

H4: Behavioral intention to use m-learning (BI) is significantly affected by social factors (SFS).

H5: Behavioral intention to use m-learning (BI) is significantly affected by facilitating conditions (FCS).

H6: Gender has significantly affected on m-learning acceptance for distance learning students.

H7: Educational level has significantly affected on m-learning acceptance for distance learning students.

H8: Type of devices in using has significantly affected on m-learning acceptance for distance learning students.

Materials and Methods

A quantitative approach was adopted, which provided statistical results related to the research scope, by systematic and empirical investigation of the gathered numerical information, which was statistically analysed. The data was gathered from a survey based on previous studies, designed to target distance learning students in Saudi higher education institutions. Five public universities which provide distance learning programs were selected: King Abdulaziz University, Taiba University, Umm Al Qura University, University of Tabuk, and Imam Mohammad Ibn Saud Islamic University. An online questionnaire was prepared using Google Forms in both English and Arabic languages, which helped the participants to understand the theme of this research. Furthermore, the participants had to be experienced in using technological aspects of m-learning services as provided by their universities. Inclusion criteria for the randomly selected students included that all of them had been enrolled in distance learning programs, and that they were sufficiently familiar with the use of technology and mobile devices due to the nature of these programs, which depend on the use of technology and mobile devices. Moreover, the researcher analysed the m-learning orientation delivered by these universities, to ensure that students were provided with adequate knowledge, courses, training videos, and guidelines for using technology and mobile devices. A pilot study was conducted among 28 students at King Abdulaziz University to obtain feedback and test the readiness of the instrument, and based on the feedback received some minor modifications were made to the instrument, after which it was implemented with the study sample.

Data Collection

University administrators were contacted by email in order to share the survey with their students, with an explanation of the study nature and the link of online survey. Moreover, the data was collected form 154 participants, who voluntarily completed the survey by clicking on the Google Forms link via the invitation email. The data for 154 participants was analysed using SPSS. The sample size was sufficient in order to represent the opinions of distance learning students towards the intention of using m-learning (Lai, 2017). The demographics of this study were based on three factors: gender, education level, and type of device. In terms of gender, there were 93 and 62 male and female participants (respectively). The vast majority of respondents (n = 151) were in the third to fifth years of their programs. Concerning the type of device used for online learning, all respondents selected mobile devices. The survey section concerning demographic features was analysed using percentages and frequencies; the section directly relating to students' level of acceptance and behavioral intention factors asked participants to rate items using a five-point Likert scale.

Questions Examining Factors in Level of Acceptance and Behavioral Intention

The survey, second part, included questions that related to examine the investigating of acceptance level, based mainly on a previous instrument (Yu, 2012; Abbad, 2021), with some additional modifications to meet the objectives of this study. Table 2 illustrates the statements that participants rated using the Likert scale.

Table 2
Questions to Explore the Level of Acceptance

Item	Measures	N items
PE1	Learning by mobile phone is useful in my studies	6
PE2	The use of m-learning enables me quickly to achieve learning tasks	
PE3	The use of m-learning increases the productivity of my learning	
PE4	The use of m-learning increases learning engagement	
PE5	Learning performance does not ameliorate by Using m-learning	
PE6	M-learning improves is the way to collaborate with teachers and colleagues	
EE1	It is easy for me to use m-learning	4
EE2	It is difficult to operate learning applications by using mobile phones	
EE3	I find that learning with a mobile phone does not require much effort	
EE4	My interaction with the m-learning system is clear and understandable	
QoS1	It is important for m-learning services to increase the quality of learning	5
QoS2	A reliable and accurate m-learning service is what I prefer	
QoS3	Safe use of mobile learning services is important to me	
QoS4	Focusing on surfing the Internet and obtaining information is important in mobile learning	
QoS5	it is difficult to communicate with the lecturer in m-learning system	
SF1	in case my lecturers recommended me to use m-learning, I will most likely do	3
SF2	in case my colleagues advise me to use m-learning, I will most likely do	
SF3	in case my college advise me to use m-learning, I will most likely do	
FC1	In general, my institution supports m-learning	5
FC2	Generally, the m-learning has been supported (infrastructure, policies, etc.) by country	
FC3	The m-learning resources are available to use	
FC4	I don't have the skills for using m-learning	
FC5	Whenever I encounter a problem with an m-learning technology, I can get support	
BI1	In my studies, I intend to use mobile learning	5
BI2	I probably will frequently use m-learning	
BI3	In the future, I plan to use my mobile services more	
BI4	Using m-learning systems is interested, I will like it	
BI5	I will motivate others students for using m-learning systems	

Results

Statistical Analysis of the Reliability and Suitability of Study Model

The Cronbach's alpha coefficients for all variables were between (0.711-0.861), which it is more than the required threshold (0.6) (Table 3), indicating the stability of the tool used in this study (Benitez, J. et al., 2020).

Table 3
Results of Cronbach's Alpha Coefficients

	Cronbach's α coefficients	N paragraphs
Independent variables		
Performance expectancy	0.711	6
Effort expectancy	0.732	4
Quality of services	0.794	5
Social factors	0.826	3
Facilitating conditions	0.811	5
Mobile use	0.861	23
Dependent variable		
Behavioral intention	0.752	5

In order to ensure that there was no significant multiple linear connection between the dimensions of the independent variable, the correlation coefficients between them were examined. The results shown in Table 4 reveal that the greatest correlation was (0.738), showing that there was no significant multiple linear correlation between the independent variables (values below 80% indicate that the sample was free from this issue) (Hair, Howard and Nitzl, 2020).

Table 4
Pearson Correlation Between Independent Variables

Variable	PE	EE	QS	SFs	FCs
PE	1				
EE	.691**	1			
QS	.230**	.217**	1		
SFs	.678**	.397**	.231**	1	
FCs	.711**	.521**	.302**	.738**	1

**. Correlation is significant at the 0.01 level (2-tailed).
Key
Performance Expectancy (PE), Effort Expectancy (EE), Quality of services (QS), Social Factors (SFs), Facilitating Conditions (FCs), Behavioral Intention (BI)

Participances Demographic and the Usage of Mobile Device

The characteristics of participants demographic and usage of mobile device is illustrated Table 5, including cumulative percentages, percentages, and frequencies for each category. The majority of participants were male (60.4%), and most were in their fourth and third years (42.2% and 35.1%, respectively). Mobile phones were the most commonly used devices to access m-learning resources during their distance learning (57.1%), followed by laptops (31.8%).

Table 5
Participants' Demographic Characteristics

	Items	N = 154		
Variable	Category	Frequency	%	Cumulative
Gender	Male	93	60.4	60.4
	Female	61	39.6	100.0
Educational level (year)	5+	32	20.8	20.8
	4	65	42.2	63.0
	2	3	1.9	64.9
	3	54	35.1	100.0
Type of device	Laptop	49	31.8	31.8
	Mobile	88	57.1	89.0
	Tablet	17	11.0	100.0

Results for Independent and Dependent Variables

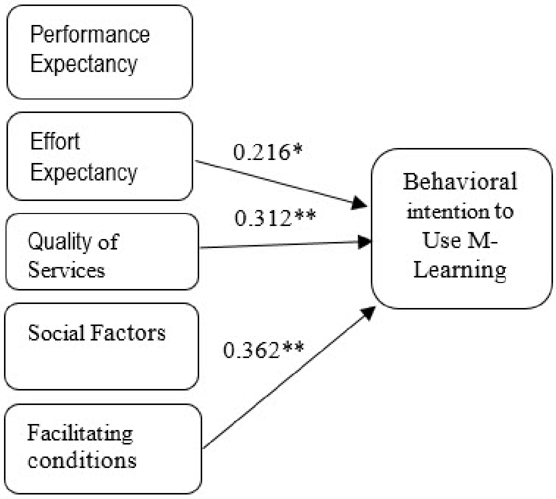
The means, standard deviations, and degrees of acceptance of m-learning are illustrated in Table 6. It can be seen that the studied Saudi distance learning students held positive attitudes towards using m-learning (3.75). The highest scores for m-learning factors were for facilitating conditions (3.99), followed by performance expectancy (3.96), and social factors (3.90). Medium acceptance was reported for effort expectancy (3.66) and quality of services (3.52). The behavioral intention for students to use m-learning also achieved a high score (3.68), indicating positive attitudes and a high degree of willingness.

Table 6
Level of M-Learning Acceptance

N	Construct	Mean	SD	Level
1	Performance Expectancy (PE)	3.69	.683	High
2	Effort Expectancy (EE)	3.66	.587	Moderate
3	Quality of services (QS)	3.52	.430	Moderate
4	Social Factors (SFs)	3.90	.813	High
5	Facilitating Conditions (FCs)	3.99	.685	High
6	Behavioral Intention (BI)	3.68	.640	High
	Average	3.75	.493	High

Regression Analysis for UTAUT Construct

Regression analysis has been used in order to examine the association between the five model elements and the BI towards using m-learning. Figure 3 illustrates the β-value for the used elements.



* Significance at p ≤0.05, ** Significance at p ≤0.01

Figure 3. β-value Graphical representations.

Discussions

Hypotheses Testing Results (H1-H5)

Multiple regression has been used to test hypotheses (H1-H5). Table 7 illustrates the results of the statistical testing for the hypothesis model, represented by a set of independent variables (social factors, effort expectancy, facilitating conditions, performance expectancy, and quality of services) and the dependent variable (behavioral intention). The outcomes indicate that FC, QoS, and EE had a significant impact on behavioral intention (with beta values of 0.326, 0.312, and 0.216, respectively), with a statistically significant p-value of less than (0.05). This means that there are differences in facilitating conditions between the distance learning students, although all participants were capable to use m-learning as a main application to communicate during their distance learning experience. This confirms findings in other countries worldwide concerning m-learning during the Covid-19 crisis (Afandi, 2022). However, the beta values for the dimensions PE and SF were statistically insignificant (<0.05).

The current study's findings on social factors disagree with the results of previous studies, which may be attributable to the distance learning students in this study having only one way (i.e., distance learning) to undertake their studies in the Covid-19 context. Regular students (i.e., under normative situations) are more affected by social factors pertaining to the use of m-learning that seems to be linked to the greater variety of choices and options open to them (Afandi, 2022; Nikolopoulou, Gialamas and Lavidas, 2020).

Based on the above, the results confirm the hypotheses of: (H2) effort expectancy (EE) significantly affects behavioral intention to use m-learning (BI); (H3) quality of services (QoS) significantly affects behavioral intention to use m-learning (BI); (H5) facilitating conditions (FCS) significantly affect behavioral intention to use m-learning (BI). There is no statistically significant evidence to support H1 or H4.

Table 7

Testing Hypotheses H1-H5

Hypothesis	Result	Conclusion
H1: (BI) is significantly affected by (PE)	Insignificant	Not supported
H2: (BI) is significantly affected by (EE))	Significant (β-value= 0.216, p=0.022 <0.005)	Supported
H3: (BI) is significantly affected by (QS)	Significant (β-value=0.312, p=0.000 <0.001)	Supported
H4: (BI) is significantly affected by (SFs)	Insignificant	Not supported
H5: (BI) is significantly affected by (FCs)	Significant (β-value=0.362, p=0.001<0.001)	Supported

Hypotheses Testing Results (H6-H8)

This study one-sample T-test was used to test H6, and one-way analysis of variance (ANOVA) in order to test H7 and H8. Table 8 shows the results, which indicate that the T- and F-values are not significant ($p<0.05$). Therefore, the students' gender, educational level, and type of devices using in m-learning have no substantive impacts on m-learning acceptance. This means that the distance learning students are homogenous with regard to their m-learning user behavior for distance learning, evidencing that the nature of distance learning programs can assume commensurate levels of technical skills and resources to use m-learning resources.

Table 8

Testing Hypotheses H6-H8

Analysis Factor	df	t	Sig. (2-tailed)	Result
Gender	152	0.975	0.331	Not supported
Educational level	3	2.065	0.107	Not supported
Device type	2	1.234	0.294	Not supported

Conclusion

This study examined a variety of m-learning adoption and acceptance issues in relation to the UTAUT paradigm. According to the findings, Saudi public university distance learning students have good latent readiness and positive attitudes toward using m-learning to further their academic objectives. This is in light of the key elements identified by the UTAUT model. Examining UTAUT model-based components on behavioral intention to employ m-learning indicated positive effects. When evaluating the questionnaire findings, it was discovered that performance expectancy, social factors, and facilitating conditions all received high scores. The findings of this study also provided support for three of the five hypotheses. The findings of the T-test and ANOVA tests provided a distinct viewpoint on the impact of various factors on the use of mobile learning, showing that gender, educational level, and the types of used devices have no appreciable effects on students' attitudes toward m-learning.

Overall, the findings indicate that the regulations governing distance learning programs and the implementation of mobile learning by Saudi universities under the direction of the Ministry of Higher Education are having a good impact and encouraging widespread use of m-learning.

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Conflict of interests

The authors declare no conflict of interest.

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