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Investigating Students' Intention to Use M-Learning:

The Mediating Role of Mobile Usefulness and Intention to Use

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ABSTRACT

Mobile learning (M-learning) has become a crucial tool for both students and educators. The unified theory of acceptance and use of technology (UTAUT), the technology acceptance model (TAM), and outside factors were all included in this study's integrative review approach to examine the variables affecting university students' intention to use M-learning and mobile effectiveness. A study at King Faisal University examined the viewpoints of 364 undergraduate and graduate students using a random sampling technique to have better understand the impact of such technological innovation on teaching. Participants in the study were invited to complete a survey created expressly for this study in order to find out if they would still be open to using M-learning to advance the cause of sustainable education. The paradigm of the study was evaluated using a structural equation modeling (SEM) approach and was based on the UTAUT and TAM technology adoption models. The findings demonstrated that each element of the research model had a positive influence on learners' behavioral intention to use M-learning (BIM); it also demonstrated the impact of that intention on long-term educational sustainability. The link between independent characteristics and users' enjoyment and adoption of M-learning is moderated by mobile usability and behavioral control to utilize M-learning. The results also showed that BIM and the utility of mobile devices increased the degree to which M-learning is liked. Mobile usability and BIM both favorably affect sustainable education in terms of user satisfaction and M-learning adaptation. These findings suggest that mobile usability and behavioral intention to utilize M-learning are the main factors influencing the adoption of M-learning in Saudi Arabia's higher education.

KEYWORDS

Adoption of Use of M-Learning, M-Learning, Mobile Usefulness, Perceived Psychological Readiness, Perceived Skills Readiness, University Management Support

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INTRODUCTION

The definition of mobile learning (M-learning) is "learning that takes place when students have access to information whenever and wherever they are using mobile technology to engage in genuine actions as part of their learning" (Al-Rahmi et al., 2021a; Martin & Ertzberger, 2013). M-learning presents a unique chance to draw on learners' formal and informal learning experiences (Alturki & Aldraiweesh, 2022; Granić & Marangunić, 2019). Mobile computing devices' mobility and flexibility enable learners to contextualize their learning in a useful way, apply what they learn to real-world challenges, and customize their learning (Sánchez-Prieto et al., 2019; Viberg et al., 2021). Since the idea of M-learning first emerged, information systems (IS) and educational specialists have examined ways to incorporate it into instructional practices. The fact that M-learning systems enable students to access their course materials over wireless networks "anytime, anywhere" is the basis for those researchers' steadfast insistence on the importance of M-learning (Al-Emran & Teo, 2020; Al-Rahmi et al., 2021b). Notwithstanding this enthusiasm, investing in M-learning technologies calls for an appreciation of students' low incentive to use them for educational purposes (Aguilera-Hermida, 2020). Students must be aware of its benefits and incorporate it into their academic lives in order for M-learning platforms to be used for educational practices (Alghazi et al., 2021).

M-learning can be utilized to lessen the problems related to schooling, according to a number of studies (Al-Rahmi, et al., 2022a; Hill et al., 1977; Kong, 2018; Qashou, 2021). According to Al-Rahmi, Shamsuddin, Wahab, Al-Rahmi, Alismaiel, et al. (2022b), M-learning transforms an instructional strategy into a student-focused one that can foster meaningful, holistic learning experiences. Additionally, M-learning gives teachers access to a wide range of pedagogies, including group work, quizzes, and educational games, all of which may be used to cater to the unique learning preferences of students (Alturki & Aldraiweesh, 2022). The availability of instructional and evaluation materials at all times and locations is made possible through M-learning (Almaiah et al., 2019). M-learning makes it possible to use graphical science experiments, which can help learners better comprehend science ideas and provide comprehensive explanations of those subjects (Liu et al., 2021). M-learning enhances lecturers' participation in their students' education, which in turn enhances students' drive and achievement in STEM-related topics, according to Gamage et al. (2022) and Kong (2018).

Many theoretical models, including the theory of reasoned action (TRA; Al-Emran et al., 2018), the technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT; Alghazi et al., 2021), and the theory of planned behavior (TPB; Ajzen, 1985), were used to comprehend the factors influencing the adoption of M-learning. Due to its simplicity, versatility, and soundness, TAM is thought to be one of the most often used theoretical models for forecasting the adoption of various technologies (Liu et al., 2021). More particularly, it was recently discovered that TAM was the most frequently utilized theoretical model for comprehending the adoption of M-learning (Aburub & Alnawas, 2019). TAM's effective explanatory ability and successful validation using a number of measurement scales were other considerations (Al-Emran et al., 2018). The TAM's fundamental variables, "perceived ease of use" and "perceived usefulness," which examine how people embrace various technologies, have good empirical backing, increasing the model's applicability across disciplines (Aburub & Alnawas, 2019; Hamidi & Chavoshi, 2018).

RELATED WORK IN M-LEARNING

Even though higher education institutions have significantly invested in M-learning initiatives, many universities still struggle to reap the benefits of these initiatives (Gamage et al., 2022; Hill et al., 1977; Kong, 2018). According to numerous studies, a successful M-learning system must be enthusiastically embraced by students in order to succeed (Qashou, 2021). In order to ensure the effectiveness of M-learning technology in educational environments, it is therefore seen as essential to investigate students' acceptance of it (Almaiah et al., 2019; Liu et al., 2021). More intriguingly, this type of research will assist designers and developers in more effectively optimizing M-learning systems and also allow students to fully utilize M-learning technology (Aburub & Alnawas, 2019; Ajzen, 1985; Al-Emran et al., 2018; Gamage et al., 2022; Hamidi & Chavoshi, 2018). The use and acceptance of M-learning systems vary greatly among university students, despite the various advantages that have been established for their use (Al-Rahmi, et al., 2022c; Almaiah et al., 2019; Hill et al., 1977; Kong, 2018; Qashou, 2021). On the one hand, declining levels of acceptance among college students have been noted in various studies (Alghazi et al., 2021; Almaiah et al., 2019; Venkatesh et al., 2003).

Numerous studies show that the low quality of M-learning systems and services and the fact that current M-learning systems don't meet students' needs and requirements are the main causes of the low level of M-learning system usage among students (Al-Rahmi et al., 2021c; Al-Rahmi, Shamsuddin, et al., 2022; Almaiah et al., 2019) . Most prior studies also ignored the possibility that MTAM (mobile technology acceptance model) factors could be crucial to the success and evaluation of M-learning systems (Al-Emran et al., 2020; Alalwan et al., 2019; Davis, 1989), so these factors are now given more attention. On the basis of these findings, it is possible to draw the conclusion that M-learning can decrease the negative effects of problems in higher education, despite the fact that STEM education faces many difficulties (Gamage et al., 2022; Hill et al., 1977; Kong, 2018) . Even though M-learning adoption factors have been extensively researched in the past, there are still many problems that need to be solved (Al-Emran et al., 2018). First, in higher education, M-learning is still being employed, and its theoretical foundation has not yet been defined (Ajzen, 1985). Second, different educational environments have different expectations for how students are to use M-learning (Aburub & Alnawas, 2019). These differences result from the influencing elements, which mostly depend on the context, infrastructure, and pupils' level of preparation. The use of mobile computing devices in classrooms also raises a number of technical and nontechnical issues (Hamidi & Chavoshi, 2018). Third, there is some discussion about the variables that affect the continued usage of M-learning systems (Venkatesh et al., 2003). Finding these elements would make it easier to comprehend how students actually use M-learning. Fourth, little research has been done on how these systems are used continuously, according to a recent comprehensive review of the literature on M-learning (Al-Emran et al., 2018). Furthermore, it has been emphasized that little is known about how social factors affect the perception of M-learning systems' effectiveness and usability; this perception in turn affects how long they are utilized. Fifth, despite the fact that many pertinent M-learning studies have used structural equation modeling (SEM) techniques to clarify the causal relationship among theoretical constructs, there is a lack of understanding regarding the use of extra analysis software, such as algorithms for machine learning and neural networks.

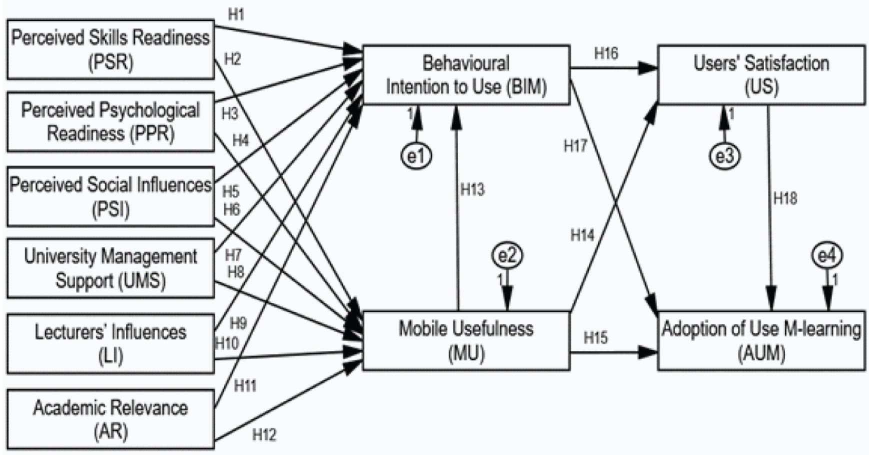
Therefore, the purpose of this study was to look at the factors affecting students' satisfaction with using M-learning technologies in order to address the aforementioned problems. More specifically, the study examined how social influence affects mobile usability and behavioral intention to use M-learning (BIM) in Saudi Arabia. By combining UTAUT (Al-Emran et al., 2020) and TAM (Davis, 1989) with outside variables, this study created a theoretical model. This work used a comparative analytical method to construct a prediction model for the adoption of M-learning using IBM SPSS and structural equation modeling (SEM-Amos), a popular method for multivariate analysis that is used to empirically assess theoretical models. This approach was applied to determine the causal links between the endogenous (independent) and exogenous (dependent) variables in this investigation. Additionally, the classifier model was used in the study to forecast dependent variables based on independent factors. We used IBM SPSS and SEM-Amos as the two main statistical programs in our investigation. Our work was divided into two primary phases. The first phase was concerned with proving the reliability of the assessments, including their construct, convergent, and discriminant validity. The structural model was examined in the second stage.

RESEARCH MODEL AND HYPOTHESES

According to Al-Emran et al. (2020), Carlsson et al. (2006), Mallat et al. (2008), and Osoba and Davis (2019), TAM is criticized for being too broad and adaptable to the adoption of technology across a wide range of disciplines. According to Carlsson et al. (2006), M-learning is more individualized, personalized, and system-focused. TAM's limited ability to explain users' attitudes toward the information system is another critique (Al-Emran et al., 2020). TAM has been challenged, as well, for implying that using information systems is required (Mallat et al., 2008). Extrinsic motivators are those that are thought to be useful or simple to employ. According to the findings of Al-Emran et al. (2020), Carlsson et al. (2006), and Mallat et al. (2008), TAM is insufficient on its own to predict and explain the acceptability of M-learning in remote regions. A fully formed prototype that can explain and predict how well the technique will be received in various contexts, such as the history and context of acquiescence and utilization of technology constructs, should be created, according to Abu-Taieh et al. (2022) and Al-Rahmi et al. (2022b), as the TAM provides an abstract lens that outlines the fundamental principles of user engagement (ease of use and usefulness).

Furthermore, theories like TAM were created at a time when digital technologies were just starting to take off, making the analysis presented here both topical and consistent with the request by Abdelwahed and Soomro (2022) and Mazaheri et al. (2020) that this model be (re)investigated in modern contexts. Hence, to fill the aforementioned gaps, MTAM (Ooi & Tan, 2016) was utilized. MTAM is specifically designed to determine whether consumers want to adopt mobile innovations in the context of research on the adoption of mobile technology. The mobile usefulness (MU) and behavioral intention to use the fundamental elements of MTAM, which updated the original TAM, have been validated in a variety of mobile adoption situations, including retailing (Chao, 2019). The meaning of MU is the same as that of PU (perceived usefulness), which expresses how adopting mobile IS (information systems) and IT (information technology) has improved users' abilities to complete tasks. PEOU (perceived ease of use), on the other hand, expresses the user's perception of the effort necessary to use a specific IS or IT from the perspective of a mobile situation. Nevertheless, this study extended the original TAM to include perceived skill readiness, perceived social power, perceived psychological preparedness, assistance from university administration, influence from lecturers, and academic relevance. While accepting M-learning, teachers and students are likely to take into consideration the six variables that have been introduced to the TAM (see Figure 1).

Figure 1. Conceptual framework



Perceived Skills Readiness

A person's subjective evaluation of their ability and competence to participate in M-learning activities is referred to as their *perceived skills readiness* for M-learning (Akour, 2013). Because they have grown up with technology, young people are driven and adept at using mobile devices (Kee & Samsudin, 2014). The findings of Osakwe et al. (2017), which demonstrated that 91.1% of pupils can utilize mobile devices and are aware of their additional functionalities, confirmed this. This demonstrates that the vast majority of students possess the skills required to make use of M-learning. Students who are proficient in technology will gain more from M-learning(Islamoglu et al., 2021). Islamoglu et al. (2021) found that online course participants who have the necessary computer technical skills display less anxiety and dissatisfaction than those who do not. If they possess the required skills, learners and teachers will find M-learning useful and straightforward to utilize. Technology users who are highly skilled are more likely to adopt a favorable attitude about it and experience less worry and irritation (Islamoglu et al., 2021). Similarly, individuals with sufficient technological abilities exhibit high levels of motivation and happiness when they operate technological instruments with ease (Kee & Samsudin, 2014). On the other hand, research suggests that teachers have a low opinion of their own readiness for online education (Cruzado et al., 2021). According to Dahri et al. (2023), users with high levels of skill readiness are better able to understand and deepen their use of technology, whereas individuals with low levels of skill readiness find it difficult to interact with technology. Through the above discussion, this study proposes the following hypotheses:

H1: Perceived skills readiness has a positive impact on behavioral intention to use.
H2: Perceived skills readiness has a positive impact on mobile usefulness.

Perceived Psychological Readiness

A user's impression of their psychological readiness (PPR) may be determined when they are potentially required to use an information system (Alenezi et al., 2010). According to MacCallum et al. (2014), negative feelings resulting from low PPR have an adverse effect on teachers' and students' attitudes, in addition to their embrace of M-learning and perception of how easy it will be to use. The relationship between PPR and PU has also been proven (MacCallum et al., 2014). In South Africa, professors and students in higher education who have been using mobile phones for some time tend to be more confident in their capacity to use them efficiently (Mutambara & Bayaga, 2021) . PPR concerning the use of M-learning for the instruction in technology-related subjects in the classroom is directly correlated with the competency of rural high school teachers and students. Through the above discussion, this study proposes the following hypotheses:

H3: Perceived psychological readiness has a positive impact on behavioral intention to use.
H4: Perceived psychological readiness has a positive impact on mobile usefulness.

Perceived Social Influences

A person's subjective sense or awareness of the influence that other people, groups, or societal norms have on their attitudes, behaviors, decisions, and beliefs is referred to as their *"perceived social influences"* (PSI; Venkatesh et al., 2012). The third element of the single framework for adoption and usage of the technological model is social effect, and numerous studies have demonstrated how advantageous this element is. In certain cases, the findings show that the association is not statistically significant. Social influence was discovered to be a crucial component for M-learning acceptance, according to Kaliisa et al. (2019). We were unable to find any solid proof of South Korean users' acceptance of M-learning, which is unfortunate (Joo et al., 2014). Culture and time may cause the impact to shift from one country to another. Numerous studies have found that SI (social influence) benefits BIM (Al-Lozi et al., 2014; Tan et al., 2012). Previous investigations using a variety of technologies have shown that SI has a considerable impact on PU (Al-Rahmi et al., 2021c; Hassan et al., 2020; Wamba & Queiroz, 2019; Zhang et al., 2020). Through the above discussion, this study proposes the following hypotheses:

H5: Perceived social influences have a positive impact on behavioral intention to use.
H6: Perceived social influences have a positive impact on mobile usefulness.

University Management Support

In order to enable and improve M-learning within their academic programs, educational institutions, specifically universities, engage in a variety of administrative and strategic actions (Saroia & Gao, 2019). The intention of users to embrace the system would therefore be impacted by this element. According to this study's definition of university management support (UMS), a higher education institution must be committed to offering the best, most up-to-date, and most robust M-learning services(Al-Busaidi & Al-Shihi, 2012; Zhao et al., 2022). To maximize the likelihood of acceptance and adoption, the technological infrastructure for M-learning must be managed by devoted staff members whose primary responsibility is to offer students immediate and knowledgeable help with utilizing the M-learning service (Barker et al., 2005). It is also suggested that students' expectations for effort and performance are affected by how they view the value of UMS. Through the above discussion, this study proposes the following hypotheses:

H7: University management support has a positive impact on behavioral intention to use.
H8: University management support has a positive impact on mobile usefulness.

Lecturers' Influences

The term *"lecturers' influences for M-learning"* refers to the manner in which lecturers or professors, in particular, have an effect on and contribute to the effective adoption of M-learning in higher education (Al-Emran et al., 2020). According to studies on the adoption of technology, social influence is an important indicator of behavioral intention to adopt a new system (Anthony et al., 2021). Someone can be affected by peers or superiors (Zhonggen & Xiaozhi, 2019). Only more authoritative influence (that of lecturers) was considered in the context of this investigation. A lecturer's degree of impact was determined by the degree of influence direct instruction had on students' propensity to embrace and apply M-learning. Earlier research indicated that people's opinions of new technology are significantly affected by the influence of superiors (Abu-Al-Aish & Love, 2013). Through the above discussion, this study proposes the following hypotheses:

H9: Lecturers' influences have a positive impact on behavioral intention to use.
H10: Lecturers' influences have a positive impact on mobile usefulness.

Academic Relevance

The degree to which M-learning activities, content, and educational resources adhere to and support the particular academic goals, objectives, and requirements of a course or educational program is referred to as *academic relevance (AR) for M-learning* (Thio, 1971). The notion of job relevance in extended TAM (Al-Emran et al., 2020) and the notion of compatibility in the transmission of innovations (Thio, 1971) are thus analogous to the concept of academic relevance. Both concepts describe how effectively the desired answer satisfies the demands of the assignment and the intended audience. In terms of academic relevance, this study examines the connection between M-learning and higher education in general. Additionally, researchers found that AR significantly affects users' perceptions of the effectiveness of an online learning system for management, which in turn impacts how much of the system is actually used (Al-Rahmi, et al., 2022a; Saroia & Gao, 2019; Venter et al., 2012). Hence, it is hypothesized that students' perceptions of the utility of augmented reality will have an impact on how useful they believe their mobile devices to be and whether or not they plan to use them for M-learning. Through the above discussion, this study proposes the following hypotheses:

H11: Academic relevance has a positive impact on behavioral intention to use.
H12: Academic relevance has a positive impact on mobile usefulness.

Mobile Usefulness

According to Scheper et al. (2019), *mobile usefulness* (MU) is the practical and functional value that users receive from mobile devices, including smartphones and tablets, in a variety of settings. In the context of M-learning, MU refers to the extent to which mobile devices and technology function as efficient tools for increasing the learning experience and fulfilling educational objectives (Al-Emran et al., 2020; Ooi & Tan, 2016). MU relates to the student's enhanced performance as a consequence of using the M-learning system, much like PU in TAM and PE in UTAUT (Ooi & Tan, 2016). Students find M-learning beneficial because it enhances study skills and teamwork with teachers and peers, boosts productivity and learning quality, and allows students to complete their academic responsibilities promptly regardless of location or time. Previous research has demonstrated that PU has a good impact on BIM (Al-Shihi et al., 2018) and even influences people's continued usage of technology (Baker-Eveleth & Stone, 2015). It gauges how much a person believes technology will aid them in achieving their objectives. When this construct is integrated into TAM, a utility element is anticipated to have a significant impact on BIM (Al-Rahmi et al., 2022C; Hamidi & Chavoshi, 2018). MU takes job performance into account and places a premium on quality and dependability (Naveed et al., 2020). Mobile technologies, for instance, can enhance students' learning capabilities and help them finish their work more quickly (Lin et al., 2020). The majority of investigations integrate MU-related components into their study designs, and it is projected that as M-learning's many benefits become more widely recognized (Anthony et al., 2021), the adoption of these investigations will rise. The benefits of usefulness for students are confirmed by a review study (Kumar & Chand, 2019). Through the above discussion, this study proposes the following hypotheses:

H13: Mobile usefulness has a positive impact on behavioral intention to use.
H14: Mobile usefulness has a positive impact on users' satisfaction.
H15: Mobile usefulness has a positive impact on adoption of M-learning.

Behavioral Intention to Use

Al-Emran et al. (2020) define *"behavioral intention"* (BI) as the mental picture of a person preparing to carry out a specific behavior. Acceptance and then actual use of a system are predicted by the intention to utilize it (Al-Emran et al., 2020; Davis, 1989). Teachers' or students' behavioral intentions to utilize the M-learning system have been found to be strongly connected with the acceptability and subsequent use of the system (Al-Rahmi et al., 2021a; Kanwal & Rehman, 2017). The goal of this study was to forecast the adoption of M-learning in remote locations where it is now unavailable and not being used. However, behavioral intention is regarded as the most accurate indication of information management utilization (Al-Emran et al., 2020; Davis, 1989). It is arguable that determining what motivates STEM students in rural high schools, their teachers, and their parents to use M-learning leads to an understanding of what motivates mobile acceptance and usage in general. This is consistent with Davis's assessment (Al-Emran et al., 2020; Davis, 1989). Therefore, testing whether PU altered people's perceptions of M-learning was the second hypothesis of this study. Through the above discussion, this study proposes the following hypotheses:

H16: Behavioral intention to use has a positive impact on users' satisfaction.
H17: Behavioral intention to use has a positive impact on adoption of use of M-learning.

User Satisfaction

According to Zhonggen et al. (2019), user satisfaction with M-learning is the general sense of fulfillment and favorable impression that students have while interacting with educational resources, activities, or platforms via mobile devices. The degree of satisfaction, comfort, and fulfillment felt by students and teachers when using M-learning resources, platforms, or technology for educational purposes is referred to as *user satisfaction for M-learning* (Doll et al., 1998). Previous research has shown that happiness has a major impact on the intention to use various mobile devices over the long run (Pham et al., 2019; Tam et al., 2020). The DeLone and McLean information systems performance model (DeLone & McLean, 2003) demonstrated empirically that user happiness had a major impact on the advantages obtained from the system. Hassanzadeh et al. (2012) highlighted that users of e-learning systems are more likely to use them and get the benefits of doing so when they are happier with the system. Perceived satisfaction, according to Cidral et al. (2018), explained 43.3% of the variance of individual impacts, indicating a considerable correlation between the two (Hassanzadeh et al., 2012). Through the above discussion, this study proposes the following hypothesis:

H18: Users' satisfaction has a positive impact on adoption M-learning.

Adoption of M-Learning in Higher Education

M-learning has recently started to be used in university teaching and learning processes. The use of wireless technologies in mobile communications has had a significant impact (Althunibat, 2015). M-learning supports traditional classroom instruction in higher education institutions by influencing students' attitudes toward learning in a favorable way. They perceive that they can access their learning activities more quickly and easily as a result of M-learning (Qashou, 2021). M-learning has shown many prospective advantages in the area of higher education as one of the technological projects. The effectiveness of learning has been improved by helping to establish an atmosphere for learning that is not constrained by time or location (Senaratne & Samarasinghe, 2019). M-learning in higher education offers a number of advantages for both teachers and students. They can disseminate academic material at any time, anywhere. Utilizing online learning materials also increases pupils' independence (Al-Emran et al., 2016). M-learning also enables learners to move freely and effortlessly. Other skills that learners acquire through M-learning include autonomy and self-study. Through seamless communication between students and instructors, M-learning permits accessibility and information participation (Ali & Arshad, 2016; Alsswey & Al-Samarraie, 2019).

M-learning includes using mobile devices for interaction between pupils and instructors as well as employing text, images, and video. In terms of potential for development, private expense reduction, time management, and student attitude toward learning, M-learning produces effective results. The potential for using multimedia (Park et al., 2012) could be the cause of these benefits. M-learning also benefits students with disabilities by enabling them to see lectures remotely on their mobile devices (Buabeng-Andoh, 2021). The acceptance and adoption of new technology by people have been the subject of numerous studies. Several models have been developed in this field (Abu-Al-Aish & Love, 2013; Saroia & Gao, 2019). Researchers that investigate M-learning tools place a strong emphasis on the subject of investigating the factors that affect students' adoption of M-learning methods in order to examine the main indications of students' intention to utilize virtual learning tools. Several models were expected. These models make an effort to incorporate the most important traits when talking about how to utilize mobile gadgets in educational settings (Gómez-Ramirez et al., 2019).

RESEARCH METHODOLOGY

To find out the answers to the study questions, a survey was conducted at King Faisal University in Saudi Arabia. Undergraduate and postgraduate students from the social science, medical science, and humanities colleges made up the target responders. There were two main sections to the questionnaire. The respondents' gender, age, and specialization were recorded in the first section's demographic data (see Table 1). Because of the nature of the information collected, an ethical clearance was obtained for this study (Ref. No. KFU-REC-2023-JUN-ETHICS1026), and data was manually and electronically collected from 364 individuals. Using a five-point Likert-type scale with response options ranging from 1 (strongly disagree) to 5 (strongly agree), the participants stated how much they agreed with each item. The adoption of this scale is supported by earlier research (Hair et al., 2012). To verify that the sample was a valid representation of the population, it was examined against pertinent criteria, such as gender, study level, and field of study. There were 364 participants who volunteered to take part and met the criteria for selection. The constructs' discriminant and convergent validity were tested using confirmatory factor analysis (CFA), and the path coefficients for all of them were determined using structural equation modeling (SEM). This research used AMOS- SEM is a specialized software tool designed for researchers engaged in structural equation modeling.

Participants

According to Hair et al. (2012), simple random sampling is a probability sampling strategy that guarantees that each member of the population has an equal chance of being chosen for the study. Therefore, basic random sampling techniques were used in this study. Students at King Faisal University who were enrolled in undergraduate and postgraduate programs were the study's target participants. The students, who are currently using M-learning systems at King Faisal University, are from various departments, including social science, medical science, and the humanities. As a result, the study's participants were able to assist us in providing answers to questions pertaining to the study's goals and questions, enabling us to learn more about the key elements that, in their eyes, influenced the adoption of portable learning systems. Because social sciences were the most popular

Table 1. Demographic profile

Demographic	Description	N	%
Gender	Female	116	31.9
	Male	248	68.1
Age	18–20	42	11.5
	21–24	60	16.5
	25–29	124	34.1
	30–34	87	23.9
	35 and above	51	14.0
Familiarity with M-learning	One year used	40	11.0
	Two years used	47	12.9
	Three years used	72	19.8
	Four years used	205	56.3
Specialization	Humanities	97	26.6
	Medical Science	74	20.3
	Social Science	193	53.0

course of study at King Faisal University, 53% of the disciplines studied had to do with educational technology (see Table 1).

Data Collection Method

Using a questionnaire survey, a quantitative methodology was used in this study. Students were given questionnaires to complete throughout the semester of 2022–2023. Data were collected from 364 undergraduate and graduate students who voluntarily and anonymously participated in a random selection process at King Faisal University. In total, 376 questionnaires were given out to the students. Because there were so many missing values, 12 surveys were discarded. As a result, 364 surveys with a response rate of 96.8% were included in the main analysis. Following the advice that the minimum feasible number of samples for quantitative studies should be N = 354 (Hair et al., 2012), the sample size for the present investigation (N = 364) is appropriate. Details about the participants are shown in Table 1.

Instrument Development

This section includes a description of the proposed study paradigm as well as the instrument evaluation criteria for each construct. Information systems (IS), expert judgment, and earlier studies on M-learning—both dependent and independent variables—were used to create and modify the suggested research model. Table 2 provides one example. Five items from Mutambara & Bayaga (2021) were modified for the perceived skill readiness (PSR) and perceived psychological readiness (PPR) scales. Five items for perceived social influences (PSI) were taken from Sabah (2016). Five elements from Ozkan et al. (2008) were converted for use in university management support (UMS). Three items from Milošević et al. (2015) and Abu-Al-Aish & Love (2013) were adapted for the lecturer influences (LI) category. Five elements from Chao (2019), Milošević et al. (2015), Naveed et al., (2020), Sabah (2016), and Venter et al. (2012), including academic relevance (AR), mobile usefulness (MU), and behavioral intention to use (BIM), were modified. Five items from Chao (2019), Milošević et al. (2015), Naveed et al. (2020), Sabah (2016), and Venter et al. (2012) were adapted to measure user satisfaction (US). Five items from Naveed et al. (2020) were modified for the Adoption of Use of M-Learning in Higher Education (AUM) survey. Three professors from King Faisal University who have a great deal of experience with M-learning applications pre-evaluated each questionnaire item to make sure it matched the questionnaire's structure and content. Three more questions on the survey's questionnaire sought information on the participants' demographics. A five-point Likert scale, from "strongly disagree" to "strongly agree," was used in the survey.

Pilot Study

A pilot test with 68 students was conducted to evaluate the validity of the questionnaire items prior to the main study. Data consistency was evaluated using Cronbach's alpha analysis, with a criteria set at a value larger than 0.7. All variables in this investigation had Cronbach's alpha values that were greater than 0.7, as shown in Table 2. As a result, the data is considered appropriate for SEM.

Evaluation of the Research Model

M-learning adoption and variables earlier starting the (SEM) study, we performed a reliability analysis test using Cronbach's alpha. The measurement's validity was then assessed using both discriminant and convergent validity analyses. Then, using confirmatory factor analysis (CFA), we evaluated the research model's model-fit indices. The proposed hypotheses were then investigated, and the factor loadings between both variables contained in the SEM were examined.

Table 2. Indicator Loadings, CR, CA, AVE

Factor	Items	Load	CA	CR	AVE	Factor	Items	Load	CA	CR	AVE
Perceived skills readiness	PSR_1	0.705	0.894	0.896	0.636	Academic relevance	AR_1	0.834	0.934	0.933	0.737
	PSR_2	0.622					AR_2	0.848			
	PSR_3	0.872					AR_3	0.855			
	PSR_4	0.892					AR_4	0.881			
	PSR_5	0.861					AR_5	0.874			
Perceived psychological readiness	PPR_1	0.792	0.852	0.856	0.665	Mobile usefulness	MU_1	0.831	0.910	0.911	0.671
	PPR_2	0.863					MU_2	0.858			
	PPR_3	0.789					MU_3	0.801			
							MU_4	0.810			
							MU_5	0.795			
Perceived social influences	PSI_1	0.841	0.916	0.917	0.690	Behavioural intention to use	BIM1	0.759	0.873	0.873	0.579
	PSI_2	0.870					BIM2	0.770			
	PSI_3	0.874					BIM3	0.720			
	PSI_4	0.807					BIM4	0.797			
	PSI_5	0.756					BIM5	0.758			
University management support	UMS_1	0.794	0.921	0.921	0.702	User satisfaction	US_1	0.847	0.922	0.923	0.705
	UMS_2	0.850					US_2	0.872			
	UMS_3	0.876					US_3	0.843			
	UMS_4	0.849					US_4	0.855			
	UMS_5	0.817					US_5	0.778			
Lecturers' influences	LI_1	0.874	0.891	0.891	0.732	Adoption of use of M-learning	AUM1	0.825	0.930	0.931	0.729
	LI_2	0.884					AUM2	0.827			
	LI_3	0.806					AUM3	0.892			
							AUM4	0.863			
							AUM5	0.861			

DATA ANALYSIS AND RESULT

In order to assess the statistical significance of loads and linkages among ideas as well as to compute some fit to assess the model's goodness-of-fit, the gathered data were analyzed and statistically evaluated using SPSS AMOS 23.0. Statistical tests were carried out to evaluate the validity and reliability of the notions. As a result, each of the item loadings, measurement precision, convergent validity, and discriminatory validity of each model validation have all been examined. Prior to doing the major evaluation in this investigation, the validity of the study tool was evaluated using a reliability test. Reliability analysis measures the consistency of components within one construct using Cronbach's alpha (α). Hair et al. (2012) suggested that Cronbach's alpha ought to be above 0.7 ($\alpha >$ 0.7) in order to be considered very reliable. (Note the table.) Additionally, Hair et al.'s interpretation (2012) explains that the Pearson correlation of anything across constructs shared in any of the features may be lower than the average variance's sum of squares. At the recommended level of 0.7 and higher, values of convergence validity that clearly distinguish themselves are displayed. The study instrument is regarded as reliable on the basis of the findings in Table 2, which demonstrate that the Cronbach's alpha and composite reliability ratings for every variable were greater than 0.7.

Analysis of Measurement Model

SEM-AMOS, an important statistical method, was used to assess the confirmatory factor analysis (CFA) results from AMOS 23. The validity of convergent unity, one-dimensionality, and discriminant reliability of this model can all be examined. In addition, Fornell and Larcker (1981) suggested using goodness-of-fit techniques, such as chi-square, normed chi-square, Tucker-Lewis coefficients (TLI), comparative fit indices (CFI), the parsimonious goodness-of-fit index (PGFI), incremental fit indices (IFI), root mean square residuals (RMR), and root mean square errors of approximation (RMSEA), to evaluate the model when estimating the highest probability. Figure 2 depicts the measure of dependent, mediator, and dependent variables, and Table 3 lists the goodness-of-fit metrics used to rank the models.

Validity and Reliability of Measures Model

The conditions for the specified reference from Fornell and Larcker (1981) were met by the discriminatory examination of the degrees of perception, which contained numerous indices for a range of thoughts. The data that the test model generated is presented in the parts that follow. The

Figure 2. The measurement of independent, mediator, and dependent variables

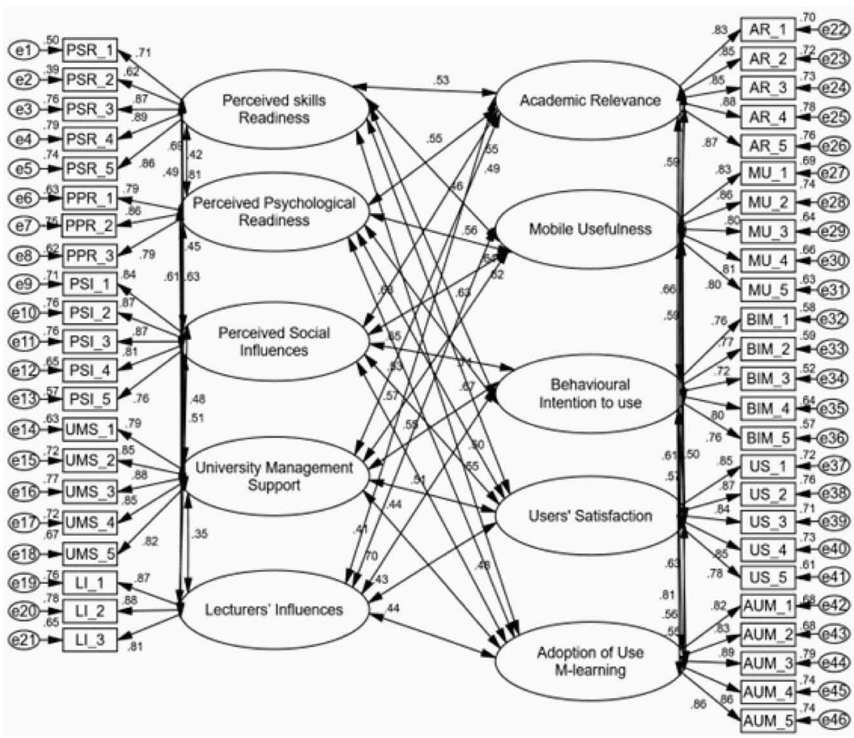


Table 3. Goodness-of-Fit indicators of the measurement model

Model	*χ2/df*	CFI	TLI	IFI	SRMR	RMSEA
Target	*≤ 5.0*	*≥ 0.90*	*≥ 0.90*	*≥ 0.90*	*≤ 0.09*	*≤ 0.08*
Model 1 (final model)	2.104	0.917	0.916	0.918	0.047	0.049

validity was identical for all constructs studied, as shown by the fact that all of the AVE validity values found in Bagozzi et al. (1998) were greater than 0.5. According to Fornell's and Larcker's argument (1981), the relationship between elements across ideas must not be more than the square of the root of the mean variance that exists in one of the constructs. Additionally, it is demonstrated that the resultant composite dependability values fall squarely within the suggested value range of 0.7 and higher.

Structural Model Analysis

Through mobile access and behavioral plans to use M-learning, TAM and UTAUT have an impact on users' happiness and uptake of M-learning. The student's performance in school serves as the foundation for all outcomes. In the discussion of hypothesis testing, they are also contrasted. Table 2 displays the reliability and validity of the findings for user satisfaction and M-learning uptake using the TAM model factors and outside variables. The proposed hypotheses were then examined using CFA during the SEM phase. Values for the composite reliability (CR), AVE, and total Cronbach's alpha (CA) were determined. This led to the acceptance of the discriminant's validity as well. The obtained CR values were also all above 0.7 and consistently in the range of 0.856 to 0.933. The CA values ranged from 0.852 to 0.934 as well. The AVE values ranged from 0.636 to 0.732, exceeding the recommended limit of 0.5. This shows that the total factor loading was minimal and greater than 0, fitting the requirements of the cited references (see Table 2; Bagozzi et al., 1998; Fornell & Larcker, 1981). The ten key constructs' hypotheses are all represented in Figures. 2 and 3, and 16 of them were accepted, while only 2 were rejected. The model's outcomes are displayed in Figure. 5 and Table 3, respectively. The key statistics of the corresponding models were consistent, which suggests that the validity and outcomes of the assumptions were verified.

Hypothesis Testing

The developed model's postulated hypotheses were examined using route analysis in SEM. Table 5 displays the results of the hypothesis testing. A total of 18 assumptions were tested, and the users' endogenous variables in the model were confirmed to exist. The study's findings supported 13 of the 14 assumptions. As a result, while H3 and H11 were rejected, the hypotheses H1 and H2, H4–H10, and H12–H18 were all supported. All the hypotheses, with the exception of two—the "link between perceived psychological readiness and behavioral intention to use" and the link between academic relevance and behavioral intention to "use"—were accepted, as indicated in Figure 3 and

Table 4. Discriminant validity matrix results

	PPR	LI	UMS	PSI	AR	PSR	MU	BIM	US	AUM
PPR	**0.859**									
LI	0.506	**0.961**								
UMS	0.332	0.282	**0.790**							
PSI	0.492	0.422	0.401	**0.887**						
AR	0.457	0.422	0.397	0.481	**0.971**					
PSR	0.536	0.663	0.354	0.429	0.471	**0.882**				
MU	0.512	0.363	0.500	0.532	0.528	0.501	**0.950**			
BIM	0.440	0.489	0.360	0.457	0.425	0.497	0.470	**0.661**		
US	0.417	0.345	0.386	0.432	0.416	0.458	0.466	0.401	**0.833**	
AUM	0.508	0.387	0.342	0.487	0.708	0.419	0.540	0.392	0.450	0.900

Figure 3. Outcomes of student group for the proposed model

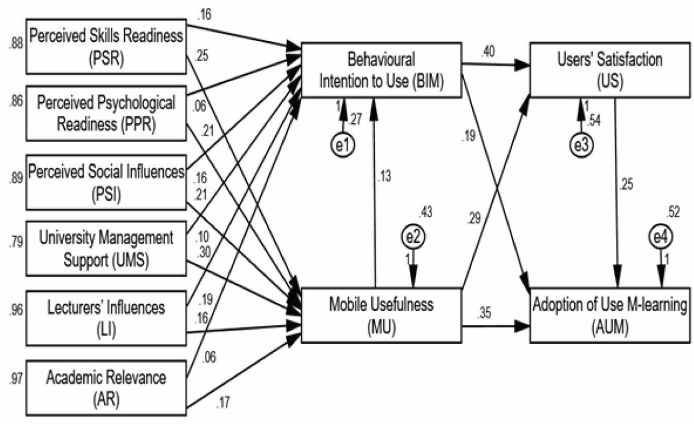


Table 5. The current sample shows that student groups can benefit from communicating with one another via mobile devices, which encourages students to use M-learning for academic purposes (= 0.349, t = 5.866). The hypothesis of each building was therefore stronger than the hypothesis of the other constructs. For instance, the idea of university support from management on mobile utility was found to be positively and significantly linked to satisfaction with and adoption of M-learning in higher education (= 0.298, t = 5.453) when compared with a different hypothesis value (e.g.,

Table 5. Results of path analysis of the structural model

H	Factors	Link	Factors	Estimate	S.E.	C.R	P-value	Results
H1	PSR	--------->	BIM	0.160	0.056	2.855	0.004	Accepted
H2	PSR	--------->	MU	0.247	0.069	3.576	0.000	Accepted
H3	PPR	--------->	BIM	0.062	0.049	1.250	0.211	Rejected
H4	PPR	--------->	MU	0.207	0.061	3.378	0.000	Accepted
H5	PSI	--------->	BIM	0.157	0.046	3.375	0.000	Accepted
H6	PSI	--------->	MU	0.215	0.057	3.751	0.000	Accepted
H7	UMS	--------->	BIM	0.096	0.046	2.100	0.036	Accepted
H8	UMS	--------->	MU	0.298	0.055	5.453	0.000	Accepted
H9	LI	--------->	BIM	0.193	0.049	3.953	0.000	Accepted
H10	LI	--------->	MU	0.156	0.061	2.554	0.011	Accepted
H11	AR	--------->	BIM	0.058	0.042	1.363	0.173	Rejected
H12	AR	--------->	MU	0.166	0.053	3.144	0.002	Accepted
H13	MU	--------->	BIM	0.133	0.049	2.738	0.006	Accepted
H14	MU	--------->	US	0.293	0.058	5.098	0.000	Accepted
H15	MU	--------->	AUM	0.349	0.060	5.866	0.000	Accepted
H16	BIM	--------->	US	0.398	0.069	5.773	0.000	Accepted
H17	BIM	--------->	AUM	0.191	0.072	2.635	0.008	Accepted
H18	US	--------->	AUM	0.253	0.061	4.159	0.000	Accepted

impact of mobile usefulness on users' satisfaction) (= 0.293, t =5.098). The relationship between university managerial support and behavioral intention to adopt M-learning has the lowest premise value (=0.096, t = 2.100).

DISCUSSION AND IMPLICATIONS

In order to analyze and evaluate the quality elements influencing students' adoption of M-learning as well as the consequences of mobile accessibility and behavioral intention to use, we studied an integrated hybrid model of the TAM and UTAUT with outside factors. We included mobile accessibility and student behavior as mediators in order to better comprehend the connection between independent aspects and users' satisfaction with the adoption of M-learning. The findings help us understand the roles that independent variables, the usefulness of mobile devices, and student behavior play in the use of M-learning. According to the research's findings, perceived mental preparedness (H1, H2, and H4) as well as perceived skill preparation (H1, H2, and H4) predicted the usefulness of mobile technology and the intent to use it. This result was in line with the observations made by Erlich et al. (2005), Iqbal and Bhatti (2015), and Mutambara and Bayaga (2021), who found that learners who had never used a computer before enrolling in an online course reported more annoyance and worry than those who had. This suggests that those who love using their mobile devices and who possess the necessary technical skills to begin and finish a task, such as academic students and instructors, believe they are psychologically prepared for M-learning. Perceived testing and utility were correlated. This demonstrates that educators who enjoy using mobile devices and have access to M-learning aren't afraid to employ it in the classroom, since they find it beneficial.

Therefore, in order to be used in higher education, M-learning needs to be taught to professors and students (Erlich et al., 2005; Iqbal & Bhatti, 2015; Mutambara & Bayaga, 2021). The study's results, however, refuted the psychological preparedness component and supported hypothesis H3, which held that psychological readiness had no beneficial effect on BIM. The optimal option is generally considered to have the following parameters: However, these results were at odds with those of earlier research (Mutambara & Bayaga, 2021). The majority of the study's findings support the hypotheses (H5 and H6) that perceived social influence affects how people view the usefulness of mobile devices and how they behave in terms of their intent to use M-learning for good. Alternatively, when a school is simple to use and accepted, mobile usefulness and ease of use become more prevalent, which has a stronger social influence.

According to earlier studies (Alyoussef, 2021; Poong et al., 2017; Sabah, 2016), perceived social impact is positively correlated with the utility of mobile devices and BIM in higher education. These results, however, are in conflict with those of previous investigations (Camilleri & Camilleri, 2022). The claimed effects of university administrative support on the utility of mobile devices and behavioral intent to employ M-learning (H7 and H8) were not revealed by analysis. In accordance with earlier studies (Alfalah, 2023; Althunibat et al., 2021; McGill et al., 2014), one potential explanation for this finding is that when users plan to use any advanced technology, they might link the technical support and dedication of the provider more with the system's level of complexity or usability than with its behavioral intent to serve the purpose of M-learning. Therefore, students are more likely to adopt M-learning if they think that the administration at their institution is committed to helping when necessary and that using online services is easy and straightforward. The results also indicate that people's impressions of how useful mobile phones are and their propensity to accept mobile education in general are positively influenced by professors (H9 and H10).

Students are more likely to adopt and use the M-learning system if they receive more motivation and support from their lecturers to do so. This correlation exists because the influence of lecturers might display superior influence. According to research on the adoption of M-learning, lecturers have a substantial impact on how useful mobile technology is and how likely users are to adopt new technologies (Alfalah, 2023; Anthony et al., 2021; Badwelan et al., 2016; Saroia & Gao, 2019). The results of this study provide evidence for the importance of lecturers' effects on students' intentions and the usefulness of mobile devices in Saudi Arabia. Unavoidably, this effect will encourage pupils to use the same resources as their lecturers. Saudi society is ingrained with the cultural ideal that academics should be cherished, respected, and held up as role models for both society and pupils. Findings regarding how academic usefulness affects mobile usability show no positive effects on the propensity to use M-learning (H11). The optimal option is generally considered to have the following parameters: These results, however, are in conflict with those of previous investigations (Al-Rahmi, et al., 2022c; Al-rahmi et al., 2021a; Alfalah, 2023; Buabeng-Andoh, 2018).

The results (H12) also show a strong direct association between the behavioral intent to use mobile devices for higher education and content. These findings have been repeatedly verified in research on M-learning (Saroia & Gao, 2019; Venter et al., 2012). This association suggests that Saudi students' behavioral intention to use mobile devices for learning in college will be influenced by their comprehension of the benefits and advantages that these tools can provide, as well as the relevance of such tools for educational work. The use of augmented reality in this study allowed students to access the M-learning platform from any location with a wireless network and the appropriate mobile device. The next section discusses the impact of mobile usability and study hypotheses (H13, H14, and H15) on user happiness, M-learning adoption in higher education, and M-learning usage behavior. These findings are in line with a prior study (Al-Rahmi, et al., 2022b) that discovered a strong correlation between comparative advantages, attitudes toward using M-learning, and the adoption of M-learning in higher education.

The Amos-SEM results demonstrate that BIM significantly and favorably influenced the users' pleasure and uptake of M-learning (H16 and H17), which were factors that could be predicted. These outcomes also matched those that had previously been published in the M-learning space (Al-Emran & Teo, 2020; Alturki & Aldraiweesh, 2022; Chao, 2019). This finding reveals that users' BIM is directly and favorably connected to their enjoyment of and uptake of M-learning in higher education. Finally, the Amos-SEM results demonstrate that user happiness has a substantial influence on the uptake of M-learning in higher education (H18). This result is consistent with prior studies that discovered a relationship between students' BIM and M-learning adoption (Alturki & Aldraiweesh, 2022; Lytras et al., 2016; Magsayo, 2022).

The third hypothesis (H3) proposed a strong correlation between behavioral desire to apply M-learning and perceived psychological readiness. The data analysis, however, refutes this theory and suggests that there might not be a substantial or statistically meaningful relationship between these two variables. These findings should be examined more deeply by discussing the following possibilities:

- External factors other than perceived psychological preparation may have a greater impact on user intention prediction than technological infrastructure, educational support, or personal preferences.
- It's likely that the concept of psychological preparation has multiple dimensions and that the research did not fully capture some aspects of it, which resulted in the hypothesis being rejected.
- Depending on the particular educational setting, the student characteristics, or the nature of the M-learning program, there may be differences in the relationship between psychological preparation and behavioral intention.

Furthermore, it is probable that there is a strong correlation between academic relevance and the behavioral desire to use M-learning, as suggested by H11. The results of this research's data analysis, however, do not support this prediction, indicating that the intention to employ M-learning may not be strongly predicted by perceived academic significance. It will be worthwhile to examine the findings more deeply and discuss the following possibilities:

- In the context of M-learning, take into consideration whether factors like perceived utility, ease of use, or technological infrastructure might be better indicators of user intention.
- The study's participants might have different ideas about what academic relevance is, which could cause differences in how this variable affects their intention to use M-learning.
- Users' impressions may alter depending on the type of educational context they are in, the nature of the academic content, the particular learning objectives, or the instructional design of M-learning apps.
- There may not be a meaningful association if specific teaching strategies or content presentation styles do not meet participants' expectations of academic relevance.
- The emphasis may need to switch to creating interesting and user-friendly learning experiences that appeal to different motives if academic relevance is not the main factor influencing the intention to utilize M-learning.
- Further study could entail looking at the function of particular categories of academic content, examining user preferences for instructional techniques, or performing cross-cultural research to find out how various demographics perceive academic relevance differently.

Theoretical and Practical Implications

By integrating the technology acceptance model (TAM) and the unified theory of utilization and acceptance of technology (UTUAT), this study adds to the body of knowledge and provides a model that can be used to recognize those four major implications. First, due to mobile convenience and behavioral intentions to use M-learning, the effects of M-learning on perceived skill preparedness, perceived psychological preparedness, perceived social influences, perceived university management support, perceived lecturer influences, and perceived academic relevance increased learner adoption of M-learning. Second, mobile usefulness and behavioral intention for using M-learning, which encourage M-learning adoption, have an impact on user happiness and acceptance of the usage of M-learning. TAM, UTAUT, and other related technologies are currently being used to create a means of understanding for classroom instruction. The study's contribution to the first model integrates UTUAT with TAM. Future mobile education will be able to improve teaching and learning outcomes by utilizing the technology acceptance strategy.

By answering the research questions, the study's key practical implications and contributions are achieved. The technological norms were initially demonstrated to be a useful model for acquiring independent variables to improve students' behavioral intention to use and mobile adoption, which increases their pleasure in M-learning and their embrace of it in college. The unified theory uses data on the acceptance and use of technology to model independent factors in order to increase the utility of mobile phones and students' behavioral intention to use them. Students are utilizing M-learning more frequently as a result. Since earlier research in these fields did not take into account how M-learning affects the accessibility of mobile gadgets and students' behavioral control to use them, our work adds considerable theoretical value to those earlier studies (Al-Rahmi et al., 2021c; Sabri et al., 2022).

The following recommendations might be made to the ministry of education, teacher training institutions, and mobile developers based on the findings of this study and earlier studies that examined the acceptance of M-learning by students (Mutono & Dagada, 2016), teachers (MacCallum et al., 2014; Sánchez-Prieto et al., 2019), and other stakeholders. Higher education learners and their teachers consider the effort needed to learn and to be skilled in using M-learning important when accepting it; as a result, M-learning developers should develop M-learning platforms that are user-friendly. Mobile developers should also include as much learning material as possible on M-learning platforms. The learning materials may include question papers and their marking guidelines, textbooks, and visualized experiments. These recommendations are based on the fact that, while accepting M-learning, students and teachers in higher education place a high value on its usability. The Ministry of Higher Education should focus on the adoption and use of M-learning among higher education teachers and learners. This can be done by raising awareness about the benefits of M-learning, providing M-learning resources to both teachers and learners, providing training on how to use M-learning, and supplying teaching materials like visualized experiments. All these improve learners' and teachers' attitudes towards M-learning, which in turn predicts its adoption. Teacher training institutions should partner with the Ministry of Higher Education to provide in-service instructors with the skills needed for M-learning. Teacher instruction institutions should also equip pre-service instructors with the skills needed for M-learning so that when they join schools, they will be able to teach using M-learning and also help other teachers do so. As a result, the following are the research's practical implications for the use of M-learning:

- Mobile platforms' learning analytics and data gathering features give teachers insightful information about the engagement and performance of their students.
- Mobile applications offer group activities, real-time communication, and collaborative projects, which help students feel more like a part of a community.
- Personalized content distribution via mobile devices and adaptive learning platforms enable tailored learning experiences.
- By removing conventional boundaries of time and place, mobile devices give students access to instructional resources at any time and from any location.
- To fully utilize mobile technology, institutions must address issues with digital literacy, device compatibility, and data security.
- Positive intentions to use mobile technologies in higher education are shaped by clear communication about the advantages of mobile integration and continued support.

In the field of education, M-learning has become increasingly popular because it offers students ease and flexibility. However, M-learning has its own set of difficulties and disadvantages, just like any technology-based strategy. Here are a few such concerns that need consideration:

- Unequal access: a digital divide may arise from differences in the availability of mobile devices and dependable internet access. It may be difficult for learners to fully engage in M-learning activities if they lack reliable internet connections or appropriate devices.
- Screen size and input restrictions: compared to desktop computers, mobile devices usually have smaller screens and fewer input possibilities. This may have an impact on how easily learnable some resources are, particularly ones that require intricate images or intricate interactions.
- Data security: there may be security hazards involved in sending private educational data over mobile networks. Strong security measures are required by educational institutions in order to safeguard student data and preserve the integrity of the classroom.
- Good pedagogy: to be effective in a mobile context, certain teaching techniques that perform well in traditional settings may need to be modified.
- Quality control: ensuring the correctness and quality of educational materials might be difficult in light of the widespread use of M-learning apps and content. Teachers must choose their resources wisely in order to uphold academic standards.

Limitation and Future Work

Like any human endeavor, this research has some limits, even though its primary goal has been accomplished. First, it is uncertain how well the results of this study can be applied to other circumstances, because it was limited to Saudi students from a particular university. Also, the sample was rather small. The validity of the results of the model analysis and the ability to generalize them would both be enhanced with a larger study design and sample size. Ultimately, the theoretical model ignored contextual factors such as performance requirements, subjective satisfaction, previous experience, and the type of M-learning activities by taking into account only five external variables (PSR, PPR LI, AR, PSI, and UMS). Future research can, however, be guided by these limits. To improve the reliability of the findings and deepen understanding of the subject, similar research might be carried out with larger sample sizes in various geographic situations. Future studies could further broaden the theoretical model by including pertinent contextual variables to address other facets of the topic. Therefore, the future work of M-learning in education holds such exciting possibilities as the following:

- Adaptive learning technology development and integration ought to be the main priorities of future work in M-learning. With the use of these technologies, learning can be made genuinely personalized by dynamically modifying both the content and the teaching methods according to the performance, preferences, and progress of each individual student.
- There is a lot of promise in investigating how AR and VR might be integrated into M-learning platforms. By enabling learners to participate in 3D simulations, virtual worlds, and cooperative activities, these technologies can provide immersive educational experiences that improve knowledge and engagement.
- Improving the social learning features of M-learning systems can encourage cooperation and information exchange. Subsequent research endeavors ought to delve into the intricacies of incorporating social elements, such as discussion boards, cooperative projects, and peer-to-peer communication, into M-learning environments.
- Future research should examine how M-learning might be tailored to various cultural contexts in light of the diversity of learners. Creating interfaces, content, and instructional practices that are sensitive to cultural differences can improve the efficacy of M-learning in a variety of international contexts.

CONCLUSION

Higher education institutions now have the opportunity to integrate cutting-edge teaching techniques into their curriculum thanks to technological advancements. M-learning management systems, which house a significant component of the entire learning process on a platform offering various cutting-edge features to both students and teachers, are a manifestation of these technological advances. The purpose of this study is to examine how Saudi Arabian university students will use M-learning and apps (like Mobile Blackboard). At King Faisal University in Saudi Arabia, data were gathered from college students using a quantitative approach and a survey questionnaire. Eight hypotheses were offered as a result of the study's research model, which was based on an expanded version of the TAM and UTAUT frameworks. The AMOS-23 model analysis tool was used. Analysis backed up 16 of the 18 hypotheses that were put forth, including the effects of PSR, PPR, PSI, UMS, and AR on MU with BIM. Two hypotheses, notably the effects of PPR and AR on BIM, were not supported by the analysis. The results shed light on the critical factors that, because they influence students' behavioral intentions toward use as well as acceptance of new M-learning systems, should be carefully considered when they are introduced. These insights are useful for researchers, developers, policymakers, and providers of online education services.

CONFLICT OF INTEREST

The author of this publication declares there is no conflict of interest.

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