**Abstract:** Smart mobile learning (M-learning) applications have shown several new benefits for higher educational institutions during the COVID-19 pandemic, during which such applications were used to support distance learning. Therefore, this study aims to examine the most important drivers influencing the adoption of M-learning by using the technology acceptance model (TAM). The structural equation modelling (SEM) method was used to test the hypotheses in the proposed model. Data were collected via online questionnaires from 520 undergraduate and postgraduate students at four universities in Saudi Arabia. Partial least squares (PLS)–SEM was used to analyse the data. The findings indicated that M-learning acceptance is influenced by three main factors, namely, awareness, IT infrastructure (ITI), and top management support. This research contributes to the body of knowledge on M-learning acceptance practices. Likewise, it may help to facilitate and promote the acceptance of M-learning among students in Saudi universities.

**Keywords:** mobile learning; distance learning; COVID-19; Saudi Arabia

1. **Introduction**

Universities throughout the world are attempting to develop electronic learning (e-learning) and mobile learning (M-learning) systems in order to merge these educational systems with the traditional ones currently used [1]. E-learning and M-learning systems have become critical in order to accomplish learning objectives in a successful way during the COVID-19 pandemic. It is critical for universities to take full advantage of e-learning in order to remain competitive in the globalised 21st century [2–4]. The recent revolution in information and communication technology (ICT) has resulted in a move away from face-to-face learning, toward e-learning. During the COVID-19 pandemic, this technology has helped universities on a global scale to ensure the continuity of learning processes [5]. It has also altered how students communicate and interact with instructors. This technological advancement has transformed the learning process through the use of e-learning systems and M-learning applications to achieve sustainable education [6–8].

The real implementation of M-learning systems in Saudi universities can offer some effective solutions for distance learning during the COVID-19 pandemic [9]. It can help Saudi students to continue their learning process, and offers them the autonomy to learn according to their own learning styles and attitudes [10–12]. In addition, online teaching sessions through smartphones will assist them in interacting with teachers at any time.
and place during the COVID-19 pandemic. M-learning has offered scope for students to undertake distance and online learning from their homes, and will help to decrease the spread of COVID-19 among students [13].

In fact, the application of M-learning systems for teaching and learning during the COVID-19 pandemic has been considered an excellent choice for both students and teachers. Despite the benefits of M-learning listed above, its widespread and effective application in the teaching and learning process remains very low among Saudi students [14–16]. One of the main issues in relation to the usage of new technology in the learning and teaching process is the acceptance of technology among students [17]. To this end, this study aims to answer the following research question:

What are the important drivers that would lead to the adoption of M-learning among Saudi students?

2. Literature Review and Research Background
2.1. Related Works on Mobile Learning Acceptance

With the increasing number of features offered by smartphones, there has been tremendous growth in interest in using mobile devices in higher education [18]. Hence, research interest in factors that affect M-learning acceptance among students has also increased. Several studies have been undertaken to explain the main drivers for the adoption of M-learning in different contexts [19–22]. According to previous studies [23–35], students’ acceptance of M-learning is an essential step in guaranteeing the full usage of this system. To achieve such acceptance, the main aspects and factors of students’ adoption of M-learning applications should be properly understood [36]. In addition, students’ needs and requirements should be correctly determined by mobile service providers and designers from the outset. Several studies have addressed this issue. For example, For example, [19] found that information technology infrastructure (ITI) is one necessary component of M-learning acceptance. As a result, the ITI in Saudi universities requires extensive analysis. Providing adequate ITI is necessary when introducing new technologies such as M-learning applications, as insufficient IT resources and infrastructure can impede the acceptance and usage of any new technology [20]. Therefore, this study adopted this factor to investigate its effect on M-learning success in Saudi universities.

In addition, previous studies [21–24] have confirmed that university management support is vital to the development of M-learning system adoption and, thus, reflects positively on the actual use (AU) and acceptance of M-learning by students. According to [24], support by university management is associated with their willingness to provide all necessary resources to ensure the development success of the M-learning project. In other words, a positive attitude among top management towards an M-learning project is a real indicator that a university will support the adoption of M-learning. Therefore, our study included this factor in the proposed model to investigate its effect on M-learning success in Saudi universities.

On the other hand, university culture could play a crucial role in how universities adopt M-learning systems. Information system researchers have found that university culture is predictive of technology adoption, including M-learning adoption [25]. According to [26], public culture development is qualitatively distinct from physical infrastructure development. The COVID-19 pandemic has led to cultural shifts in attitudes towards distance learning technologies, as well as possible resistance from students to the use of these new technologies [27–30]. Hence, this study investigates the effect of university culture on M-learning success in Saudi universities.

Moreover, several researchers have indicated that one of the main issues that should be addressed to increase the involvement and use of M-learning applications is inadequate awareness of the technology’s existence [31–35]. Prior studies have shown that awareness is crucial in the adoption of M-learning systems. Therefore, this study adopted this factor to investigate its effect on M-learning success in Saudi universities.
Finally, in our proposed model, we adopted two main constructs of the TAM model as predictors of acceptance and usage of M-learning, namely, perceived ease of use (EUS), and perceived usefulness (PUS). Previous studies [36–40] have confirmed that these two factors could play a crucial role in the success, usage, and acceptance of M-learning systems. In general, users do not like to use systems that require high levels of skill or are highly complex. Several studies have supported the belief that EUS influences users’ intention to use a particular technology [40–43]. Similarly, previous research has indicated that users find M-learning technology useful and productive if its use does not require much time and effort [44–48]. Hence, it can be argued that students are more likely to use M-learning services if they find that doing so is not complicated. Similarly, the success of an M-learning system would increase if users realised the importance of such a system in improving their performance.

2.2. Overview of Mobile Learning as a Distance Learning Tool

During the COVID-19 pandemic, many universities around the world started to use distance learning platforms, such as M-learning platforms, Blackboard, and others [49]. For example, many universities in Saudi Arabia—such as King Faisal University (KFU)—used the Blackboard and M-learning systems as distance learning tools, as a result of the decision by the Saudi government to close all universities during the COVID-19 pandemic [50]. M-learning systems served as online classrooms in which smartphones could be used by instructors and their students to continue the learning process during the COVID-19 pandemic. An M-learning system enables instructors to upload all learning materials, learning activities, assignments, and quizzes. On the other side, students can access online classrooms and interact with instructors through online classes, download learning materials, and submit homework using the M-learning system. An M-learning platform is a distance learning platform with many features that support the learning and teaching processes for all education levels in universities. It also contributes to ensuring that lesson plans are carried out and the educational goals of the curriculum are met [50–53]. An M-learning system features a package of educational tools to support the teaching and learning processes. It is a virtual classroom that enables learners and their teachers to meet simultaneously via virtual meetings, or at any convenient time through recorded lessons [54–57]. In addition, the platform includes excellent features for ease of communication between students and teachers, such as email service, Microsoft Teams, and a variety of channels for communication between students, teachers, and parents [58].

2.3. Factors Affecting the Mobile Learning Success Context

Several recent studies have examined a number of factors that could influence the acceptance, adoption, usage, and implementation of M-learning. For example, [59–61] found that information technology infrastructure (ITI) is one necessary component of M-learning acceptance. As a result, the ITI in Saudi universities requires extensive analysis. Providing adequate ITI is necessary when introducing new technologies such as M-learning applications, as insufficient IT resources and infrastructure can impede the acceptance and usage of any new technology [62]. Therefore, this study adopted this factor to investigate its effect on M-learning success in Saudi universities.

In addition, previous studies [63–67] have confirmed that university management support is vital to the development of M-learning system adoption and, thus, reflects positively on the actual use (AU) and acceptance of M-learning by students. According to [54], support by university management is associated with their willingness to provide all necessary resources to ensure the development success of the M-learning project. In other words, a positive attitude among top management towards an M-learning project is a real indicator that a university will support the adoption of M-learning. Therefore, our study included this factor in the proposed model to investigate its effect on M-learning success in Saudi universities.
On the other hand, university culture could play a crucial role in how universities adopt M-learning systems. Information system researchers have found that university culture is predictive of technology adoption, including M-learning adoption [68]. According to [69], public culture development is qualitatively distinct from physical infrastructure development. The COVID-19 pandemic has led to cultural shifts in attitudes towards distance learning technologies, as well as possible resistance from students to the use of these new technologies. Hence, this study investigates the effect of university culture on M-learning success in Saudi universities.

Moreover, several researchers have indicated that one of the main issues that should be addressed to increase the involvement and use of M-learning applications is inadequate awareness of the technology’s existence [70]. Prior studies have shown that awareness is crucial in the adoption of M-learning systems. Therefore, this study adopted this factor to investigate its effect on M-learning success in Saudi universities.

Finally, in our proposed model, we adopted two main constructs of the TAM model as predictors of acceptance and usage of M-learning, namely, perceived ease of use (EUS), and perceived usefulness (PUS). Previous studies [71–73] have confirmed that these two factors could play a crucial role in the success, usage, and acceptance of M-learning systems. In general, users do not like to use systems that require high levels of skill or are highly complex. Several studies have supported the belief that EUS influences users’ intention to use a particular technology [74–77]. Similarly, previous research has indicated that users find M-learning technology useful and productive if its use does not require much time and effort [77–80]. Hence, it can be argued that students are more likely to use M-learning services if they find that doing so is not complicated. Similarly, the success of an M-learning system would increase if users realised the importance of such a system in improving their performance.

Based on the above discussion, we adopted ITI, university management support, university culture, awareness, EUS, and PUS in our proposed model, in order to examine their roles in increasing the acceptance of M-learning in Saudi universities.

3. Hypotheses of the Proposed Model

In this work, our proposed model was established by using the TAM model plus five external factors to determine the main drivers influencing M-learning acceptance in Saudi universities. According to previous studies [40–43], the TAM model is one of the most suitable models to measure the acceptance of M-learning among users. This model comprises five main factors—namely, AU, intention to use (IU), attitude (AT), EUS, and PUS—according to Davis [44–46]. These factors are considered to be predictors of the acceptance and usage of M-learning, according to previous studies [46–48]. Figure 1 presents the pictorial presentation of the TAM model constructs.

![Figure 1. Technology acceptance model.](image-url)
ITI refers to the combination of hardware, software communication networks, and software applications that should be offered by universities to enable students to access their online learning systems. Providing adequate ITI is necessary to introduce new technologies such as M-learning applications. Insufficient ITI resources can impede the acceptance and usage of any new technology [49]. Previous studies [50–53] have indicated that ITI is one necessary component of M-learning acceptance as shown in Figure 2. As a result, ITI in Saudi universities requires extensive analysis. Hence, this study proposes the following hypothesis:

**Hypothesis 1 (H1).** ITI positively affects M-learning acceptance among students.

According to [54], support from university management is associated with their willingness to provide all of the necessary resources to ensure the development success of an M-learning project. In other words, the positive attitude of top management towards an M-learning project is a real indicator of a university's support for the adoption of M-learning. Previous studies [55,56] have confirmed that university management support is vital to the development of M-learning system adoption and, thus, reflects positively on student AU and acceptance of M-learning. Hence, this study proposes the following hypothesis:

**Hypothesis 2 (H2).** University management support positively affects M-learning acceptance among students.

Universities should be prepared for any emergency conditions, such as the COVID-19 pandemic, and pursue alternative strategies to implement distance learning, such as adopting M-learning applications. Therefore, university culture issues can significantly affect the adoption of M-learning systems. According to [57], public culture development is qualitatively distinct from physical infrastructure development. The COVID-19 pandemic led to cultural shifts towards distance learning technologies, as well as possible resistance from students to the use of these new technologies. Thus, university culture could play a crucial role in how universities adopt M-learning systems. Information systems researchers have found that university culture is predictive of technology adoption, including M-learning adoption [58]. Hence, this study proposes the following hypothesis:

**Hypothesis 3 (H3).** University culture positively affects M-learning acceptance among students.

Student awareness of new technology, such as M-learning applications, is still limited [58]. Therefore, universities should increase the awareness among those of their students who lack adequate and essential technical information. According to [59], awareness has a strong impact on M-learning acceptance among users. Moreover, several researchers have indicated that one of the main issues that should be addressed in order to increase the involvement and use of M-learning applications is inadequate awareness of the technology’s existence [60]. As prior studies have shown that awareness is crucial in adopting M-learning systems, the following hypothesis is proposed:

**Hypothesis 4 (H4).** Awareness positively affects M-learning acceptance among students.

Based on the TAM model, AU can be determined directly from one construct, namely, IU. In addition, AU can be determined indirectly from three constructs—namely, AT, EUS, and PUS—by the moderation of IU. Within the context of our study, the TAM model hypothesises that the three key constructs for AU of M-learning are students’ perceptions of EUS, PUS, and IU.

In the M-learning context, we used the two main constructs of the TAM model as predictors of acceptance and usage of M-learning, namely, perceived EUS and PUS. EUS can be defined as the degree to which users perceive that using an M-learning system will be free of effort. PUS refers to the extent to which users perceive that using an M-learning
system will improve their learning performance. In the TAM model, EUS and PUS affect AT toward using M-learning. PUS and AT affect IU, and IU affects AU of M-learning systems.

In general, users do not like to use systems that require high levels of skill or are complex. Several studies have supported the belief that EUS influences users’ intentions to use a particular technology [31–35]. Similarly, prior literature has indicated that users find M-learning technology useful and productive if its use does not require much time and effort [36–38]. Hence, it can be argued that students are more likely to use M-learning services if they find that using such services is not complicated. Similarly, the success of an M-learning system would be increased if students realised the importance of such a system in improving their performance. Hence, we formulated the following hypotheses in our proposed model:

Hypothesis 5 (H5). EUS positively affects M-learning acceptance among students.

Hypothesis 6 (H6). PUS positively affects M-learning acceptance among students.

Figure 2. The proposed model for explaining the acceptance of an M-learning system.

4. Methodology

In this work, to test the hypotheses in the proposed model, the SEM method was used to determine the main drivers influencing M-learning acceptance in Saudi universities. In the context of M-learning acceptance, several previous studies have used the SEM method to examine students’ acceptance [61]. These studies have indicated that the SEM method is capable of effectively discovering relationships between variables. In addition, it is an advantageous data analysis method, and tests the structural model in TAMs [62]. Consequently, we used the SEM method to test the hypotheses in the proposed model.

4.1. Data Collection and Participants

This study is based on an empirical examination of Saudi universities that are engaged in the adoption of distance learning activities, such as M-learning systems. The study collected data from four universities in Saudi Arabia, namely, KFU, King Saud University (KSU), King Khalid University (KKU), and Al-Dammam University (DU). The study gathered data from 520 respondents from the four universities as follows: KFU = 215, KSU = 105, KKU = 110, and DU = 90. To collect the data from respondents,
we distributed the online questionnaire to all respondents during online classrooms, with assistance from their instructors.

The participants were 520 students enrolled in the Information System Analysis and Design course at undergraduate level and the Advanced Analysis and Design course at postgraduate level at four universities in Saudi Arabia (see Table 1). The courses, offered through the College of Information Technology, were taught online via the Blackboard system. The majority of respondents were in their sophomore or junior year. There were many more female students (69.2%, \( n = 360 \)) than male students (30.8%, \( n = 160 \)). Most were aged between 21 and 25 (78.8%, \( n = 410 \)). About 88.4% reported owning an iPhone, and 92.3% had had the experience of using an iPhone in the learning process while attending an online class during COVID-19.

Table 1. Analysis of demographic information.

| Characteristic                        | Sample (n) | Frequency (%) |
|---------------------------------------|------------|---------------|
| Gender                                |            |               |
| Male                                  | 160        | 30.8%         |
| Female                                | 360        | 69.2%         |
| 18–20                                 | 30         | 5.7%          |
| 21–25                                 | 410        | 78.8%         |
| Over 25                               | 80         | 15.3%         |
| Age                                   |            |               |
| Undergraduate                         | 395        | 75.9%         |
| Postgraduate                          | 125        | 24.0%         |
| Level                                 |            |               |
| Undergraduate                         | 395        | 75.9%         |
| Postgraduate                          | 125        | 24.0%         |
| Mobile Owner                          |            |               |
| iPhone                                | 460        | 88.4%         |
| Android                               | 60         | 11.6%         |
| Prior Experience with Mobile Learning Apps |     |               |
| Yes                                   | 480        | 92.3%         |
| No                                    | 40         | 7.7%          |
| Universities                          |            |               |
| KFU                                   | 215        | 41.3%         |
| KSU                                   | 105        | 20.1%         |
| KKU                                   | 110        | 21.1%         |
| DU                                    | 90         | 17.3%         |
| Total                                 | 520        | 100%          |

4.2. Research Measurements

To ensure that the items in the online questionnaire were measured in a valid and reliable manner, validated scales from prior studies were used for all constructs in our study. For instance, the items for the IT infrastructure construct were adopted from [3–5], items for university management support and university culture from [7–9], and items for awareness from [10]. Items for PUS and EUS were taken from [12]. Finally, the AU of M-learning was measured using items from [13], which assess the extent to which universities have adopted an M-learning system. All variables were quantified using a scale with poles ranging from strongly disagree (1) to strongly agree (5).

To ensure that the questionnaire items were valid and clear, we sent the questionnaire to seven faculty members with experience in the M-learning field, so that they could check the appropriateness and clarity of all questions and the appropriateness of each item for each construct. Based on the expert feedback, we corrected all comments and then re-sent the questions to them. The expert results indicated that all items were clear and appropriate for each construct.

5. Data Analysis and Results

5.1. Reliability Analysis

In this study, reliability analysis was conducted using Cronbach’s alpha on the data collected to measure the internal consistency of each construct. Table 2 presents the values of Cronbach’s alpha for all constructs. The results indicate that all values were higher than 0.70, which is acceptable according to [63]. This means that the reliability values for all constructs were accepted for further analysis.
Table 2. Reliability and convergent validity analyses.

| Constructs                        | Cronbach's Alpha | (AVE > 0.5) |
|-----------------------------------|------------------|-------------|
| IT Infrastructure                 | 0.792            | 0.937       |
| University Management Support     | 0.873            | 0.918       |
| University Culture                | 0.821            | 0.829       |
| Awareness                         | 0.890            | 0.811       |
| Ease of Use                       | 0.905            | 0.850       |
| Perceived Usefulness              | 0.897            | 0.882       |
| Actual Use                        | 0.852            | 0.912       |

5.2. Convergent and Discriminant Validity Analysis

To conduct the validity analysis, convergent and discriminant validity were analysed. As shown by the results in Table 3, AVE values were greater than the threshold of correlation values between two variables, indicating that these values were acceptable according to [65].

Table 3. Discriminant validity analysis.

|   | ITI  | UMS  | UC   | AW   | EUS  | PUS  | AU   |
|---|------|------|------|------|------|------|------|
| ITI| 0.945|      |      |      |      |      |      |
| UMS| 0.797| 0.921|      |      |      |      |      |
| UC | 0.630| 0.758| 0.894|      |      |      |      |
| AW | 0.646| 0.684| 0.545| 0.882|      |      |      |
| EUS| 0.759| 0.769| 0.563| 0.689| 0.901|      |      |
| PUS| 0.769| 0.792| 0.643| 0.707| 0.790| 0.879|      |
| AU | 0.530| 0.623| 0.506| 0.643| 0.527| 0.614| 0.974|

5.3. Structural Model Analysis

According to the findings of the SEM modelling test, as shown in Table 4, all six proposed hypotheses in the research model were accepted. The findings revealed that the ITI factor influenced the AU of M-learning positively (β-value = 0.357, p < 0.001), with this result supporting H1. The findings also indicated that the factor of university management support had a significant influence on the AU of M-learning (β-value = 0.378, p < 0.001); this result means that H2 is accepted. In addition, H3 was supported by the present study’s findings, indicating that university culture has a negative influence on the AU of M-learning (β-value = −0.395, p < 0.001); this result means that H3 is accepted. The results also indicated that awareness has a significant influence on the AU of M-learning (β-value = 0.327, p < 0.001). Thus, the results indicated that H4 was supported. Finally, we also found that EUS and PUS had significant influence on the AU of M-learning (β-value = 0.351, p < 0.001 and β-value = 0.342, p < 0.001, respectively). Thus, the results indicated that H5 and H6 were supported.

Table 4. Results of structural equation modelling analysis.

| Hypotheses | Path   | Impact       | β   | SE   | t-Value | Results  |
|------------|--------|--------------|-----|------|---------|----------|
| H1         | ITI→AU | Positive (+) | 0.357| 0.051| 4.733   | Supported|
| H2         | PEU→AU | Positive (+) | 0.378| 0.042| 4.137   | Supported|
| H3         | PU→AU  | Negative (−) | −0.395| −0.075| −1.331  | Supported|
| H4         | BI→AU  | Positive (+) | 0.327| 0.044| 3.471   | Supported|
| H5         | CQ→AU  | Positive (+) | 0.351| 0.091| 3.114   | Supported|
| H6         | SYQ→AU | Positive (+) | 0.342| 0.06687| 5.108  | Supported|
6. Discussion

The results indicated that the TAM model constructs with four external factors (ITI, university management support, university culture, awareness, EUS, and PU) play a primary role in increasing the acceptance of M-learning in Saudi universities. The findings indicate that all factors have a significant influence on M-learning acceptance among students.

Based on the results, the ITI factor influences the AU of M-learning positively, because it enables students to access information, increases the utility of learning activities, increases interactivity with instructors, and improves the efficiency of the learning and teaching processes. On the other hand, the ITI in Saudi Arabia is very strong, with good internet penetration and high usage among students. Based on the findings, the present study concluded that providing high ITI specifications would lead to greater acceptance of M-learning among students. This finding is consistent with prior studies [66,67].

In addition, the findings indicate that the factor of university management support has a significant influence on the AU of M-learning among students in Saudi universities. In other words, universities should prioritise top management support when deciding to implement new technologies such as M-learning systems, so as to ensure the successful development process of such systems from the first step to the last. University management support includes top managers’ pledges and commitments to embrace M-learning systems, provide the necessary resources and financial support, and ensure that a high-quality system is offered in order to ensure effective student usage of M-learning. Saudi universities have high levels of management capabilities that could help in implementing M-learning systems successfully. Our findings are consistent with those of prior studies [66,67]. The present study concluded that university management support is one of the most significant factors influencing the acceptance of M-learning among students in Saudi universities.

Our findings indicate that university culture has a negative influence on the AU of M-learning among students in Saudi universities. This implies that an incorrect university culture could impede the implementation of M-learning in Saudi universities. This study found that university culture had a negative impact on students’ willingness to accept M-learning. The main reason for this result is the cultural differences between students, which may affect their acceptance. For example, the COVID-19 pandemic led to cultural shifts towards distance learning technologies, as well as possible resistance from students to the use of such technologies. Based on these findings, university culture could play a crucial role in how universities adopt M-learning systems. Previous studies have found that university culture is predictive of technology adoption, including M-learning adoption [68–72].

Furthermore, our findings indicate that there is a significant and positive correlation between awareness and AU of M-learning. The study found that a majority of Saudi students are unfamiliar with mobile applications and how to use them. This study found that when the percentage of awareness among students of how to use M-learning systems is very low, there is a decrease in their acceptance of such systems. This result is consistent with prior research [72–77].

Finally, this study found that both EUS and PU have a significant and positive correlation with AU of M-learning. This indicates that when students find an M-learning system to be user-friendly, simple, easy to use, clear, and useful for the learning process, this could encourage them to use it effectively; thus, this will reflect on their opinions about accepting the M-learning system. Based on this result, this study recommends that designers and developers take those two factors into consideration in the development of an M-learning system. Previous studies [77–79] have confirmed that EUS and usefulness are among the primary dimensions that motivate users to accept any type of educational technology. Our findings are consistent with those of prior studies [80].

Research Contributions

This study makes both theoretical and practical contributions. Focusing on the theoretical contribution, this study contributes to the body of knowledge on M-learning acceptance by providing a new model that captures the most significant drivers of such
acceptance among students in public Saudi universities. Second, this study clarifies that important factors—such as ITI, awareness, university management support, and university culture—played a key role in increasing the acceptance of M-learning systems during COVID-19 pandemic, and will ensure the continuity of the learning process through the use of this distance learning tool. Third, this study confirms that the TAM model is suitable for analysis of the factors influencing students’ acceptance of M-learning. With regard to practical contributions, the findings of this study can help Saudi universities to better understand the process of M-learning project implementation. The universities should consider important factors related to ITI, awareness, university management support, and university culture in order to improve the acceptance of M-learning systems among students. Finally, this study’s findings will benefit decision makers, designers, and developers in universities to ensure that students participate actively in using M-learning systems during the COVID-19 pandemic.

7. Conclusions, Limitations, and Future Work

Despite the major benefits of M-learning, the widespread and effective application of such technologies in the teaching and learning processes has remained low among Saudi students during the COVID-19 pandemic.

To address this issue, this study developed six direct hypotheses using the TAM model to explain the main drivers influencing M-learning acceptance. The SEM method was used to test the hypotheses in the proposed model. Data were collected via online questionnaires from 520 undergraduate and postgraduate students at four Saudi universities. PLS–SEM was used to analyse the data. The findings indicated that TAM model constructs with four external factors—namely, ITI, university management support, university culture, awareness, EUS, and PUS—play a primary role in increasing the acceptance of M-learning in Saudi universities. The findings indicated that all of the studied factors have a significant influence on M-learning acceptance among students. This research contributes to the body of knowledge on M-learning acceptance practices. Likewise, it may help to facilitate and promote the acceptance of M-learning among students in Saudi universities.

Although this work makes several interesting contributions, several limitations should be covered in future work. First, further investigation into the drivers of M-learning acceptance among students is needed. Second, future work could explore teachers’ perceptions and needs in relation to adopting M-learning systems. Finally, there is a need to investigate other important factors related to system quality and usability factors, as well as their effects on students’ acceptance of M-learning systems.

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