

Article

Employing the TAM Model to Investigate the Readiness of M-Learning System Usage Using SEM Technique

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Abstract: During COVID-19, universities started to use mobile learning applications as one of the solutions to support distance learning. The readiness of universities to apply new systems, such as mobile learning applications, is considered one of the critical issues to ensure the system's success. Determining the most important aspects of readiness to use mobile learning is a key step to adopt mobile learning in an effective way. To address this issue, this research aims to determine the most important determinants influencing mobile learning readiness by employing the Technology Acceptance Model (TAM). The Structural Equation Modelling (SEM) method was used to test the hypotheses in the proposed model. The results showed that the relationship between mobile learning readiness and awareness, IT infrastructure and top management support was positively significant. In conclusion, the findings will be of value to decision makers and mobile learning developers in universities to enhance the development of mobile learning applications. In addition, it may help facilitate and promote the usage of mobile learning applications among users.

Keywords: distance learning; mobile learning applications; readiness; SEM; COVID-19



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1. Introduction

During the COVID-19 pandemic, many universities around the world started to use distance learning platforms, such as mobile learning platforms, Blackboard platform and others [1]. Many universities around the world are attempting to develop e-learning and mobile learning systems in their settings, in order to merge these educational systems with the current traditional teaching method [1]. E-learning and mobile learning systems have become critical in order to accomplish these objectives. It is critical for universities to fully take advantage of e-learning to remain competitive in the globalized twenty-first century [2–4]. The recent revolution in information and communication technology (ICT) has resulted in a move from face-to-face learning to electronic learning. Throughout COVID-19, on a global scale, this technology has helped universities to maintain the continuation of the learning process [5]. It has also altered how students communicate with instructors and interact with them. Because of this technological advancement, the learning process has been transformed into e-learning systems and mobile learning applications, in order to achieve sustainable education [6–8].

The real implementation of mobile learning systems into 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 offer them the autonomy to learn, depending on their learning styles and attitudes [10–12]. In addition, online teaching sessions through smartphones will assist them to interact with teachers anytime and anywhere during the COVID-19 pandemic. Mobile learning opened the scope for conducting distance learning and online learning between students from their home; this tool will help in decreasing the spread of coronavirus between them [13].

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

What are the important determinants influencing mobile learning readiness during COVID-19 among users?

2. Literature Review

According to the literature, the adoption of mobile learning applications across several platforms, such as Android and IOS, can offer some effective solutions for students and universities during the COVID-19 pandemic [13–15]. It can help students to continue their learning process and offers them the autonomy to learn according to their own learning styles and attitudes [16–19]. In addition, online mobile learning sessions will assist them to interact with teachers anytime and anywhere during COVID-19. Mobile learning applications have offered scope for students to undertake distance and online learning from their homes and will help decrease the spread of coronavirus among them [20–22].

With an increasing interest in mobile learning in the higher education context, it is important for universities to be aware of the importance of integrating mobile learning applications for new-generation students, as well as the quality factors that can help them to use these applications in effective ways [23–25]. The research on mobile learning in higher education is still in the early stages [26–29], and there are a limited number of studies that focus on the role of readiness factors on mobile learning development research and the adoption of mobile learning [30–32]. It is important to equip designers and developers with the necessary readiness factors to develop and implement mobile learning applications in ways that enhance student learning and facilitate learning activities [33–35].

Several studies have been undertaken to explain the main drivers for the adoption of mobile learning in different contexts [29–32]. According to previous studies [33–35], which confirmed students' acceptance of mobile learning, this acceptance is an essential step in order to guarantee the full usage of this system. To achieve that, the main aspects and factors of students' adoption of mobile learning applications should be understood effectively [36]. In addition, students' needs and requirements should be determined by mobile service providers and designers correctly from the beginning. To address this issue, several studies have been conducted. For example, Ref. [37] proposed a model to examine the students' adoption of mobile learning applications in Jordan. The authors used the TAM model, adding quality factors, including quality of content design, quality of learning content, functionality, interface design and interactivity. The results indicated that quality factors have a strong effect on students to adopt mobile learning applications. Ref. [38] extended the TAM model to identify the determinants that promote the use of mobile learning applications among students. Resistance to change and attachment have been shown by empirical results to have an important influence on behavior regarding mobile learning applications. Ref. [39] proposed a structure for M-learning acknowledgment, dependent on integrating the Technology Acceptance Model (TAM) with the refreshed DeLone and McLean's model (DL&ML). The examination intended to research the impact

of value components and individual variables on students' fulfillment and expectation to the utilization of the M-learning network. The outcomes presumed that quality components identifying with framework quality, data quality, and administration quality are fundamental measurements for guaranteeing understudies' fulfillment and goal to the utilization of the M-learning framework. A study conducted by [40] explored the key factors that affect students' acceptance of mobile learning. The study applied the Unified Theory of Acceptance and Use Technology (UTAUT) model and revealed that perceived data quality, similarity, trust, awareness, accessibility of assets, self-adequacy, and security are the principal sparks of mobile learning acceptance among students.

In fact, the adoption of mobile learning applications in universities for teaching and learning has been considered an excellent choice, for both students and teachers. Despite the benefits of mobile learning listed, its widespread and effective application in the teaching and learning process remains very low among students [36–38]. One of the main issues in relation to the usage of new technology in the learning and teaching process is technological readiness among students [39]. Therefore, this research aims to fill the following research gap in the literature:

What are the important determinants influencing mobile learning readiness during COVID-19 among users?

3. The Proposed Model

3.1. TAM Model

The proposed model in this study was constructed by employing some constructs from the TAM model, adding four external factors to determine the main drivers influencing mobile learning readiness. According to the literature (Refs. [40–43]), the TAM model is one of the most suitable models to measure readiness to new technologies. This model includes five main factors, including actual use (AU), intention to use (IU), attitude (AT), ease of use (EUS) and perceived usefulness (PUS), and was developed by Davis [44–46]. These factors are considered as predictors of mobile learning readiness according to previous studies [46–48]. Figure 1 presents the pictorial presentation of the TAM model constructs. Based on the TAM model, actual use can be determined directly based on one construct, namely, intention to use. In addition, actual use can be determined indirectly based on three constructs, namely, attitude, ease of use and perceived usefulness by the moderation of intention to use. Based on the context of our study, the TAM model hypothesized that the three key constructs for actual use of mobile learning are the students' perceptions of ease of use, their perceptions on its usefulness and their intention to use.

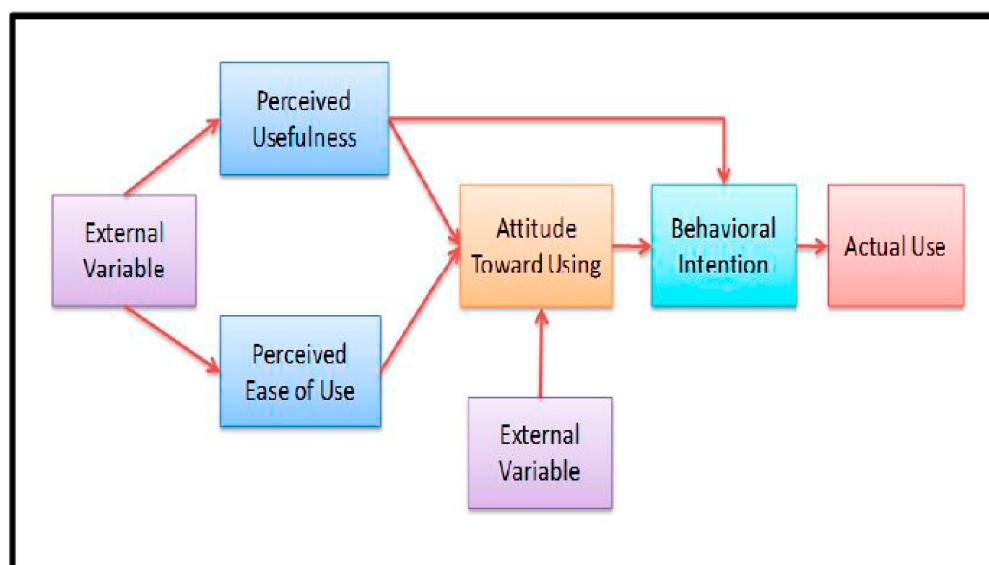


Figure 1. TAM model.

In the mobile learning context, we used the two main constructs of the TAM model as predictors of acceptance and usage of mobile learning, namely, perceived ease of use (EUS) and perceived usefulness (PUS). EUS can be defined as the degree to which users perceive that using the m-learning system will be free of effort. PUS refers to the extent to which users perceive that using the m-learning system will improve their learning performance. In the TAM model, EUS and PUS affect attitudes toward the use (AT) of mobile learning. PUS and AT affect IU, and IU affects the actual use of the mobile learning system. Based on the above, we formulated the following hypotheses in our proposed model:

Hypothesis 1 (H1). *Ease of use positively affects mobile learning acceptance among students.*

Hypothesis 2 (H2). *Perceived usefulness positively affects mobile learning acceptance among students.*

3.2. External Factors

Information Technology Infrastructure (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 information technology infrastructure is necessary for introducing new technology, including mobile learning applications. Otherwise, insufficient resources of information technology and infrastructure will impede the acceptance and usage of any new technology [49]. Previous studies [50–53] indicated that Information Technology Infrastructure is one of the necessary components of mobile learning acceptance. As a result, IT infrastructure in Saudi universities requires extensive analysis. Based on that, this study proposes the following:

Hypothesis 3 (H3). *IT infrastructure positively affects mobile learning acceptance among students.*

According to [54], support from the level of university management is associated with their willingness to provide all the necessary resources to ensure the development success of the mobile learning project. In other words, the positive attitude of top management towards the mobile learning project is a real indicator of a university to support mobile learning adoption. Previous studies [55,56] confirmed that university management support is vital to the development of mobile learning system adoption, which reflects positively on student actual use and acceptance of mobile learning. Based on that, this study proposes the following:

Hypothesis 4 (H4). *University management support positively affects mobile learning acceptance among students.*

Universities should be prepared for any emergency conditions, such as the COVID-19 pandemic, and pursue alternative strategies for implementing distance learning, including mobile learning application adoption. Based on that, university culture issues can significantly affect the adoption of mobile learning systems. According to [57], the 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 use these new technologies. Thus, university culture could play a crucial role in how universities adopt mobile learning systems. In Information systems, researchers found university culture is predictive of technology adoption, including mobile learning adoption [58]. Based on that, this study proposes the following:

Hypothesis 5 (H5). *University culture positively affects mobile learning acceptance among students.*

Student awareness about new technology, such as mobile learning applications, is still limited [58]. Therefore, universities should increase the awareness among their students, especially those who lack adequate and essential technical information. According to [59], the awareness factor had a strong impact on the mobile 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 mobile learning applications is inadequate awareness of the technology's existence [60]. Prior studies have shown that awareness is crucial in adopting mobile learning systems. As a result, the following hypothesis was proposed:

Hypothesis 6 (H6). *Awareness positively affects mobile learning acceptance among students.*

4. Methodology

In this research, for evaluating the proposed model, SEM method was performed in order to determine the main drivers influencing readiness to use mobile learning applications. In mobile learning acceptance context, several previous studies used the SEM method for examining students' acceptance [61]. These studies indicated that SEM method is capable of discovering relations among variables effectively. In addition, it is an advantageous data analysis method and tests the structural model in technology acceptance models [62]. Based on that, we used the SEM method to test the hypotheses in the proposed model for our study.

In order to achieve the research objective, we have conducted four main steps as shown in Figure 2. In the first step, we analyzed the related previous studies on mobile learning in order to determine the importance role of the factors in the proposed model, which act as theoretical foundation of our proposed model in this study. In the second step, we established the research model based on TAM model with four external factors. In the third step, we used the quantitative method in order to collect the data. Then, we conducted a pilot study in order to check the reliability and validity of the research model measurements in step four. Finally, in step five, we tested the proposed model using SEM technique. In the sections bellow we will present more details about each step in the research methodology. Figure 3 presents the proposed model.

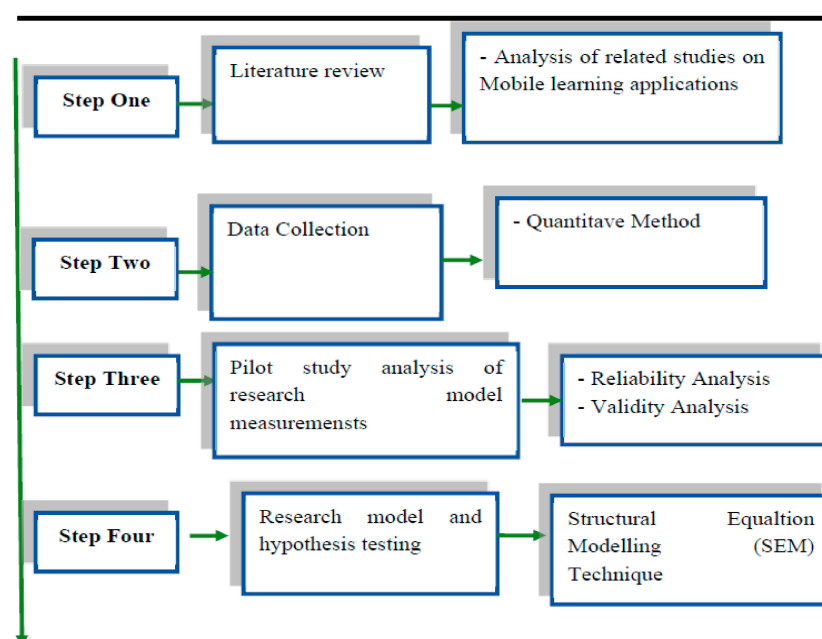


Figure 2. Research Method.

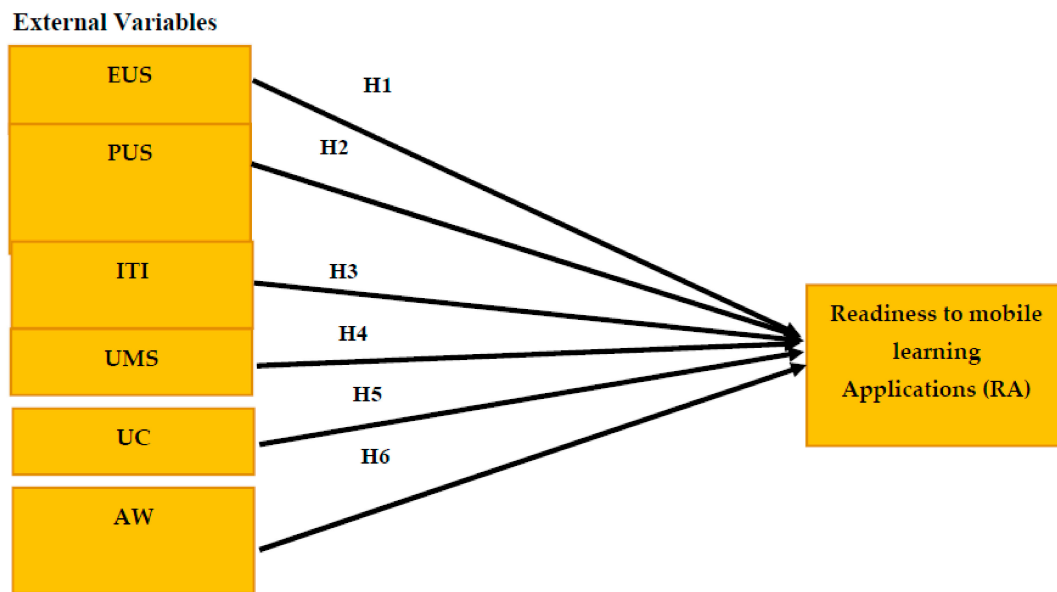


Figure 3. The proposed model for explaining the readiness of mobile learning.

4.1. Data Collection and Participants

The participants were 600 students enrolled in the Information System Analysis and Design course at undergraduate level and Advanced Analysis and Design course at postgraduate level from 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 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%
Age	18–20	30	5.7%
	21–25	410	78.8%
	Over 25	80	15.3%
Level	Undergraduate	395	75.9%
	Postgraduate	125	24.0%
Mobile Owner	Android	60	11.6%
	iPhone	460	88.4%
Prior experience with Mobile Learning App	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	Total	520	100%

4.2. Population of the Study

This study is based on an empirical examination of Saudi universities that are engaged in distance learning adoption activities such as mobile learning system. The study collected the data from four universities in Saudi Arabia namely King Faisal University (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 = 240), (KSU = 130), (KKU = 110) and (DU = 100). For collecting the data from respondents, we distributed the online questionnaire for all respondents during online classes with assistance from their instructors.

4.3. Research Measurements

To ensure 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 IT infrastructure construct are adopted from [3–5], items for university management support and university culture from [7–9], items for awareness from a study conducted by [10]. Items for perceived usefulness and ease of use from [12]. Finally, the actual use of mobile learning is measured using items from [13], which assess the extent to which universities have adopted mobile learning systems. All variables were quantified using a scale with poles ranging from strongly disagree (1) to strongly agree (5).

4.4. Measurement Items Pre-Test

After preparing initial measurement items based on the hypotheses, it was essential to ensure survey questions adequately captured desired phenomena. Therefore, an expert panel was convened comprising IT professionals, researchers in the fields of IT and faculty members. The panel was briefed firstly with the aim of the study and secondly, were provided with the questionnaire and asked if the survey questions were appropriate to explore the aim of the study. Pre-testing helped the researchers gauge the clarity of questions to understand whether the instrument captured the desired phenomena and to verify if any important variables were omitted. Feedback served as a basis for correcting, refining, and enhancing the survey questionnaire. Changes were made and several iterations were conducted by panel members.

4.5. Pilot Study

A pilot study was performed to detect any weaknesses in the survey instrument. The purpose of the pilot study was to test its wording and the sequence and layout of the questions. In this study, 38 participants (29 males and 9 females) were invited to undertake the pilot study. They were given the questionnaires in English. However, some respondents found difficulty in answering the survey questions. They identified problems with unfamiliarity with the survey process, understanding the wording of the questionnaire and had limited understanding of the concepts of top management support. Therefore, further changes were conducted with all 29 participants.

5. Data Analysis and Results

5.1. Reliability Analysis

In this study, reliability analysis was conducted using Cronbach's alpha on the data collected, as a step for measuring the internal consistency of each construct. Table 2 presents the values of Cronbach's alpha for all constructs. The results indicated 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 analysis.

Constructs	Cronbach's Alpha	AVE
Ease of use	0.792	0.937
Perceived Usefulness	0.873	0.918
University management support	0.821	0.829
Awareness	0.890	0.811
University culture	0.905	0.850
IT infrastructure	0.897	0.882
Readiness	0.852	0.912

5.2. Convergent and Discriminant Validity Analysis

To conduct the validity analysis, convergent and discriminant validity were performed. First, convergent validity analysis was conducted through applying the average variance extracted (AVE). Table 2 shows the findings of AVE analysis, which indicate that all values were higher than (>0.5); this means that these values were acceptable according to [64]. Based on that, all values of AVE for all constructs were correct for the next step of analysis.

Second, discriminant validity analysis was performed by applying the square root of AVE values for all variables. Based on the results in Table 3, AVE values were greater than the threshold of correlation values between two variables, which indicates that these values were acceptable, as mentioned by [65].

Table 3. Discriminant validity analysis.

	EUS	UMS	UC	AW	ITI	PUS	RA
EUS	0.821						
UMS	0.797	0.863					
UC	0.630	0.758	0.990				
AW	0.646	0.684	0.545	0.775			
ITI	0.759	0.769	0.563	0.689	0.887		
PUS	0.769	0.792	0.643	0.707	0.790	0.743	
RA	0.530	0.623	0.506	0.643	0.527	0.614	0.765

5.3. Structural Model Analysis Using SEM

This research aims to answer the following research question: what are the important determinants influencing mobile learning readiness during COVID-19 among users? To achieve this objective, we used the SEM technique in order to identify the most important determinants of readiness for mobile learning applications. SEM results are discussed below.

According to the findings of the SEM modelling test, as shown in Table 4, all six pro-posed hypotheses in the research model were accepted. The findings revealed that ease of use and perceived usefulness had significant influence on the actual use of mobile learning (β -value = 0.421, $p < 0.001$) and (β -value = 0.417, $p < 0.001$), respectively. Thus, the results indicated that hypotheses H1 and H2 were supported. The study indicated that the IT infrastructure (ITI) factor influenced the actual use of mobile learning positively (β -value = 0.399, $p < 0.001$), with this result supporting hypothesis H3. The findings also indicated that the factor of university management support had a significant influence on the actual use of mobile learning (β -value = 0.331, $p < 0.001$), this result means that H4 was accepted. In addition, H5 was also supported according to the current study findings, which indicated that university culture had a positive influence on the actual use of mobile learning (β -value = -0.371 , $p < 0.001$); this result means that H5 was accepted. The results also indicated that awareness had a significant influence on the actual use of mobile learning (β -value = 0.405, $p < 0.001$). Thus, the results indicated that hypothesis H6 was supported.

Table 4. Results of Structural Equation Modelling analysis.

Hypotheses	Path	Impact	β	<i>p</i> -Values	SE	<i>t</i> -Value	Results
H1	EUS→RA	Positive (+)	0.421	0.006	0.051	4.733	Supported
H2	PUS→RA	Positive (+)	0.417	0.019	0.042	4.137	Supported
H3	ITI→RA	Positive (+)	0.399	0.001	0.075	1.331	Supported
H4	UMS→RA	Positive (+)	0.331	0.005	0.044	3.471	Supported
H5	UC→RA	Positive (+)	0.371	0.009	0.091	3.114	Supported
H6	AW→RA	Positive (+)	0.405	0.022	0.06687	5.108	Supported

6. Discussion

During COVID-19, universities started to use mobile learning applications as one of the solutions to support distance learning. The readiness of universities to apply new systems, such as mobile learning applications, is considered one of the critical issues to ensure the system's success. Determining the most important aspects of readiness to use mobile learning is a key step to adopt mobile learning in an effective way. To address this issue, this research aimed to determine the most important determinants influencing mobile learning readiness by employing the Technology Acceptance Model (TAM). The SEM method was used to test the hypotheses in the proposed model.

Our findings indicated that the TAM model constructs with four external factors, namely IT infrastructure, university management support, university culture, awareness, ease of use and perceived usefulness, have a primary role in increasing the acceptance of mobile learning in Saudi universities. The findings indicated that all factors have a significant influence on mobile learning acceptance among students.

Based on the results, the IT infrastructure factor influenced the actual use of mobile learning positively. This is because IT infrastructure enables students to access information, increases the utility of learning activities, increases the interactivity with instructors and improves the learning and teaching process efficiency. On the other hand, the IT infrastructure in Saudi Arabia is very strong, with high internet penetration and high usage among students. Based on the findings, the current study concluded that providing high specification IT infrastructure would lead to the greater acceptance of mobile learning among students. This finding is consistent with prior studies [66,67].

In addition, the findings indicated that the factor of university management support had a significant influence on the actual use of mobile learning among students in Saudi universities. In other words, universities should prioritize top management support when deciding to implement new technologies, such as mobile learning systems, to ensure the development process of mobile learning systems is successful, from the first step to the end. University management support includes top managers' pledges and commitments to embrace mobile learning systems, provide the necessary resources, financial support and ensure to offer high-quality systems for student usage of mobile learning systems effectively. Saudi universities have a high level of management capabilities that could help in implementing mobile learning systems successfully. Our findings are consistent with prior studies [66,67]. The current study concluded that university management support is one of the most significant factors influencing the acceptance of mobile learning among students in Saudi universities.

Our findings indicated that university culture had a negative influence on the actual use of mobile learning among students in Saudi universities. This implies that incorrect university culture could impede the implementation of mobile learning in Saudi universities. This study found that university culture had a negative impact on students' willingness to accept mobile learning. The main reason for this result is the cultural differences between students and, thus, 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 use these new technologies. Based on the findings, university culture could play a crucial role in how universities adopt mobile learning systems. Previous studies found that university culture is predictive of technology adoption, including mobile learning adoption [64–66].

Furthermore, our findings indicated that there is significant and positive correlation between awareness and actual use of mobile learning. The study found that the 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 on how to use mobile learning systems is very low, this will lead to a decrease in the acceptance of mobile learning systems. This result is consistent with prior research by [66,67].

Finally, the study findings found that both the factors ease of use and perceived usefulness had significant and positive correlation with actual use of mobile learning. This indicates that when students find the mobile learning system user-friendly, simple, ease to use, clear and useful for the learning process, it could encourage them to use it effectively; thus, this will reflect on their opinion to accept the mobile learning system. Based on this result, this study recommends designers and developers to take those two factors into consideration in the development of mobile learning systems. Previous studies [68–70] confirmed that ease of use and usefulness are among the primary dimensions that motivate users to accept any type of educational technologies. Our findings are consistent with prior studies [66,67].

6.1. Research Implications

This study has both theoretical and practical implications. Focusing on the theoretical contribution first, this study contributes to the body of knowledge on mobile learning acceptance by providing a new model that captures the most significant drivers of mobile learning acceptance among students in public Saudi universities. Second, this study clarifies that important factors, such as IT infrastructure, awareness, university management support and university culture, play a key role in increasing the acceptance of mobile learning systems during the COVID-19-pandemic, and this will ensure the continuation of the learning process through using this distance learning tool. Third, this study confirms that the TAM model's suitability for analyzing the factors influencing the students' acceptance of mobile learning. In terms of the practical contribution, the findings of this study can help Saudi universities in better understanding the process of mobile learning project implementation. The universities should consider important factors related to IT infrastructure, awareness, university management support and university culture, in order to improve the acceptance of mobile learning systems among students. Finally, the study's findings will benefit decision makers, designers and developers in universities to ensure that students participate actively in using mobile learning systems during the COVID-19 pandemic.

6.2. Limitations of the Study

Despite this work presenting several interesting contributions, several limitations should be covered in the future work. First, further investigation into the drivers of mobile learning acceptance among students is needed. Second, future work could explore the teachers' perceptions and their needs to adopt mobile learning systems. Finally, there is a need to investigate other important factors related to system quality factors and usability factors and their effect on students' acceptance of mobile learning systems.

7. Conclusions and Future Work

This research aimed to explore the important determinants influencing mobile learning readiness during COVID-19 among users. To achieve this objective, the SEM technique was used. Therefore, this study developed six direct hypotheses using the TAM model to explain the main drivers influencing mobile 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 universities in Saudi Arabia. PLS-SEM was used to analyze the data. The findings indicated that the TAM model constructs with four external factors, namely IT infrastructure, university management support, university culture, awareness, ease of use and perceived usefulness, have a primary role in increasing the acceptance of mobile learning in Saudi universities. The findings indicated that all factors have a significant influence on mobile learning acceptance among students. This research contributes to the body of knowledge and mobile learning acceptance practices. Likewise, it may help facilitate and promote the acceptance of mobile learning among students in Saudi universities.

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