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Article

A New Technological Model on Investigating the Utilization of Mobile Learning Applications: Extending the TAM

Rima Shishakly [1], Mohammed Amin Almaiah [2,3,4,*], Shaha Al-Otaibi [5], Abdalwali Lutfi [6,7,*], Mahmaod Alrawad [6] and Ahmed Almulhem [8]

[1] Management Department, College of Business Administration, Ajman University, Ajman 346, United Arab Emirates
[2] Department of Computer Science, Aqaba University of Technology, Aqaba 11947, Jordan
[3] King Abdullah the II IT School, The University of Jordan, Amman 11942, Jordan
[4] Fellowship Researcher, INTI International University, Nilai 71800, Malaysia
[5] Department of Information Systems, College of Computer and Information Sciences, Princess Nourah Bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia
[6] College of Business, King Faisal University, Al-Ahsa 31982, Saudi Arabia
[7] Applied Science Research Center, Applied Science Private University, Amman 11931, Jordan
[8] College of Education, King Faisal University, Al-Ahsa 31982, Saudi Arabia
* Correspondence: m_almaiah@asu.edu.jo (M.A.A.); aalkhassawneh@kfu.edu.sa (A.L.)

Abstract: Mobile learning has become increasingly important for higher education due to its numerous advantages and transformative potential. The aim of this study is to investigate how students perceive and utilize mobile learning (m-learning) services in universities. To achieve this objective, a conceptual model was developed, combining the TAM with additional new determinants, including perceived security, perceived trust, perceived risk, and service quality. The primary goal of this model is to assess the adoption of m-learning apps among users in university settings. To evaluate the proposed model, SEM was utilized to test the research model. The findings of the study highlight the critical roles of perceived security, perceived trust, and service quality in promoting the adoption of m-learning apps. Moreover, the results indicate that perceived risk negatively impacts both students' trust and their attitudes towards using mobile learning services. The study reveals that the perceived trust, and service quality factors positively influence students' attitudes towards adopting m-learning apps. These research findings hold significant implications for universities and academia, offering valuable insights to devise effective strategies for increasing the utilization of m- learning services among students. By gaining a deeper understanding of students' perceptions and acceptance, universities can optimize their m-learning offerings to cater to students' needs and preferences more effectively.

Keywords: m-learning; adoption; TAM; perceived security; perceived trust; service quality

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1. Introduction

During the recent years, major transformations and advancements have emerged in the field of educational technologies [1–3]. This made a new shift in the higher education sector by providing several technologies like smartphones concerning the delivery of learning materials [4–7]. One of such technologies is the mobile learning applications, which offer a number of significant opportunities for students to learn at any time anywhere. M-learning refers to the distance learning that is delivered through different mobile computing devices, including smartphones, tablets, and other mobile devices [8–10]. Unlike online learning systems, mobile learning has received remarkable attention due to its low cost, convenience, and flexibility [11–13].

Mobile learning applications are becoming more commonly used after COVID-19 pandemic in universities [14]. Recently, mobile learning applications have been used without students' commitment to attend classrooms the universities [15–18]. Furthermore, students can utilize mobile learning applications with no fees or cost [19]. From above benefits, through using mobile learning applications will enhance students' quality of learning significantly [20–23].

Although the powerful benefits of mobile learning applications provided by universities, the percentage usage of m-learning apps is still low in universities [24]. Mainly, the utilization rate of m-learning apps is unsatisfactory up to now [25–28]. Almaiah [29] indicated that only 33% of students utilize the mobile learning services and this percentage is still very low. Therefore, there is need to understand the factors associated with the usage of m-learning apps in order to assure its successful use.

In the realm of exploring the acceptance and usage of m-learning apps, numerous studies have been investigated in the literature [30–33]. These studies aim to comprehend the primary determinants associated with the adoption of m-learning apps. However, it is crucial to acknowledge that the usage patterns of m-learning apps before the COVID-19 pandemic were distinct from those observed after its onset. As a result, most current research has shifted its focus exclusively to this topic, and studies on mobile learning [34].

Drawing on the preceding discussion, the key objective of this work is to examine the pivotal technological determinants that influence students in their exclusive usage or non-usage of m-learning apps. Despite the presence of high technical support and advanced infrastructure technologies in Jordanian universities, the penetration rate of m-learning apps in the country remains unsatisfactory [35]. Thus, this study aims to cover this gap by proposing a conceptual model for the acceptance of m-learning apps in Jordan. As such, the study is guided by the following objective:

- To analyze the primary determinants that could influence the utilization of m-learning apps.

2. Literature Review

2.1. M-Learning Apps

Through using m-learning apps, a significant change was observed in performance of students. A number of studies showed the various advantages of mobile learning platforms such as convenience of time, easy access and lessen cost [36–38]. According previous studies [39–41], most of the learners preferred the learning through mobile learning and performed the learning successfully in classrooms through using mobile learning devices, thus, these advantages create the difference between online learning and face to face learning. Where, many studies recommended for increasing the use of m-learning apps as learning tool for students [42,43]. In addition, mobile learning tool become more usable among students as being increasingly used as complementary tool for learners after COVID-19 pandemic. This proves there is necessary for conducting more studies about investigating the main drivers influencing the intention to use mobile learning in Jordanian universities.

M-learning apps might give universities a means for their students to interact with them directly through services, learning materials, online learning sessions and learning activities. Universities, ministry of information technology and communication, mobile companies, governments, students, should work together to improve the usage of m-learning apps. M-learning apps offer several benefits, such as easily download learning materials, easily access online sessions and it is now flourishing specifically after COVID-19 pandemic [39]. Within the higher education landscape, a diverse array of solutions employing various approaches and technologies, such as Blackboard, Zoom, and others, are prevalent. Consequently, this study seeks to construct a novel model aimed at comprehending the usage of m-learning apps. The conclusions drawn from this paper hold significant implications for the utilization of m-learning apps. Moreover, this study stands as one of the pioneering efforts in investigating the factors influencing students' exclusive adoption or non-adoption of m-learning apps in universities.

2.2. The Importance of M-Learning

Mobile learning has become increasingly important for higher education due to its numerous advantages and transformative potential. Previous studies highlighted the importance of m-learning apps, including (1) accessibility and flexibility: Mobile learning allows students to access educational content anytime and anywhere, breaking free from the constraints of traditional classroom settings. This flexibility enables learners to study at their own pace, making education more accessible to individuals with busy schedules or geographical constraints, (2) personalized learning: Mobile learning apps and platforms often incorporate adaptive technologies and personalized content delivery, tailoring the learning experience to individual student needs and preferences. This personalized approach enhances engagement and knowledge retention, as students receive content relevant to their specific learning styles and interests, (3) interactive learning experience: Mobile learning offers various interactive elements, such as quizzes, videos, simulations, and gamified activities. These interactive features enhance student engagement and make the learning process more enjoyable and effective, (4) collaborative learning opportunities: Mobile learning fosters collaboration among students through discussion forums, social media integration, and group projects. This collaborative approach promotes peer learning, knowledge sharing, and the development of teamwork skills, (5) real-world relevance: Mobile learning allows educators to integrate real-world scenarios and case studies into their teaching materials. Students can apply theoretical concepts to practical situations, fostering critical thinking and problem-solving skills, (6) continuous learning: With mobile learning, students can engage in continuous learning beyond the confines of traditional academic calendars. They can review course materials, access resources, and participate in discussions even during breaks or holidays, promoting ongoing knowledge acquisition, (7) diverse learning resources: Mobile learning provides access to a vast array of digital learning resources, including e-books, articles, podcasts, and videos. This abundance of resources enriches the learning experience and enables students to explore various topics beyond their standard curriculum, (8) immediate feedback and Assessment: Mobile learning applications often offer instant feedback and assessment features, allowing students to gauge their progress and identify areas for improvement. This timely feedback enhances the learning process and motivates students to strive for continuous improvement, (9) cost-effectiveness: Mobile learning can reduce the need for physical textbooks and printed materials, leading to cost savings for students and institutions. Additionally, mobile learning eliminates the need for students to commute to physical campuses, saving time and expenses, (10) inclusivity and customization: Mobile learning can be adapted to cater to diverse student populations, including students with disabilities or different learning needs. By offering customizable content and accessibility features, mobile learning ensures inclusivity in education.

In conclusion, mobile learning plays a crucial role in higher education by providing enhanced accessibility, flexibility, interactivity, and personalized learning experiences. As technology continues to advance, m-learning apps are expected to become even more integral to the education landscape, shaping the future of higher education worldwide.

2.3. Related Works

Several prior studies have investigated various factors influencing mobile learning adoption. One prominent factor among these is perceived risk. Girish et al. [40] conducted a study revealing that perceived risk significantly impacts the intention to use an e-learning system. Similarly, Alwahaishi [41] demonstrated a positive relationship between perceived risk and students' intention to use an e-learning system. However, none of the previous studies have explored the effect of perceived risk on trust regarding the adoption of mobile learning. Consequently, the present study seeks to examine the relationships between perceived risk and perceived trust. Furthermore, perceived security emerges as a fundamental factor ensuring the success of technology adoption. Girish et al. [40] revealed in their study that perceived security positively influences the intention to use an e-learning system. Correspondingly, Lu et al. [41] confirmed a positive relationship between perceived security and students' intention to use an e-learning system. Considering the sensitive information associated with using e-learning systems, breach of security can lead to the violation of students' privacy, potentially deterring the usage of e-learning systems.

Surprisingly, only a limited number of studies have explored the effect of perceived security on perceived trust in adopting mobile learning applications. Hence, this study aims to investigate the relationships between perceived security and perceived trust concerning the adoption of mobile learning applications.

In the context of the TAM model, perceived ease of use and perceived usefulness are acknowledged as pivotal determinants affecting the utilization of new applications [42]. Prior studies, exemplified by the research conducted by Castiblanco et al. [42], have established the significant impact of both perceived ease of use and perceived usefulness on the intention to use e-learning systems. Correspondingly, Weerathunga et al. [43] demonstrated a positive relationship between perceived ease of use, perceived usefulness, and students' intention to use e-learning systems. Building upon this foundational understanding, the present study aims to examine the relationships between perceived ease of use, perceived usefulness, and the intention to use mobile learning applications. Moreover, quality factors have been identified as critical determinants fostering users' adoption of new technology [44–46]. As such, this research endeavors to investigate the relationships between quality factors and the intention to use m-learning apps. Additionally, perceived trust emerges as another crucial factor that encourages users to adopt new technology. Girish et al. [40] observed that perceived trust significantly influenced the intention to use e-learning, while Alwahaishi [41] provided evidence of a positive relationship between perceived trust and students' intention to use e-learning systems. However, limited studies have explored the impact of perceived trust on the intention to utilize m-learning apps. Based on above, this paper aims to test the effect perceived trust on the intention to utilize m-learning apps.

This paper addresses the aforementioned literature gap by proposing a technological model that integrates the TAM with technological determinants to explore the primary drivers influencing students' exclusive usage of m-learning apps in universities. The research aims to provide valuable insights to decision-makers in universities, aiding them in better understanding their students' needs and preferences to encourage the utilization of m-learning apps. The study's outcomes are expected to bridge the literature gap by investigating the acceptance of m-learning apps, specifically by examining the effect of technological determinants on their actual usage. Ultimately, the findings offer crucial recommendations and insights for decision-makers in universities and academic researchers, shedding light on the critical factors that encourage learners to embrace m-learning apps in the post-COVID-19 pandemic era.

3. The Proposed Mobile Learning Model and Technology Acceptance Models

To explore which students' perspectives factors explain m-learning apps adoption, a conceptual model is developed based on TAM theory in Figure 1. The proposed framework incorporates TAM constructs to explain firstly the possible students' reactions to mobile learning acceptance or rejection, and secondly students' cognitive factors supporting adoption of m-learning apps.

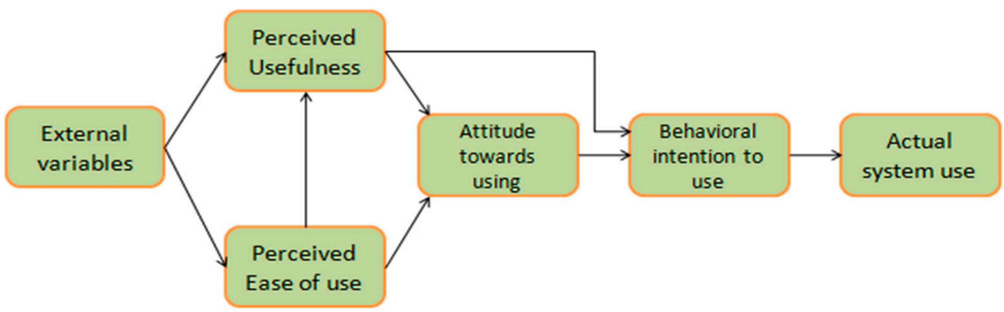

Figure 1. The TAM model.

There are several technology adoption models, one of these comprehensive model is the TAM. Which it has been widely utilized for measuring the adoption of m-learning apps studies [44–47]. Many scholars recommended that the original version of the TAM must be used to investigate the usage behavior towards new technologies among users [48–51]. TAM is an extended version from the original UTAUT model and it is a set of variables from several models like TPB and TRA [52].

According to Figure 1, TAM model was included from five constructs, namely perceived ease of use, perceived usefulness, and attitude toward to use, intention to use and actual use [53]. Based on results from literature, which recommended that TAM is better than the other theoretical frameworks in explaining the variance (R^2) in usage behaviours from 40% to 52% and intention behavior from 56% to 74% and, respectively [54]. In addition, TAM model was used to predict students' behavioural intentions and teachers' attitudes towards online learning systems [55]. Based on these recommendations, TAM model was selected as a theoretical framework for establishing the technological model in this research to explain the primary determinants influencing the continuous intention to use m-learning apps with higher accurate than the original TAM. Figure 2 presents the technological model for this work. In the following sections, the hypotheses of this study will be discussed.

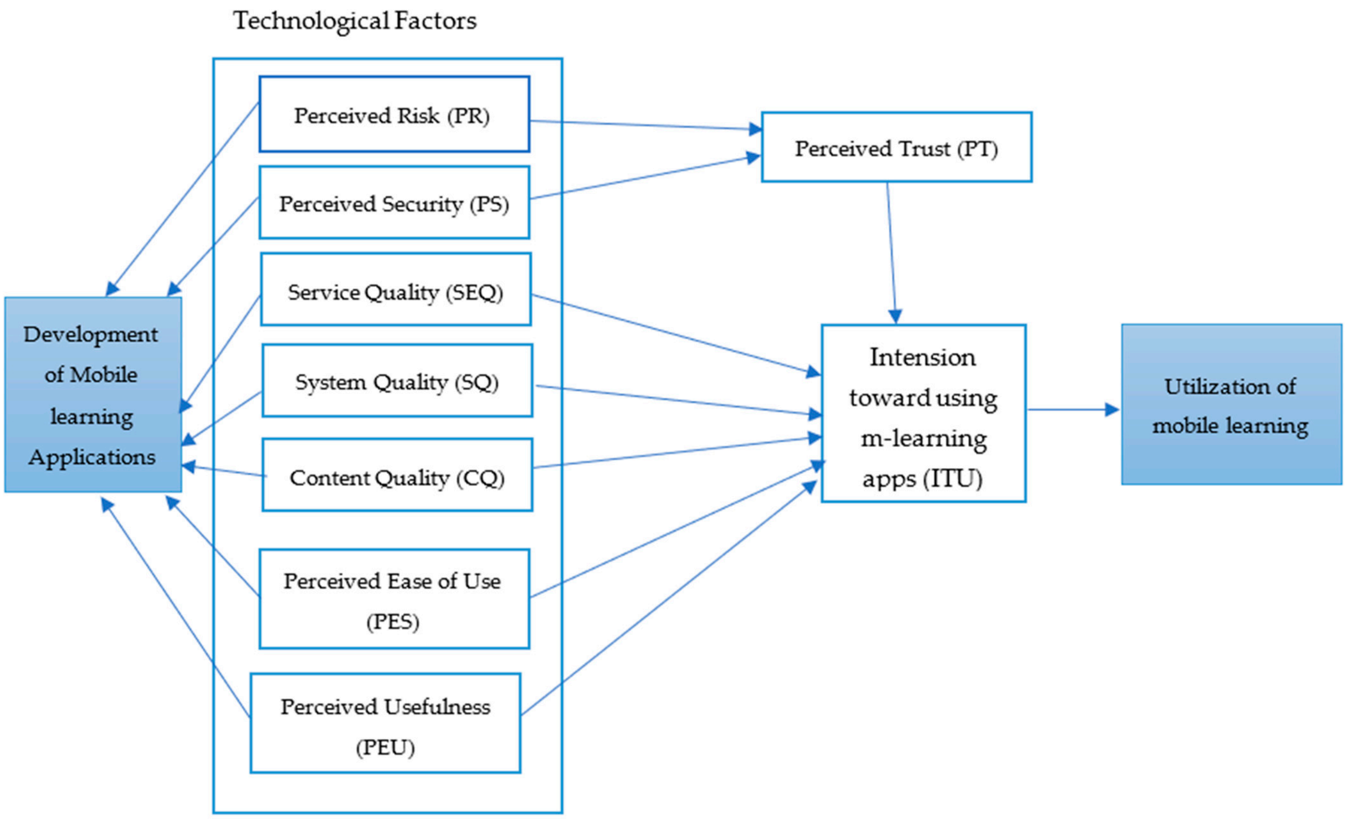

Figure 2. The Proposed Model.

3.1. Perceived Risk (PR) of M-Learning

PR refers to the extent to which potential users perceive mobile learning applications as posing potential dangers [48]. It stands as a significant deterrent to the adoption technologies. When users contemplate whether to embrace a technology, they weigh the perceived risks against the conveniences it offers. The level of perceived risk can notably impact users' decisions to adopt or reject the technology. Previous studies in the realm of mobile learning have consistently demonstrated a negative correlation between perceived risk and user acceptance [49–52]. Moreover, researchers [53–55] have argued that perceived risk and perceived trust are interconnected, as lower levels of perceived risk tend to foster higher levels of user trust. In light of this, the following hypotheses are put forward:

H1. *Perceived risk negatively affects perceived trust.*

H2. *Perceived risk negatively affects the intension toward using m-learning apps.*

3.2. Perceived Trust (PT) of M-Learning

Trust plays a pivotal role in determining the successful adoption of novel technologies [56]. In the context of mobile learning, trust emerges as a primary determinant influencing its acceptance and usage among users. Specifically, users place their trust m-learning apps, primarily due to the perceived absence of risks in their learning activities and the perceived benefits they derive from the platform. This trust, in turn, fosters student loyalty, particularly when mobile learning services are viewed as highly trustworthy [57]. Conversely, a lack of trust in mobile learning applications leads to diminished student loyalty and reduced trust. To assess the impact of perceived trust on the attitude towards using mobile learning services, we have introduced the trust factor into the TAM in our study. Therefore, we propose the following hypothesis:

H3.. *Perceived trust can have either a positive or negative effect on the intension toward using m-learning apps.*

3.3. Perceived Security (PS) of M-Learning

PS of m-learning apps refers to the extent to which a user believes that utilizing a m-learning apps will be highly secure, devoid of any risks [58]. The successful adoption and acceptance of mobile learning services by students critically hinge on the assurance of security defense techniques that safeguard users' services, transactions, privacy, and personal information. Consequently, prioritizing security measures becomes paramount in fostering the trust of students and encouraging their active engagement with the mobile learning application. Conversely, the absence of robust security measures undermines user trust and acts as a deterrent to the usage of mobile learning applications. Consequently, learning institutions, particularly the universities, allocate substantial budgets to invest in security mechanisms such as multifactor authentication encryption methods, to instill confidence in their users. In our study, we posit that the provision of high-security procedures will enhance users' trust, leading to a positive effect on their attitude towards using m-learning apps. Based on that:

H4. *Perceived security positively affects perceived trust.*

H5. *Perceived security positively affects the intension toward using m-learning apps.*

3.4. Perceived Usefulness (PU) of M-Learning

Perceived usefulness is defined as the extent to which the utilization of m-learning apps will yield benefits for students in conducting their learning activities [59]. Existing literature [60–63] has consistently emphasized that perceived usefulness serves as a robust predictor within the TAM and exerts a positive influence on users' attitudes towards adopting and using technology. This observation has also been evident in studies related to e-learning [64,65], which have confirmed a positive relationship between perceived usefulness and users' intention to use e-learning systems. In our study, perceived usefulness assumes a pivotal role in encouraging students to accept the m-learning apps, particularly when they anticipate deriving significant benefits from embracing this new technological advancement. Therefore, we propose the following hypothesis:

H6. *PU has a positive effect on the intension toward using m-learning apps.*

3.5. Perceived Ease of Use (PEU) of M-Learning

PEU represents the important predictor within the TAM. PEU refers to the level of ease associated with utilizing an m-learning apps. When students perceive an m-learning apps as user-friendly and easy to navigate, it enhances the likelihood of adoption. Moreover, if students find the interaction with the m-learning apps to be straightforward, comprehensible, and unambiguous, it positively influences their attitude towards using the application. Extensive prior research [66–68] has consistently highlighted PEU as the most influential predictor, with a positive impact on users' attitudes towards adopting new technologies. Researchers focused on studying e-learning [69,70] they found that PEU exhibits a positive relationship with users' intention to use e-learning. In the research model, PEU assumes a crucial role in improving the utilization of m-learning apps, particularly when they expect a seamless and effortless experience with the platform. Consequently, following hypothesis have been proposed:

H7. *PEU has a positive effect on intension toward using m-learning apps.*

3.6. System Quality (SQ) of M-Learning

In the DL&ML model, system quality dimension represents a fundamental construct comprising high-quality features that are essential in any system, including elements like navigability, functionality, availability, and flexibility [4,5]. DL&ML [6] suggested that the selection and application of system quality measurements should be contextually driven, tailored to the specifics of the study. In the realm of educational technologies research, system quality has emerged as a critical metric influencing the adoption and usage of educational platforms by students. Previous studies have revealed that system quality had a significant impacts on the actual utilization of m-learning apps. Based on the above discussion and drawing upon the framework of system quality dimension, we have developed our proposed research model, leading to the formulation of the following hypotheses:

H8. *The quality of the system will exert a significant influence on the intension toward using m-learning apps.*

3.7. Service Quality (SEQ) of M-Learning

The attainment of excellent quality in m-learning apps represents the foundational step towards the success of an m-learning apps [71–73]. Students assess the SEQ of m-learning apps based on their experiences with the application and the perceived value it offers to them. Prior research [74–77] has consistently demonstrated that higher SEQ corresponds to a greater perceived value, consequently leading to more positive attitudes towards using the technology. As service quality serves as a measure of the benefits associated with the application or product services, a higher quality mobile learning application is perceived to have greater value. Given this perspective, when students perceive a mobile learning application to offer high-quality services that meet their satisfaction, it significantly enhances the likelihood of adoption. Notably, recent papers [78–80] have identified SEQ as a potent predictor in the DL&ML model, with a strong influence on actual utilization. Furthermore, research in the field of e-learning [81–84] has confirmed a positive relationship between service quality and students' intention to use e-learning. In the research model, SEQ assumes a crucial role in improving the utilization of m-learning apps, particularly when they anticipate receiving high-quality services through its usage. Therefore, we propose the following hypothesis:

H9. *SEQ has a strong effect on the intension toward using m-learning apps.*

3.8. Content Quality (CQ) of M-Learning

The DL&ML model's second quality measurement pertains to content quality, which denotes the excellence of content concerning its design, format, and accuracy, thus being an essential aspect of any system [2]. In the domain of m-learning apps research, recent studies have highlighted content quality as a pivotal predictor significantly influencing the adoption and utilization of m-learning apps [2]. Found that the quality of content plays a crucial role in increasing the actual utilization of m-learning apps. Similarly, ref. [4] discovered that content quality emerges as the primary predictor affecting the actual utilization of m-learning apps. Based on the preceding discussion and grounding our proposed research model on the measurement of content quality, we put forward the following hypotheses:

H10. *CQ will exert a significant effect on the intension toward using m-learning apps.*

3.9. Intension toward Using (ITU) M-Learning Apps

As per the model of TAM, intension toward using m-learning refers to a user's subjective probability of adopting an m-learning apps. It stands as the primary predictor not only within the TAM model but also for other models like UTAUT, TRA, and etc. Research in the domain of e-learning [85–87] has consistently confirmed a positive relationship between attitude toward use and users' intention to use e-learning systems. In light of these findings, our study considers attitude toward use as a pivotal factor in predicting students' utilization of the m-learning apps. Thus, we proposed the following hypothesis:

H11. *ITU has a strong effect on the actual use of m-learning apps.*

4. Research Methodology

4.1. Data Collection Method

This work used a quantitative method research methodology which is appropriate for studying students' reactions to mobile learning acceptance or rejection, and secondly students' cognitive factors supporting adoption of mobile learning in Jordanian universities [78]. It is also a suitable method when there is a need to explore users' behavior [79]. As such the use of a quantitative method approach is an essential tool that include all proposed factors in the research model.

4.2. Participants of the Study

In our research, we selected the research participants accurately, who they are used the mobile learning system during the COVID-19 and they have experiences of using mobile learning. We are expected they have experience and insights to contribute to this study. Data was collected from 445 university students from three Jordanian universities, who they used Blackboard through their mobile devices to learn many courses during the pandemic. An online questionnaires were distributed to collect the data. After selecting the participants, these were approached directly by the courses instructors in the three Jordanian universities. The author was discussed with courses instructors directly for an initial conversation. Then, we distributed the questionnaires for the participants using online link has been sent to their emails. Most of participants have responded positively to participate in the study.

4.3. Measurement Instrument

In this paper, we focused on establishing strong survey instrument to adequately measure TAM model for mobile learning adoption among students. Hence, we conducted an extensive literature review of articles and conference papers on TAM published between 2020–2022. Then, we adopted the TAM items from previous studies. The items of perceived ease of use and perceived usefulness have been extended from as study conducted by Almaiah and Alamri [80]; constructs of perceived risk, trust and perceived security have been adopted from [66]; items of social Influence, service quality and attitude were adopted from a study performed by Dwivedi et al. [81]. This research was established mainly for university students, therefore items reported in TAM research and mobile learning adoption research were considered for modification in the context of Jordan. The study questionnaire used a 5-point Likert scale [82], includes these scales (strongly disagree, disagree, neutral, agree, and strongly agree), respectively [82].

The questionnaire of this study included three sections: demographic questions, mobile learning use and students' opinion on mobile learning adoption attributes in the proposed model. As Arabic is the native language in Jordan, we translated the questionnaire from English to Arabic by three English lecturers experts from University of Jordan. Then, the questionnaire was validated by 3 professors and master students, containing 7 constructs with a total of 21 items. The results of pilot analysis is represented in Table 1.

Table 1. Analysis of Pilot study.

No	Factors	Pilot Test	Final Test
1	PS	0.713	0.884
2	PT	0.781	0.840
3	PR	0.809	0.892
4	SEQ	0.722	0.889
5	PU	0.785	0.887
6	PEU	0.768	0.874
7	SQ	0.782	0.860
8	CQ	0.808	0.894
9	ITU	0.794	0.929
10	AU	0.812	0.817

5. Results and Analysis

The analysis of the structural model (inner model) involved the use of the R-squared (R^2) test and the relevance test through correlation and path estimations, which were applied to assess the structural equation model using Partial Least Squares (PLS). The R-squared (R^2) value is employed to gauge the impact of a latent variable on a dependent latent variable. As reported by [88–92], the R^2 results ranged from 0.487 to 0.762, indicating the appropriateness of the model. In addition to the R^2 test, structural equation modeling (SEM) was utilized to evaluate the reliability and validity of the variables. The data were analyzed using SPSS 23.0 and clever PLS 2.0.

5.1. Reliability and Validity of Measures

In this study, the validity and reliability of each factor's measurement were assessed using coefficient alphas, composite reliabilities, and average variances (AVE). Cronbach's alpha, a commonly used reliability statistic, was employed to evaluate internal consistency. The Confirmatory Factor Analysis (CFA) results, as reported by Hair et al. [93], indicated favorable outcomes, with loadings of 30 items exceeding 0.70 and convergent validity ranging from 0.862 to 0.953. Additionally, the validity of the results was further demonstrated by Cronbach's alpha values, which ranged from 0.834 to 0.929. Moreover, the R Square values were observed to vary between 0.489 and 0.762, while AVE values fell within the range of 0.678 to 0.892. Table 2 provides a comprehensive summary of these findings.

Table 2. Factor Analysis and Factors Loadings.

Factors	Items	Factors Loadings	Composite Reliability	Cronbach's Alpha	AVE	R Square
Intension toward using	ITU1 ITU2 ITU3	0.872 0.929 0.788	0.885	0.834	0.751	0.649
System Quality	SQ1 SQ2 SQ3	0.878 0.890 0.872	0.922	0.866	0.785	0.654
Actual Use	AU1 AU 2 AU 3	0.880 0.897 0.803	0.932	0.884	0.788	0.489
Perceived Risk	PR1 PR2 PR3	0.801 0.878 0.886	0.946	0.891	0.809	0.652
Perceived Ease of Use	PEU1 PEU2 PEU3	0.856 0.888 0.789	0.886	0.880	0.704	0.669
Perceived Usefulness	PU1 PU2 PU3	0.875 0.915 0.760	0.875	0.809	0.722	0.684

Table 2. *Cont.*

Factors	Items	Factors Loadings	Composite Reliability	Cronbach's Alpha	AVE	R Square
Perceived Security	PS1 PS2 PS3	0.837 0.782 0.886	0.872	0.869	0.678	0.731
Service quality	SEQ1 SEQ2 SEQ3	0.929 0.918 0.924	0.963	0.929	0.892	0.765
Perceived Trust	PT1 PT2 PT3	0.861 0.927 0.831	0.947	0.874	0.766	0.623
Content Quality	CQ1 CQ2 CQ3	0.885 0.896 0.894	0.884	0.808	0.730	0.642

5.2. Measurement Construct Validity

Construct validity refers to the degree to which products accurately represent the intended ideas for which they were developed [93]. This validation was established through a thorough examination of various research aspects that received substantial empirical support. The components required for the customized structure, along with their corresponding loadings, are presented in Table 3 [93].

Table 3. Analysis of Discriminant validity.

No	Factors	1	2	3	4	5	6	7	8	9	10
1	Intension toward using	1.000									
2	Actual Use	0.655	1.000								
3	Service Quality	0.752	0.618	1.000							
4	Perceived Ease of Use	0.566	0.588	0.531	1.000						
5	Perceived Risk	0.666	0.702	0.712	0.588	1.000					
6	Perceived Security	0.750	0.633	0.778	0.636	0.784	1.000				
7	Perceived Trust	0.768	0.629	0.828	0.526	0.621	0.722	1.000			
8	Perceived Usefulness	0.618	0.626	0.523	0.609	0.649	0.725	0.549	1.000		
9	System Quality	0.626	0.619	0.566	0.417	0.543	0.523	0.563	0.450	1.000	
10	Content Quality	0.612	0.611	0.567	0.444	0.522	0.549	0.569	0.445	0.456	1.000

5.3. Testing the Model

The adequacy of the structure model's overall fit was examined to validate its use in this investigation. The model demonstrated appropriate values for absolute fit measures, including GFI (0.934), CFI (0.955), IFI (0.951), NFI (0.959), RMSEA (0.959), and RMR (0.048), as determined during the progressive model iterations, aligning with established literature guidelines [94–99]. The study's assumptions were evaluated, and correlations were established using Smart PLS 2.0. The results of the path coefficients and corresponding T-values are presented in Table 4.

Table 4. Testing of hypotheses.

No	Hypotheses Links	Path Coefficient	Mean	S.D.	T-Values	Type
1	PR → PT	−0.093	0.081	0.081	−0.684	Negative
2	PR → ITU	−0.293	0.161	0.127	−1.660	Negative
3	PT → ITU	0.331	0.340	0.117	2.989	Positive
4	PS → PT	0.065	0.090	0.137	0.582	Positive
5	PS → ATU	0.067	0.088	0.127	0.668	Positive
6	PU → ITU	0.034	0.061	0.111	0.442	Positive
7	PEU → ITU	0.443	0.453	0.119	4.172	Positive
8	SQ → ITU	0.062	0.087	0.170	0.461	Positive
9	SEQ → ITU	0.064	0.070	0.123	0.669	Positive
10	CQ → ITU	0.081	0.086	0.168	0.439	Positive
11	ATU → AU	0.172	0.166	0.129	1.319	Positive

According to the results presented in Table 4, testing the proposed model, consisting of 10 determinants and 30 items for each construct, revealed that all hypotheses were accepted. Firstly, the two hypotheses explored the relationships between perceived risk and perceived security (−0.093) and between perceived risk and intension toward using m-learning −0.293), with both hypotheses being supported. Additionally, the correlation between perceived trust and intension toward using m-learning (0.331). In addition, perceived security and perceived trust (0.065), and perceived security and intension toward using m-learning (0.067) led to the acceptance of all these hypotheses. Moving on to another hypotheses, the correlations between perceived usefulness and intension toward using m-learning (0.034) and between perceived ease of use and intension toward using m-learning (0.443) were both supported. Furthermore, the associations between system quality and intension toward using m-learning (0.062) and service quality and intension toward using m-learning (0.064), content quality and intension toward using m-learning (0.081). Lastly, the relationship between intension toward using m-learning and actual use (0.172) was found to be significant and was, therefore, accepted.

6. Discussion

The primary goal of this work was to propose a conceptual model by integrating the determinants from the TAM with 6 new determinants, namely: perceived risk, perceived trust, perceived security, service quality, system quality and content quality. The aim was to investigate the primary determinants influencing users' decision to either adopt or abstain from using exclusive m-learning apps. This research seeks to assist universities in gaining a deeper understanding of their students, with the ultimate goal of enhancing the utilization of m-learning apps provided to them. Our research endeavors aimed to address the existing research gap concerning the limited investigation into m-learning apps acceptance, specifically by examining the impact of perceived trust, perceived risks, and service quality on the actual usage of mobile learning. The anticipated outcomes are expected to contribute significantly to the understanding of m-learning apps acceptance in the context of post-COVID-19 pandemic Jordanian universities. Ultimately, our study's findings offer crucial recommendations and insights for both universities and academic research, shedding light on the critical factors that encourage students to embrace m-learning apps in the aftermath of the COVID-19 pandemic.

The study's findings unveiled a negative impact of perceived risk on both trust and intension toward using m-learning apps. This outcome can be attributed to the inherent risks associated with these applications, making them vulnerable to potential attacks and student information fraud perpetrated by hackers. Consequently, this negative result significantly influences students' trust in m-learning apps. Our findings align with previous studies in the context of e-learning systems [100–107]. Furthermore, this research provides evidence of a connection between perceived risk and students' trust. Indeed, when students contemplate adopting a technology, they weigh the perceived danger against the convenience it offers. Prior studies [108–112] have also posited the existence of a link between perceived risk and perceived trust, suggesting that users' trust can be bolstered when perceived risk levels are minimized.

Furthermore, our study revealed a positive impact of perceived trust on students' intension toward using m-learning apps. This outcome can be attributed to the fact that students' trust is heightened by the secure and risk-free learning environment provided by the university through the m-learning apps, along with the numerous benefits it offers. Additionally, our research established a significant connection between perceived trust and student loyalty, particularly when m-learning apps are perceived as highly trustworthy. These findings are consistent with previous studies conducted in the context of e-learning systems [113–115], where it was demonstrated that users' trust plays a crucial role in the successful utilization of e-learning.

The study's findings revealed a positive impact of perceived security on both trust and intension toward using m-learning apps. This outcome can be attributed to the implementation of robust security defense techniques, which prioritize safeguarding students' services, activities, privacy, and personal information. Ensuring such security measures is crucial for the successful utilization of m-learning apps. Additionally, our research substantiates the existence of a significant relationship between perceived security and users' trust. As a result, universities consistently allocate substantial budgets to invest in security mechanisms for their m-learning apps, such as multi-factor authentication and transaction encryption. Our findings align with previous studies conducted in the context of e-learning [116–120], which demonstrated that the provision of high-security procedures leads to increased user trust and subsequently enhances their attitude towards using the e-learning.

This study further establishes that perceived ease of use and perceived usefulness exert a positive impact on students' intention toward using m-learning apps. This indicates that emphasizing the simplicity of the m-learning apps is a crucial aspect in ensuring its successful utilization. Moreover, the research demonstrates that perceived ease of use alone, without a strong sense of usefulness, may be insufficient to encourage students to utilize m-learning apps. This can be attributed to the fact that when students perceive the interaction with the mobile learning application as simple, understandable, and clear, their positive attitudes towards its usage are heightened. Our findings are in line with prior research [66–68], which highlights perceived ease of use as the most influential predictor in the TAM and as having a positive effect on intention towards technology adoption. Studies focused on e-learning [69,70] have further confirmed the positive relationship between perceived ease of use and users' intention to use e-learning.

Based on the findings of this study, it is evident that service quality exerts a significant and direct positive influence on intention toward using m-learning apps. This underscores the importance of prioritizing the development of m-learning apps with high-quality services to ensure successful utilization. Additionally, our research demonstrates that the development of m-learning apps lacking in high-quality features and services may prove insufficient in encouraging students to utilize m-learning apps. Consequently, when students perceive a m-learning apps as offering high-quality services that meet their satisfaction, it increases the likelihood of their adoption of the application. Our findings align with prior research [78–80], which emphasizes the role of service quality as one of the strongest predictors in the DL&ML model, having a positive effect on actual technology usage. Studies focused on e-learning [81–84] have provided confirmation that service quality exhibits a positive relationship with users' intention to use e-learning. Thus, in our study, service quality will play a crucial role in encouraging students to adopt and use mobile learning applications, particularly if they expect high-quality services from this application. Additionally, our findings revealed a positive impact of the system quality factor on students' intention towards using m-learning apps. However, our results do not align with previous e-learning studies [72,73], which found no significant relationship between system quality and intention towards using m-learning apps. Furthermore, our research indicated a positive impact of intention towards using m-learning apps on actual use of m-learning apps. Our findings are consistent with previous studies in e-learning [85–87], which confirmed a positive relationship between intention towards using m-learning apps and actual use of e-learning. Thus, in our study, intention to use will play a significant role in predicting students' utilization of m-learning apps.

6.1. Research Implications

This study offers to the literature several theoretical and practical implications for the continuous usage of mobile learning platform in post COVID-19. First, this the first study that extended the TAM model for predicting the actual use of mobile learning platform in post COVID-19. It's expected that there is increased use of this technology among students and this will enhance students' learning performance and learning outcomes. Second, the findings of this study showed that the proposed model provided empirical evidence of the significant factors that enhance the actual use of mobile learning platform in Jordanian universities. Third, the results also provided valuable insight into students' attitudes and continuous intention to use mobile learning platform in post COVID-19. Fourth, the findings provided suggestions for universities and developers to deeply understand the technological factors that should be considered when developing mobile learning platform. Fifth, the findings also offered recommendations for university teachers to create interesting and attractive learning materials. This enables students to stay focused, as well as not become bored when using mobile learning platform. Sixth, the technological resources of mobile learning platform should be optimal and appropriate to solve the technical problems such as poor of internet. When supported with adequate infrastructures such as hardware, software, and the internet, students are more likely to continuously use mobile learning platform. Seventh, mobile learning developers should develop mobile learning platform that meet the students' requirements and their learning needs. As well as, the ease of using this platform for learning should be necessarily considered during the development process. Finally, the role of universities to encourage students to use mobile learning platform as an additional leering supplement tool is considered one of the effective method for enhancing learning performance.

6.2. Limitations and Future Work

Although this research provides valuable recommendations, it is essential to acknowledge certain limitations in our study that can guide future research endeavors. Firstly, the proposed model in this study could be further enhanced by incorporating additional factors related to system quality, content quality, and technological aspects. This enhancement aims to offer more robust research solutions to effectively address the issue of mobile learning adoption. Secondly, the scope of our empirical study is confined to the Jordanian population. Replicating the findings in other countries would be intriguing as it enables examination for worldwide generalizability and investigation of cultural aspects relevant to mobile learning acceptability. Lastly, it is worth noting that this study solely focuses on students' perceptions. Future work could explore the perspectives of experts and teachers, aiming to gain insights into their opinions and experiences in successfully adopting mobile learning applications.

7. Conclusions

In the aftermath of the COVID-19 pandemic, mobile learning applications have emerged as indispensable tools for students to carry out their learning activities. Universities have also recognized the growing inclination of their students towards utilizing mobile learning services via mobile devices in recent years. Against this backdrop, this research endeavors to explore students' perceptions and behaviors concerning the usage of mobile learning services in Jordanian universities. To achieve this objective, the study adopts the Technological Acceptance Model (TAM) as its theoretical framework, while also incorporating external factors such as perceived security, perceived trust, perceived risk, system quality, content quality, and service quality. Furthermore, the primary objective of the proposed model in this study was to assess users' acceptance of mobile learning services within Jordanian universities. Structural Equation Modelling (SEM) was employed to analyze the proposed hypotheses in the model. The findings unveiled the significant roles played by perceived security, perceived trust, and service quality in enhancing the adoption of mobile learning services. Additionally, the study revealed that perceived risk had a negative impact on both students' trust and their attitudes toward the use of mobile learning services. These research findings offer valuable insights into the critical factors that could bolster mobile learning adoption among students, thus providing universities and academia with the opportunity to implement new strategies aimed at increasing the utilization of mobile learning applications in Jordanian universities.

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