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Actual Use of Mobile Learning Technologies during Social Distancing Circumstances: Case Study of King Faisal University Students

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Abstract: The most current highly infectious disease, which has become a global health challenge permeating entire sectors of society, is COVID-19. In the education sector, the transmission of COVID-19 has been curbed through the closure of institutions and the facilitation of online learning. The main objective of this study was to propose an integrated model of the unified theory of acceptance and use of technology combined with the DeLone and McLean model, to examine the influence of quality features, namely, performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), and social influence (SI), on the intentions and satisfaction of users toward mobile learning (m-learning) use in the context of Saudi learning institutions. The study obtained m-learning user data using an online questionnaire, after which the data were exposed to partial least squares structural equation modeling to test the proposed research model. The findings supported the influence of PE, EE, and FC on intention toward m-learning use but did not support the significant influence of SI. Moreover, system, intention, and user satisfaction were found to positively and significantly influence m-learning-system usage, with system, information, and service quality being top drivers of such user intention and satisfaction. The results reflect the required information concerning the strategies of higher institutions to enhance m-learning-system acceptance among students, with general implications for learning acceptance and usage.

Keywords: m-learning; COVID-19; D&M model; UTAUT; Saudi Arabia; universities

1. Introduction

Technological developments all over the world have wrought dynamic changes in different societal fields, including education. In the context of Saudi Arabia in the 21st century, such changes are brought about in the education sector from time to time through curriculum changes, eventually leading to digital learning [1]. Data reported by the General Authority for Statistics in the country also revealed that, as of 10 March 2021, Internet usage among the citizens of Saudi Arabia increased to 92.5%, indicating that the society is a technology-consumptive one and needs digital services and devices to achieve fulfillment. Digital media usage in the 21st-century-learning process is likely to be enhanced for students' advantages. According to Butler, Camilleri, Creed, and Zutshi [2], younger participants are more inclined to embrace mobile learning (m-learning) technology compared to older ones, and the use of laptops, hybrids, smartphones, and tablets in m-learning applications will increase on the home front and on the go.

The current pandemic of the 21st century is COVID-19, stemming from the novel coronavirus referred to as severe acute respiratory syndrome 2 (SARS-CoV-2), which was officially declared as such by the World Health Organization (WHO). The majority of global institutions were taken aback by the COVID-19 pandemic, with education, as well as other sectors, being inevitably affected [3]. Consequently, governments of countries all over the world strove to contain the effects of the virus by implementing measures such as social distancing, restrictions on face-to-face interactions, closure of universities and educational institutions, and travel bans [4,5]. The adoption of these non-pharmaceutical strategies impacted universities at all levels. It was reported that as of 4 April 2020, the pandemic had prevented more than 1.5 billion students all over the globe from attending classes in schools and universities [6]. It is clear that in uncertain times, the teaching and learning techniques used should match the changing societal demands [7]. In the transformational process of education, active teaching methods and technology incorporation into learning surroundings become inevitable, if not necessary [1–3]. Thus, amid the COVID-19 pandemic, the use of online learning and m-learning technologies for teaching and training processes has become essential [8,9]. In particular, m-learning technologies and tools such as smartphones and tablets have various features that work toward enhancing mobile student learning (e.g., timely information access, customized interfaces, context sensitivity, rapid and real-time communication, feedback opportunities, etc.) [10]. Device-skilled students are adept at using technologies for applying digital m-learning at home or on the go. Thus, there is a need to develop digital device usage during the COVID-19 pandemic through suitable methods in education. According to Alyoussef [11], technology must be integrated in all curriculum levels (input process and procedures) in order to leverage its use in trying times.

Generally speaking, m-learning refers to education through the Internet/networks using personal mobile devices (m-devices), such as tablets and smartphones, to receive learning materials [12]. It is in fact one of the top useful tools for students' learning. Educational institutions in the time of COVID-19 have been promoting online student learning, with learning maintained between teachers and students. The closure of educational institutions because of the pandemic turned these institutions toward using online learning as a recourse [13], as it can be conducted using m-learning. According to a UNESCO report [6], after the pandemic outbreak, students can continue studying and learning through remote means, and m-learning has become useful for this purpose (i.e., learning and teaching activities).

Despite the considerable investments by higher-learning institutions in m-learning projects, the majority of these projects still fail to meet the expected system benefits [14–16]. Dedicated studies have shown that m-learning technology should be completely accepted among students to be successful; otherwise, the result will be failure [17,18]. In a related study, students' acceptance of m-learning technology was found to be an important step to ensure m-learning technology success in the learning environment [19,20]. This type of study has implications for designers and developers, when it comes to the optimization of m-learning systems, enabling students to leverage the full potential from this type of learning technology [21].

Moreover, m-learning applications present several benefits to university students, where the use and acceptance of m-learning systems differ from one institution to the next [22–24]. The literature findings revealed that the level of acceptance among university students has remained low [5,25]. Other studies [3,26] maintained that the low level of m-learning-system use and acceptance among students stems from the low quality of m-learning systems and services; others mentioned the inability of such systems to meet the needs and requirements of students, while some additional studies overlooked quality factors as having a key role in successful m-learning systems and their evaluation [26,27]. Hence, such factors should be examined for their influence on m-learning quality. The present study examines the relationships between unified theory of acceptance and use of technology (UTAUT) factors (performance expectancy [PE], effort expectancy [EE], social influence [SI], and facilitating conditions [FC]) as well as factors of the DeLone and McLean (D&M) model (service quality, information quality, and system quality) on the usage and acceptance of m-learning applications.

Accordingly, this paper is organized in the following way. Section 2 presents the study background and a literature review regarding m-learning. Section 3 presents the theoretical framework and the development of the research hypotheses. Section 4 enumerates the details of the employed methodology, sampling procedure, and data-collection procedure. Section 5 contains the summarized version of the findings and results. Lastly, Section 6 presents the discussion, recommendations, and conclusion.

2. Literature Review

2.1. M-Learning in Saudi Arabia

On a global level, the use of smartphones is increasing, and this holds true in the Middle East. Alsenaidy and Ahmad [28] reported that Saudi Arabia is the top leading 4G market in the region, with a considerable number of youth accepting and using modern technology enthusiastically. Mobile Internet technology developments and extensive smartphone usage are the main drivers of development in the country. The Saudi government has also invested in technological infrastructure development by supporting Internet-enabled services and developing mobility networks [29]. Hence, the proliferation of smartphones in the country has resulted in the successful and dominating nature of m-learning in learning practices [30]. m-learning, which is the delivery of learning to students at any time and place through m-devices, has been exploited by higher educational institutions using mobile learning-management-system (LMS) services [11].

However, despite the developed level of telecommunications, m-learning remains in the implementation stage, particularly in the context of developing nations [5]. While m-learning has met adoption success in developed nations, their developing counterparts are still struggling to succeed in achieving complete and extensive usage of the same [12]. In the case of Saudi Arabia, m-learning has been adopted and implemented by many students, but engagement and satisfaction levels remain low among them. Alghazi et al.'s [10] recent study contended that certain factors (organizational and technological) are the core challenges in these countries. Althunibat et al. [14] highlighted the differences in the challenges faced by different countries, contexts, and institutions. Successful m-learning implementation, for instance, has been evidenced to be a critical challenge among students.

2.2. Related Works on m-Learning

The system adoption of users is crucial to ensuring system achievement in information systems (IS). Thus, the factors that drive the adoption of students toward using m-learning systems should be identified, recognized, and assessed. With the adoption of m-learning systems in current times, researchers and providers of m-services are striving to understand the adoption requirements comprehensively [31–35], as new-technology adoption is the initial phase to its application success [36–40]. This issue has been addressed by researchers by examining and determining the top critical factors of m-learning-system acceptance using traditional acceptance models (e.g., TAM, D&M, UTAUT and TRA), among others. To begin with, Almaiah [21] used UTAUT to examine the major factors influencing m-learning acceptance among students, and their findings showed that technology infrastructure and quality factors are the top significant factors that motivate students' acceptance and use of e-learning platforms. Additionally, Almaiah et al. [1] found system quality, service quality, content quality, technology infrastructure, awareness, university-management support, security concerns, and training to be drivers of the increased use of the Madrasati platform in the Saudi context. In the Jordanian case, Almaiah et al. [19] used and evaluated an extended TAM with an additional eight external factors, namely, learning-content quality, content-design quality, interactivity, functionality, user–interface design, accessibility, personalization, and responsiveness, to examine m-learning-acceptance among students in Jordan. Their findings indicated that quality factors influenced the m-learning-application acceptance of students. Meanwhile, a comprehensive technical-quality-requirements framework was proposed by Almaiah et al. [33] for m-learning apps, which adopted the Delphi method for data collection, evaluation, and analysis. The study results showed 19 technical quality requirements, categorized into 6 quality dimensions for developing the applications. In a similar study, Almaiah [38] brought forward a model for m-learning applications among students in Jordan using TAM with the addition of quality factors (quality of content design and learning content, functionality, interface design, and interactivity). The author found quality factors to have the highest impact on m-learning-application adoption among the examined students.

Other models were adopted by other studies. For example, Alyoussef [41] conducted an empirical evaluation of an integrated model of UTAUT–TAM and found perceived FC, PE, EE, SI, and enjoyment to have a significant impact on the perceived ease of use and usefulness of the system. They also found PE to have a negative significant effect on perceived ease of use, and both perceived ease of use and perceived usefulness to have a positive impact on attitudes toward m-learning-use, perception, and actual use. TAM, along with the updated D&M model, was adopted by Almaiah and Alismaiel [12] to test the effect of three quality factors on the acceptance of m-learning applications. The authors showed that system quality, content, and services were top motivators of students' adoption and use of m-learning applications.

In addition to the above studies, Almaiah and Alamri [23] brought forward an m-learning-acknowledgement structure based on TAM- and D&M-model integration, to study the effects of value components and individual variables on m-learning-network use and learning fulfillment among students. The findings showed that quality components, framework quality, data quality, and administration quality ensured satisfaction among students and their use of the m-learning framework. Cheng [42], likewise, adopted TAM integrated with innovation-diffusion theory (IDT) to predict the major m-learning-acceptance factors in the case of Taiwan and found that compatibility, convenience, and navigation (technological factors) enhance m-application acceptance and use among students. In the same line of study, Al-Shihi et al. [43] brought forward a model using TAM and UTAUT to examine the major determinants of m-learning in Oman. The results of their data analysis supported the significant effects of enjoyment, efficient learning, suitability learning, social learning, and excitability learning on m-learning acceptance.

Several studies have evidently been carried out to identify m-learning-acceptance and m-learning-adoption factors, but the main factors motivating m-learning acceptance from the perception of students need further investigation, as no universal model has been proposed to examine the effects of such factors on m-learning-system acceptance among university students.

3. Theoretical Framework and Hypothesis Development

3.1. Unified Theory of Acceptance and Use of Technology

UTAUT was proposed as an influential model to shed light on the technology use behavior of users [44–46]. It posits that the behavioral usage of technology (behavioral intention toward technology acceptance) can be gauged by using the individual's attitude toward such use. Distinctly, in comparison to its predecessors, UTAUT reflects an overall picture of technology acceptance, and being an extension of theory of planned behavior (TPB) [18], it is a prediction tool of behavioral intention [39]. Behavioral-intention prediction using technology and its actual use in UTAUT involve the identification of four main direct determinants, namely, PE, EE, SI, and FC, with four moderating factors, namely, age, gender, experience, and voluntariness [47]. Notably, PE and EE conceptually represent relative performance and complexity, respectively, in IDT, while in TAM, they are represented by perceived usefulness and perceived ease of use, respectively. Similarly, SI and FC represent subjective norms and perceived behavioral control, respectively, in the case of TPB [34]. UTAUT applications have generally been limited to the main effects, with only a few studies examining the moderating effects. Based on [18,34], UTAUT's weaknesses lie in its missing factors.

Importantly, UTAUT models have managed to explain the differences between technology use and behavior throughout several contexts, but, despite the extensive examination of m-learning technologies and their validity in IS, as evidenced by academicians, students' acceptance of these technologies has rarely been the focus of such research [17]. This finding is significant given that the systems' acceptance of students differ from that of professionals, as the former may not possess sufficient self-efficiency and experience to use such systems, making them more likely than professionals to be challenged in m-learning application [34,39]. Hence, focus on this demographic is crucial.

The popularity of UTAUT does not negate its weaknesses, which include the failure to include entire factors that have a significant influence over a user's acceptance of innovative technology, as these variables can also be determinants of attitudes toward use. In other words, UTAUT examined internal motivations but not external ones, and it focused on use outcomes of information technology (IT) and not the use process itself. In relation to this, Davis [48] noted that UTAUT's ability to gauge and predict determinants of new-system and technology acceptance could be enhanced by external variables. Thus, it is recommended to extend UTAUT by adding external factors that would increase the explanatory power of the model, which is why, in this study, additional external variables are included and integrated into UTAUT.

3.2. DeLone and McLean Model

The successful adoption of IS and technologies in the education field has been a main concern among researchers, application developers, and educator circles, and the majority of authors have dedicated their work to identifying IS success factors. For successful IS, the D&M model developed by DeLone and McLean [49] seems to be the most extensively employed model. The authors brought forward three types of quality factors, system quality, information quality, and service quality, along with user satisfaction, intention to use, and net benefits, to include in their model. In this regard, a system equipped with quality characteristics will enable the user to have a positive experience and be satisfied, contributing more to their level of intention to use [49]. Researchers are of the consensus that quality-related factors play a key role in IS success [27,37], and, currently, the updated D&M model is the most extensively adopted for IS/IT success [22]. Thus, the D&M model is used in the presently proposed research.

3.3. Extended UTAUT and D&M Model

According to Venkatesh et al. [46], UTAUT supports a robust theoretical basis for the relationships between acceptance antecedents and an individual's intention to use. However, the explanatory power of UTAUT needs to be improved through the addition of external variables within its constructs, to resolve the model's weaknesses. UTAUT does not contain all the variables that have the potential to influence technology acceptance [50]; in relation to this, external variables can enhance the model's ability to measure and predict new system-/technology-acceptance determinants [48]. Hence, additional external variables should be added to the main UTAUT construct. Another UTAUT drawback is its oversight of determinants that could enhance system quality, service quality, design, and implementation as well as their influence on the system and technology acceptance of users [48]. UTAUT solely concentrates on presenting information concerning PE and EE, SI, and FC, without including the effects of system improvement factors that could contribute to system and technology acceptance.

Evidently, the D&M model also has some drawbacks, one of which is the incomplete coverage of IS-success dimensions [51]. To begin with, the model fails to address the importance of usefulness and ease of use in successful IS [37]. Although the updated D&M model presents robust theoretical support for the contribution of quality factors (system quality, information quality, and service quality), along with usefulness and ease of use, to successful IS, it still fails to provide theoretical support for the relationships among the quality factors and the beliefs and intention to use of individuals in the m-learning context. Thus, on the basis of the integrated UTAUT and D&M models, the weaknesses of each model can be countered. The developed research model to examine intention toward using m-learning among Saudi students is presented in Figure 1.

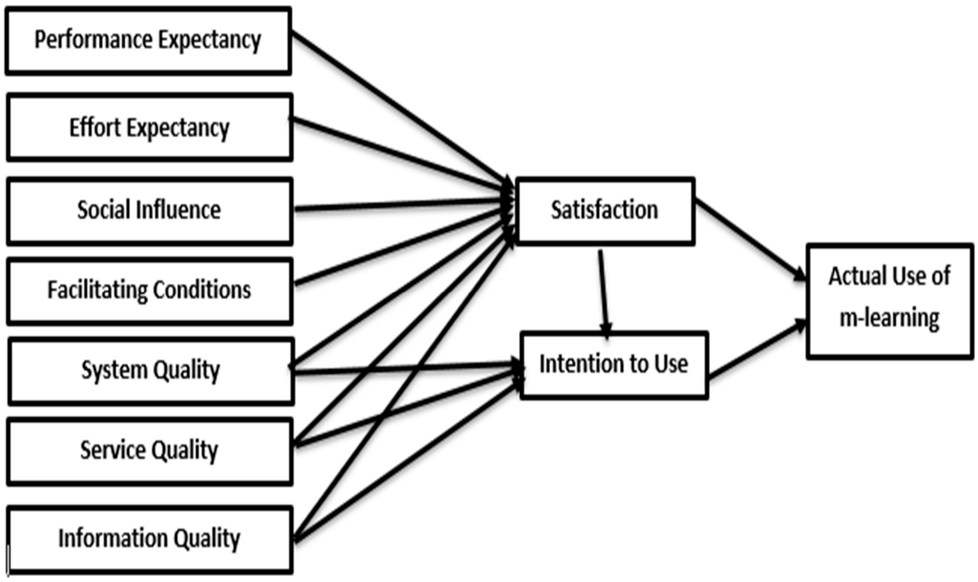

Figure 1. Model of the current study.

3.4. Performance Expectancy

PE refers to the level to which a user benefits from a specific technology in completing an activity [46]. The expectation of intention to use information and communication technology systems often involves the integration of perceived enjoyment in UTAUT [52]. In the context of South Korea, m-learning was examined by Sung et al. [53] using UTAUT, and, based on the study outcome, there is a significant relationship between PE and behavioral intention. This result was similarly found in other prior studies [54,55]. Other researchers have also made use of UTAUT, including Botero et al. [56] and Nikolopoulou [57], who revealed that perceived enjoyment, perceived usefulness, and perceived ease of use are interconnected. Thus, in this study, it is hypothesized that:

Hypothesis 1 (H1). *Performance expectancy of m-learning has a positive significant influence on the user's intention to use.*

3.5. Effort Expectancy

This variable is defined as the level of effort that the user is convinced they have to exert to complete a task [46], and it has been evidenced to be a crucial variable of UTAUT in examining the intentions of users toward new-technology adoption [58,59]. For instance, Sung et al. [53] revealed that m-learning acceptance is affected by EE in the South Korean context, and Kaliisa et al. [55] supported the variable's significant relationship with perceived usefulness and perceived ease of use. Nikolopoulou [57] also used UTAUT in their study and found significant interrelationships among EE, perceived usefulness, and perceived ease of use. Therefore, in this study, it is proposed that:

Hypothesis 2 (H2). *Effort expectancy of m-learning has a positive significant influence on the user's intention to use.*

3.6. Social Influence

According to past studies [34,46,60], SI refers to the level to which an individual is convinced that important others in their life believe that they should make use of the new technology/system. Along the same line of study, Lutfi [34] contended that people important to the individual may influence their final decision, and Arain et al. [22] found students to be influenced by other people on social networks when it comes to m-learning-service use. In the case of m-learning, SI was referred to by Alasmari and Zhang [18] as the level to which the student is convinced that others think they should make use of corresponding services. This variable was also synonymously considered as a subjective norm and is included in the theory of reasoned action (TRA) [46]. On the basis of relevant past studies and UTAUT [22,34], SI is considered to contribute significantly to behavioral intention toward m-learning usage. Thus, this study proposes the following hypothesis for testing:

Hypothesis 3 (H3). *Social influence has a positive significant influence on the intention to use m-learning.*

3.7. Facilitating Conditions

This variable is described as the required organizational and infrastructural conditions provided to support system usage [34,46,60]. In the m-learning case, FC is described as the current sufficient resources facilitating the student's access to m-learning services [22]. This construct is covered in UTAUT, with the initial proposer of the model revealing the significance of FC in IS usage [34] and other studies supporting this finding [18,22]. The present study refers to FC as the level to which individuals perceive that technical and organizational infrastructures exist to support their system usage, which—in this case—is FC influencing the use of m-learning systems among students. In a similar line of argument, individual support, training, accessible materials for skills and knowledge enhancement, and access to the m-learning system all function toward facilitating system usage. Thus, this study proposes the following hypothesis for testing:

Hypothesis 4 (H4). *Facilitating conditions have a positive and significant influence on the intention to use m-learning.*

3.8. System Quality

According to DeLone and McLean [49], system quality is a desirable element denoting the quality of the performance and functionality of the IS [61]. In addition, it is a major factor for IS success [49], representing the degree to which desirable IS characteristics are present in the system. System quality is generally measured through ease of use, response time, accessibility, flexibility, usefulness, and reliability of the system [4]. It is a critical factor in making sure that m-learning applications succeed [8] and has been proven to significantly and positively influence e-learning satisfaction [12,62] and intention toward using e-learning [12,63]. Hence, in this study, system quality is considered to positively influence the satisfaction and intention toward m-learning use among students.

Hypothesis 5 (H5). *System quality has a positive and significant influence on students' satisfaction with m-learning.*

Hypothesis 6 (H6). *System quality has a positive and significant influence on students' use of m-learning.*

3.9. Service Quality

In the m-learning context, service quality refers to the level of service quality that the system presents in light of meeting students' expectations in terms of reliability, privacy, security, assurance, and responsiveness [12,49]. According to Arain et al. [22], service quality is the level of and overall support for the service quality received and expected by users from the IS (e.g., training or helpdesk), while other researchers mentioned its importance as an independent variable owing to the dynamic changes in IS over the years [49].

DeLone and McLean [49] stated that service quality is the main element that drives IS success, and Almarashdeh et al. [64] supported its critical role as a determinant of the successful design of an LMS. Similarly, Alshurideh et al. [27] supported the significant influence of service quality on learners' satisfaction and intention to use, which lead to their improved use of the e-learning system. Service quality is often measured through the system's ability to deliver a service that meets the expectations of potential users [56]. This may be exemplified by the following: when users experience issues in system use, they expect quick service to solve the problem, and if the request for timely service is met with fairness and reliability, then the satisfaction level of the users will be improved [41,57]. On the other hand, if the service quality falls short of meeting the users' expectations, then they will not be inclined to use the system. Thus, it is predicted that service quality has a hand in shaping the attitude of users and their satisfaction with the service. This study proposes that service quality has a positive and significant impact on the satisfaction and intention of students to use m-learning.

Hypothesis 7 (H7). *Service quality has a positive and significant influence on students' satisfaction with m-learning.*

Hypothesis 8 (H8). *Service quality has a positive and significant influence on students' intention to use m-learning.*

3.10. Information Quality

Information quality is a major determinant of IS and m-learning performance, and it has a crucial role in achieving learning objectives and addressing the challenges resulting from low information quality [61]. Quality learning information and materials need to have precision, accuracy, and timely, suitable, and updated elements. M-learning systems need to present sufficient, accurate, and useful learning materials enriched with multimedia content, enabling learners to search for and conduct their learning activities with ease. Researchers who have dedicated their work to the variable's influence [12,37] contend that content quality plays a major role in forming the satisfaction of students with their m-learning-system usage. Similarly, Almaiah et al. [1] noted that information quality has a significant relationship with intention toward m-learning usage [63]. Thus, this study proposes that information quality positively impacts the satisfaction and intention of use among students when it comes to m-learning.

Hypothesis 9 (H9). *Information quality has a positive and significant influence on students' satisfaction with m-learning.*

Hypothesis 10 (H10). *Information quality has a positive and significant influence on students' intention to use m-learning.*

3.11. Satisfaction

As opposed to selling, supplying, or serving, businesses aim to meet the needs and satisfaction of customers [64]. Individuals' perceptions of the level to which their needs, goals, and desires have been met are represented by their satisfaction [12] and their complete IS view [65]. Notably, user satisfaction is the level to which the user's pleasure is met when it comes to using IS and its supporting services [61]. In the updated IS success model, it is posited that system use comes before satisfaction, and if this leads to satisfaction, then this will ultimately lead to higher intention toward usage [61]. In prior studies [12,27], satisfaction has a positive influence on the user's intention toward e-learning service use. Specifically, Almarashdeh et al. [64] supported the positive and significant influence of satisfaction on actual use of the e-learning system. Hence, this study proposes that satisfaction has a positive and significant influence on the user's intention to use and actual use of m-learning.

Hypothesis 11 (H11). *Satisfaction has a positive and significant influence on the user's intention to use m-learning.*

Hypothesis 12 (H12). *Satisfaction has a positive and significant influence on the user's actual use of m-learning.*

3.12. Intention to Use and Actual Use

Intention to use is the primary dependent variable and top determinant of a user's acceptance, and TAM refers to it as the inclination of the individual toward using new technology. Intention may be described as an attitude; as mentioned by DeLone and McLean [49], it as an emotional and psychological entity that provides a description of the user's beliefs and a mind state that is formed by their experience. An individual's behavior is mainly a good or a bad one, and this influences their behaviors [66–69]. Behavior is the socially formed attitude of the users, concerning a value that is an outcome of a sensitive activity, directed toward a position, issue, person, or event (the attitude object).

According to Davis [48], intention to use new technology has a major role in its actual usage, and based on TAM, behavioral intention to use is the top determinant of actual system use. Moreover, the TRA considers it to be the top predictor of the same [70]. In the m-learning-usage–acceptance domain, researchers have also focused on the intention and actual use of m-learning. To begin with, Binyamin and Zafar [70] contended that intention to use has a significant influence on the actual use of m-learning, while Almaiah and Alismaiel [12] focused on the positive role of the variable on usage. In a similar study line, Petter et al. [61] found that complexity can be steered clear of by not distinguishing between intention to use and system use in the IS success model, albeit the former is generally considered a construct in the individual level. The positive relationship between intention to use and actual use of technology was supported by Venkatesh et al. [46,71] as well. Therefore, this study proposes that intention to use positively and significantly impacts the actual use of m-learning:

Hypothesis 13 (H13). *The intention to use m-learning has a positive and significant influence on its actual use.*

4. Methodology

4.1. Study Design

Learning carried out through m-learning involves the use of personal m-devices, such as tablets and smartphones, to access learning content online. M-learning is characterized as flexible, enabling the access of students and learners to educational content at any time and place. In this study, the higher education students' perceptions of m-learning in light of PE, EE, SI, FC, and IS success-quality factors are examined with their actual use during the COVID-19 pandemic. Survey copies were distributed to obtain data regarding the way King Faisal University students use m-learning. An efficient outcome was ensured through the division of analyses into two sections. First, data were collected from university students (undergraduates and postgraduates) using questionnaire copies. The students were from various faculties (i.e., information system and management, engineering, and social science). The study results were obtained to determine the influence of the examined factors on the students' level of m-learning acceptance.

4.2. Instrumentation

The research objectives were achieved through a survey instrument, and the data collected were exposed to an in-depth analysis (Table 1). The questionnaire included 10 constructs, with the measurements adopted from the following studies: PE and EE measurement items from Thomas, Singh, and Gaffar [72]; SI items from Alghazi, Kamsin, Almaiah, Won, and Shuib [10] and Thomas et al. [72]; FC items from Alowayr and Al-Azawei [73]; intention-to-use measurement items from Almaiah and Alismaiel [12]; and system-service, information-quality, satisfaction measurement items (SAT), and actual-use items (AU) from DeLone and McLean [49].

Table 1. Research instrument with references.

Constructs	Reference
PE	Thomas et al. [72]
EE	Thomas et al. [72]
SI	Alghazi et al. [10] and Thomas et al. [72]
FCs	Alowayr and Al-Azawei [73]
IU	Lin [11]
SYQ	DeLone and McLean [49]
SEQ	DeLone and McLean [49]
INQ	DeLone and McLean [49]
SAT	DeLone and McLean [49]
ACU	DeLone and McLean [49]

4.3. Data Collection and Analysis

Data participants comprised 428 individuals. Through Sekaran and Bougie's [74] proposed guidelines, the initial targeted minimum sample size was found to be 384, which was ultimately selected from King Faisal University. The sample size is considered to be acceptable in exploratory research for its representation of the perspectives of students concerning m-learning usage. Data obtained from the 435 questionnaire copies were exposed to SPSS analysis. The participating students were from different faculties. At the initial stage of data collection, the researcher introduced the study objectives along with the definition of m-learning. Based on the analysis of the demographic profile, 66.6% were males and the remaining 33.4% were females, most of whom were under 19 years old. The majority of the respondents were between 17 years and 22 years (77.5%), were undergraduate students (92.1%), and had been using m-devices for over 7 years (73.8%).

Data analysis was conducted using partial least squares structural equation modeling (PLS-SEM) (Smart PLS 3.0 software), which was chosen based on its ability to analyze simultaneous series of relationships, as opposed to other statistical methods that can only analyze a single relationship between variables (e.g., multiple regression, multivariate analysis of variance) [75–78]. SEM is also deemed to be a confirmatory approach, different from other approaches that are descriptive in nature and, hence, unable to test theoretical models. Therefore, this study made use of Smart PLS 3.0 to assess the measurement and structural models. The data analysis results are presented in the next sections.

5. Results

5.1. Assessment of the Measurement Model

In this phase of assessment, tests were conducted to ensure sufficient construct convergence and factor loadings, based on the following criteria: Cronbach's alpha values (0.7), composite reliability (0.7), and average variance extracted (AVE) (0.50) [79]. The study also tested for discriminant validity with the help of the Fornell-Larcker criterion, and the findings showed sufficient inter-construct correlations without excessiveness (refer to the AVE results in Table 2), indicating a good discriminant validity level among the constructs [79]. All the squared roots of AVE proved to be higher on the diagonal line than the correlation coefficients between constructs, thus depicting construct-level discriminant validity (see Table 3).

Table 2. Relevant indicators of the measurement model.

Latent Construct	Cronbach's Alpha (CA) $\alpha \geq 0.70$	Composite Reliability (CR) ≥ 0.70	AVE ≥ 0.50	R2
PE	0.900	0.930	0.770	
EE	0.750	0.830	0.510	
SI	0.840	0.890	0.620	
FCs	0.800	0.850	0.580	
SYQ	0.850	0.890	0.630	
SEQ	0.830	0.880	0.590	
INQ	0.860	0.900	0.550	
IU	0.900	0.930	0.770	43.4
USAT	0.910	0.940	0.790	79.6
Actual Use (AU)	0.850	0.900	0.690	63.7

Table 3. Fornell-Larcker discriminant validity correlation matrix (AVE square root).

	AU	SYQ	INQ	PE	SEQ	USAT	SI	EE	IU	FCs
AU	**0.83**									
SYQ	0.35	**0.72**								
INQ	0.56	0.37	**0.74**							
PE	0.56	0.37	0.44	**0.71**						
SEQ	0.69	0.33	0.67	0.54	**0.79**					
USAT	0.73	0.33	0.68	0.52	0.58	**0.88**				
SI	0.32	0.14	0.43	0.29	0.35	0.41	**0.79**			
EE	0.50	0.37	0.42	0.37	0.52	0.49	0.32	**0.76**		
IU	0.54	0.32	0.52	0.45	0.62	0.63	0.41	0.36	**0.77**	
FCs	0.48	0.31	0.34	0.29	0.47	0.46	0.15	0.36	0.33	**0.89**

Note: The values in bold represent the square root of the AVE.

5.2. Assessment of the Structural Model

The significance of the direct effects proposed in the structural model was assessed using path coefficients, t-statistics, and p-values. Table 4 presents the summarized version of the factors' findings. The results indicate that the hypothesis between PE and IU was supported (H1) (β = 0.085; t = 2.160, $p < 0.05$), as is the one between EE and IU (H2) (β = 0.199; t = 4.760, $p < 0.001$). However, the hypothesis between SI and IU (H3) was not supported (β = 0.000; t = 0.010). H4, which was between FC and IU, was supported (β = 0.146; t = 3.050, $p < 0.001$). Moving on to H5, H7, and H9, which refer, respectively, to the hypotheses between SYQ and US (β = 0.179; t = 5.330; $p < 0.001$), between INQ and US (β = 0.387; t = 7.441; $p < 0.001$), and between SEQ and US (β = 0.067; t = 2.261; $p < 0.010$), they were all supported. Moreover, the results for the hypotheses between SYQ and IU, SEQ and IU, and INQ and IU (H6, H8, and H10, respectively) all showed significant outcomes (β = 0.125; t = 2.600; $p < 0.001$, β = 0.351; t = 5.132; $p < 0.001$, and β = 0.057; t = 1.902; $p < 0.050$, respectively). The relationship between US and IU was also supported in H11 (β = 0.434; t = 8.042, $p < 0.001$), and the same was true with US and AU (H12) (β = 0.569; t = 15.109; $p < 0.001$). Lastly, IU was found to be a top predictor of the AU of m-learning (H13) (β = 0.279; t = 6.652; $p < 0.001$), thus supporting the hypothesis.

Table 4. Result of hypothesis testing of the direct relationship model.

Path of Hypotheses	β Coefficient	t-Value	p-Value	Result
H1. PE → IU m-learning	0.085	2.160	0.020 *	Supported
H2. EE → IU m-learning	0.199	4.760	0.000 ***	Supported
H3. SI → IU m-learning	0.000	0.010	0.500 *	Not supported
H4. FCs → IU m-learning	0.146	3.050	0.000 ***	Supported
H5. SYQ → US	0.179	5.330	0.000 ***	Supported
H6. SYQ → IU m-learning	0.125	2.600	0.000 ***	Supported
H7. INQ → US	0.387	7.441	0.000 ***	Supported
H8. INQ → IU m-learning	0.351	5.132	0.000 ***	Supported
H9. SEQ → US	0.067	2.261	0.010 **	Supported
H10. SEQ → IU m-learning	0.057	1.902	0.030 *	Supported
H11. US → IU m-learning	0.434	8.042	0.000 ***	Supported
H12. US → AU m-learning	0.569	15.109	0.000 ***	Supported
H13. IU m-learning → AU	0.279	6.652	0.000 ***	Supported

Note: Significant at * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$ (one-tailed test).

6. Discussion

This study used the IS success model integrated with UTAUT to examine the perceptions of m-learning users and analyze the quality features that influence users' intentions and satisfaction with the system. The findings of this study are expected to provide detailed information on the behavioral patterns of users when it comes to m-learning. The uniqueness of the study lies in its tackling of m-learning usage using the integrated IS success model and UTAUT. Past studies that examined the variables only focused on intention to use rather than actual use through intention to use, which is where the current focus is placed. The findings of the current study are expected to enrich the literature concerning the behavioral patterns of users toward m-learning use.

The findings showed a favorable and significant relationship to the predictors and, in effect, the actual m-learning application. Based on the regression analysis of the structural model, the results indicated the significant influence of all the factors, with the exception of SI, confirming the major role of PE in predicting the intention toward m-learning and its use ($p < 0.00$). Past studies also reported similar findings when it comes to the significant prediction of m-learning intention by PE during the COVID-19 pandemic, where m-learning is often used [12]. It may, thus, be stated that if students feel the usefulness of m-learning in their learning, they will be more inclined toward its adoption. Another relationship that the study examined is between EE and intention to use, and a significant one was found ($p < 0.00$), indicating that the ease of using m-learning may reinforce its usefulness. Therefore, students who perceive how easy it is to use m-learning will be more willing to use it, adopt it, and place importance on it. In other words, an easy-to-use or user-friendly m-learning system is one that saves students' time and effort during effective learning. The findings also supported a significant relationship between FC and m-learning intention, similar to past studies on m-learning [10,12]. This outcome shows that users often observe if m-learning meets their learning requirements in terms of Internet speed, usage costs, and convenience, among others, as such requirements will contribute to their perceptions of system quality and, in effect, increase their intention toward its adoption and use. Given that m-learning is new technology, FC needs to be present for students' enhanced use of m-learning.

The outcome of the analysis rejected the significant influence of SI on the behavioral intention of students toward m-learning usage. This finding is aligned with that reported by Almaiah and Alismaiel [12], who found no significant influence of SI on m-learning acceptance among students owing to the experience of users with m-devices. Generally speaking, pressures from SI and important other factor did not make a difference in the users' adoption of new technology, as intention to use is based on usefulness taking precedence. The results indicate that peers, parents, and lecturers also need to be familiar with the advantages of m-learning to be able to have a significant influence. Accordingly, lecturers and administrators of higher-learning institutions have to use new technologies such as m-learning to be able to convince the students of their usefulness and their benefits. Promoting the use of m-learning through appropriate means and conditions can motivate students to learn using the m-learning platform, and one such way is to promote the advantages of the system among students.

In Table 3, it is evident that user satisfaction and intention to use both positively influence the behavioral use of m-learning, similar to past studies, and this holds true for actual usage as evidenced by Hassanzadeh et al. [80]. User intention was also found to significantly influence the actual use of the system [80].

Considering that user satisfaction and intention to use positively influence actual use, it can be stated that service quality, system quality, and information quality have positive effects on the same through satisfaction and intention. These are the elements of the m-learning system that win over user confidence, particularly system quality, confirming the reported results of Hassanzadeh et al. [80], who found system quality to be the top determinant of user satisfaction with m-learning in the Iranian context. Both Motaghian et al. [81] and Tajuddin et al. [62] also found positive effects of system quality on user's satisfaction, while Fang, Chiu, and Wang [82] found the same result in m-learning cases. Moreover, other related studies found system quality to have a positive influence over the user's intention toward system usage. Thus, all of the above findings from past and current research indicate that the provision of a technology/application that is satisfying and user-friendly, with structural design that is flexible, environmentally friendly, reliable, secure, and timely, with interactive features that will greatly contribute to its intention to use and actual use. Added to the above, the system also has to suitably organize time within the environment, content printing and transferring, smooth system control, and a fixed menu for users, with content information in the form of images, sounds, and videos as well as an m-learning communication evolution toward communication and video conferencing, all of which will enhance the interests in and attractiveness of the system to students.

This study also found that information quality has a significant influence on m-learning satisfaction and intention, which means that providing accurate, comprehensive, current, and required information to users, with pedagogical organization, is a must. In the same line of argument, m-learning-system sharing with other universities can serve as an enriching information hub. Along with the above quality aspect, service quality also significantly influences m-learning satisfaction, similar to other past studies [62,83,84]. Service quality was also supported, to have a significant influence over the intention of users toward using m-learning, in Hassanzadeh et al. [80] and Ramayah et al. [63]. To this end, the following tasks are recommended: establishment of an effective online assistant and help desk providing the management of courses, provision of a cooperative learning approach involving those who are interested in active learning, provision of a hub where users can present their feedback and opinions, provision of online instruction and education and public training courses for skills improvement and for those who are new to using the applications and digital devices, establishment of an online help software-design team to ensure up-to-date facilities, and organization of an internal network to supply online services to users and carry out system evaluation as well as system-capabilities improvement.

7. Contributions

The study findings have contributions to theory and practice, which will, in turn, have implications for university administrators, service providers, and academic researchers. Practically, the study results are useful for designing and implementing the m-learning system for its effective use. Understanding the perceptions and acceptance of students of m-learning can, likewise, lead to better system designs. Educational-institution administrators and managers need to examine m-learning acceptance among students, when developing their course content. Additionally, through in-depth understanding of the drivers of technology acceptance and use behavior, quality m-learning systems with high effectiveness and efficiency can be developed. M-learning-system use and acceptance can also pave the way for adopting other m-learning systems within the scope and interest of the university administrator.

The proposed m-learning model also provides a description of the determinants of m-learning use among university students. These factors may be used to bring about the involvement and use of m-learning among students, and with the development of an m-learning platform, students can access course information or related information in an easy and timely manner. With their increasing familiarity, students can move on to using advanced m-learning strategies, such as generating, sharing, collaborating, and capturing information for their courses. The results also have implications for university policy makers, in light of the training programs to be provided, on the way a learning system can be shifted to enhance the knowledge of students via m-learning. Designers and developers of the system may also make use of the findings to meet students' needs and steer clear of system failure.

Theoretically, the study contributes to m-learning and the acceptance of new IT innovations, particularly m-learning in higher-learning institutions. The study proposed an m-learning model that encapsulated critical factors from the D&M model and UTAUT, which were left out from previous studies, to test their effects on the intention to use m-learning among students. The unique nature of this study lies in the combination of the examined distinct factors (Figure 1) and their effects on intention to use and actual use. To this end, to the best of the authors' knowledge, this is the first study to investigate the impact of such factors on the intention of students toward m-learning use in higher-learning institutions. Thus, in addition to filling the gap in the literature, this study presents an extensive examination of the quality factors that affect m-learning usage. It contributes to the understanding of the current circumstance in higher-learning institutions, when it comes to m-learning use. The model can be used as a guide for future studies concerning new-technology usage and acceptance, as it presents information on m-learning and new-technology adoption.

Finally, the effects of quality factors (system quality, information quality, and service quality) on m-learning acceptance and usage have been under-studied in the literature, so including such factors contributes further to the literature. This study is one of the pioneering efforts to examine the quality factors' effects, combined with UTAUT factors, on the intention to use m-learning among students of higher-learning institutions.

8. Conclusions, Limitations, and Future Studies

This research explored the effects of factors on m-learning intention to use and actual use, through a proposed model that combined UTAUT and quality factors. Technology-acceptance models were validated in light of m-learning usage among university students. The benefits of the UTAUT and D&M models were highlighted in presenting new information regarding m-learning acceptance and use. In fact, although m-learning has a key role in new-information provision during learning and study activities in the current century, no past study has examined university students' attitudes toward it in the context of Saudi Arabian universities. Both the UTAUT and D&M models appeared to be sufficient in providing findings on the examined phenomenon in this context.

Therefore, this study presented considerable implications for researchers, practitioners, system developers, service providers, and academics, when it comes to research-approach recognition for model validation in institutions of higher learning. It focused on nine UTAUT and D&M models as determinants of m-learning adoption for m-learning; specifically, the proposed study model included the following factors; FC, PE, EE, SI, service quality, system quality, information quality, intention toward m-learning usage, satisfaction, and actual m-learning usage. Owing to sample limitations, this study was unable to consider all the m-learning features and determinants affecting acceptance on the side of users. Nonetheless, it does contribute to providing information on m-learning in the university context.

Another study limitation is the population constraint, which is only concerned with higher-education institutions. Owing to the study-design limitations and the adopted approach utilized, future studies may adopt an interview approach to gain more information concerning the perceptions of students and educators on m-learning usage. Future studies may also look into the areas through cross-validation of the model and examination of additional factors. A qualitative study design may benefit future research on analyzing the perspectives of different groups. Following the validation of technology acceptance models in the university context, the findings may be adapted to different contexts for model analysis in terms of its applicability. IS application use may be enhanced through the extension of studies to other technology-based industries using a significant number of samples.

Indubitably, the study has several contributions, but the limitations mentioned cannot be ignored. Another limitation is the cross-sectional approach adopted, which has led to findings that cannot be used to confirm the long-term causal relationships among the model factors. This limitation calls for the need to conduct a longitudinal study to validate the same. Added to this, the study sample covered only a single public Saudi university, limiting the generalizability of findings. Hence, future studies may use larger-sized samples covering both private and public universities. This need stems from the fact that the perceptions of the students in King Faisal University may not represent the perceptions of all students of the global situation. Future studies may also include the perceptions of instructors and system designers, when it comes to m-learning usage during the pandemic in institutions of higher learning. Another future research endeavor that can be based on this study is to compare the perspectives of university students from other nations, as this would extend the findings and provide a better understanding of the phenomenon. Lastly, future studies may also look into moderating variables, such as gender, age, and experience, and their role in the relationships among the examined factors.

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