# EXAMINING FACTORS DETERMINING THE BEHAVIORAL INTENTION TO USE MOBILE LEARNING SYSTEMS IN HIGHER EDUCATION: AN INTEGRATIVE FRAMEWORK DURING THE COVID-19 PANDEMIC

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## ABSTRACT

*This paper explores mobile learning (m-learning) acceptance and use through integrating UTAUT and IS success models to examine whether quality factors (including "Information Quality," "System Quality" and "Service Quality") and behavioral factors (including "Performance Expectancy," "Social Influence" and "Facilitating Conditions") predict students' satisfaction and their intention to use m-learning systems. Data were collected through surveys from a total of 383 higher education male and female students in the United Arab Emirates (UAE). Structural equation modelling and path analysis were employed to test the proposed research model, showing that "Information Quality," "System Quality," "Service Quality," "Performance Expectancy," "Social Influence," "Facilitating Conditions," and "Satisfaction" determined students' intentions to use m-learning. "Satisfaction" was the most important antecedent of user behavior with m-learning, and "Performance Expectancy" was found to have the highest effect on "Satisfaction." The study's contribution to the advancement of m-learning acceptance and usage is connected to the theory and practice.*

**Keywords:** *mobile learning; IS (Information System) success; UTAUT; quality factors; satisfaction; UAE*

## 1 INTRODUCTION

The education industry has been very slow to adopt technology and has lagged behind in making the most of technological advancements (Smith, 2020), limited to the use of personal digital assistants (PDAs) and other portable digital devices. With rapid advancements in technology in the late 1980s and in parallel with the rise of learner-centered pedagogical movements, the interest in PDAs started diminishing as smart phones offered the same application and web functionalities but with greater mobility. During 2005, mobile learning (hereby denoted as m-learning) became a recognized term (Kukulska-Hulme, 2007), referring to the learning process that is conducted across various time and space contexts. Learners can benefit from access to learning materials through smart mobile devices such as smartphones and tablet computers (Chao, 2019). As a dynamic learning environment, the use of smart mobile devices (Mohammadi, 2015) is changing the education landscape and providing learners with capabilities such as ease of access, flexibility, improved communication and interactivity, immediacy, and self-organized and self-directed learning, as well as facilitating corporate training, offering personalized learning, and presenting an effective technique for delivering lessons and gaining knowledge (Almaiah & Alismaiel, 2019; Bidin & Ziden, 2013; Mohammadi, 2015). Studies further show that m-learning can significantly improve students' learning experiences through achieving positive gains in academic achievement while enhancing their creativity, critical thinking, and conversational skills (Olarte-Ulherr, 2014). M-learning has become a critical component of higher education (Almaiah & Alismaiel, 2019; Chao, 2019), supported by recent studies (Hamidi & Jahanshaheefard, 2019; Kim et al., 2017) showing that many universities have extended their online learning platforms to include mobile services (Albashrawi & Motiwalla, 2020; Almaiah & Alismaiel, 2019; Mohammadi, 2015). Despite being hailed as a transformative paradigm (Rahi et al., 2019), students' interest in and usage of m-learning fall below expectations (Chao, 2019; Kim et al., 2017).

On March 11, 2020, the World Health Organization (WHO) declared the outbreak of COVID-19 a global pandemic (Cucinotta & Vanelli, 2020), causing significant disruptions to education across the world. M-learning presented as invaluable pioneering technology for ensuring continuity of learning through leveraging delivery of learning while committing to safety measures. It enabled students to access learning materials without restrictions to time and space and allowed them to regulate their own learning, and it facilitated assessment for students and instructors. Literature indicates that m-learning was not considered part of formal learning across several institutions until the outbreak of COVID-19 (Al-Emran, 2020); hence, it could be argued that the determinants affecting acceptance and adoption of m-learning in the past might be different from the factors influencing its employment during COVID-19 and post pandemic. There needs to be a re-evaluation of the determinants affecting the actual use of m-learning during and beyond the era of COVID-19 with a special focus on quality factors to understand how the quality of the learning content would influence the students' decisions to adopt m-learning in future crises (Al-Emran, 2020). Accordingly, this study examines the determinants affecting students' adoption of m-learning during the era of COVID-19 through integrating quality and behavioral factors as the antecedents of students' satisfaction and their intention to use m-learning in the United Arab Emirates (UAE) in case of a future crisis and beyond. Through investigating the behavioral intentions of higher education students to adopt m-learning, our study proposes a hybrid model that combines the IS Success model (particularly Delone and McLean's (DL&ML) model) and the Unified Theory of Acceptance and Usage of Technology (UTAUT) model. A full understanding of those determinants would help in shaping new trends of learning in the future that can be fully based on digital and smart mobile technologies.

Prior studies have focused mainly on a particular set of constructs to explain the variance in adoption and usage of technologies—namely performance expectancy, effort expectancy, social influence, and facilitating conditions—without any reference to personal dispositions (Dweveidi et al., 2017) such as attitudes and user satisfaction. This is further supported by a consensus in the literature that shows that only about 25% of studies employing the UTAUT model did not include any further constructs that are not part of the original model. Therefore, little research has been conducted on m-learning adoption with integration of UTAUT and IS quality factors (Almaiah & Alismaeli, 2019; Mohammadi, 2015). The present study fills the research gap by applying established IS acceptance and use theoretical models to systematically examine the antecedents of m-learning success. An integrative framework would reinforce the significance and predictability of findings (Rahi et al., 2019). Our study seeks to combine key factors of the UTAUT model including performance expectancy, social influence, and facilitating conditions, with the updated DL&ML model, with quality factors such as system quality, information quality, and service quality, to predict satisfaction and system use. We advance the body of knowledge on this subject and investigate the mediating role of performance expectancy and satisfaction to adopt m-learning. The newly developed integrated technology model expands the scope of technology adoption decisions and provides a reference to researchers and policymakers for deciding future development directions and approaches related to the implementation of m-learning.

The main research objectives are formulated as follows:

(1) What factors determined m-learning adoption in UAE during the pandemic?

(2) Are learners' intentions determined by their satisfaction?

(3) Which factors from each model are more influential on m-learning satisfaction and intention to use?

## 2 LITERATURE REVIEW

### *2.1 Definition of Mobile Learning*

M-learning is a new way to access information. While the usage of mobile and associated devices in learning is not distinctively novel (Todoranova & Penchev, 2019) and despite its recognition, a single unified definition has not been established (Chao, 2019). This study defines m-learning as a learning process that enables learners to access information and learning content, anytime and anywhere, through mobile technologies such as smartphones and tablets. The promotion of two-way communication over an app benefits learners in their interactions with faculty, officials, and their classmates, and is a significant feature of learning (Al-Nassar, 2020; Todoranova & Penchev, 2019). A growing number of experts ascertain that m-learning will increasingly play an essential role in the development of teaching and learning methods for higher education over the next few years (Almaiah & Alismaeli, 2019; Chao, 2019). However, the popularity of mobile learning in higher education will be dependent on the acceptance of this technology by the users themselves. This highlights the need for the present research.

For a long time, researchers aimed at identifying factors influencing the adoption of mobile learning technologies (Alsswey & Al-Samarraie, 2019). Aspects such as performance expectancy, effort expectancy, and social influence have all been extensively explored in the literature (AlHujran et al., 2014; Shorfuzzaman & Alhussein, 2016). In the UAE, the findings of a study by Murshidi (2017) revealed that the popularity of m-learning among undergraduate students could be attributed to its immediacy as it enables quick submission of assignments that render users' performance to be efficient. Similarly, Al-Emran and Shaalan (2015) observed that increased acceptance and better attitude towards m-learning were demonstrated by UAE students and faculty compared to those in other neighboring states like Oman. Moreover, as expected, 99% of the sample owned a mobile device in the form of a smartphone or tablet. In September 2012, the UAE launched the world's largest shift of the education system to m-learning, whereby more than 14,000 tablets were distributed to students in federal institutions. Reports following the implementation of the project revealed that teachers showed high levels of preparedness and confidence in adopting m-learning technologies (Tamer, 2014). These findings support the UAE's vision of leading the Middle East in adoption of smart technologies through fundamentally changing mindsets. The rise in smart device ownership in the UAE over the past 10 years, combined with the state's high internet penetration rates and government bodies' vision to embrace technology, has transformed nearly every aspect of life in the UAE, including communication, running errands, paying bills, etc. (Everington, 2018). Accordingly, the UAE technology market has provided a competitive advantage to attract foreign direct investments, which increased in 2020 by 44.2% from the previous year amid the pandemic, where investments across the globe historically plunged (Rahman, 2021).

This paper strives to add to this theoretical body of knowledge, noting the perception of UAE university students in using m-learning systems post–COVID-19. A greater understanding of this field helps in shaping new trends of learning in the UAE in the future based on smart mobile technologies and mobilizing effective mobile education.

### *2.2 Theoretical Framework*

A number of theoretical models emerged in recent decades to determine and explain users' acceptance of m-learning systems. The majority focused on users' beliefs and intention to engage in certain behaviors. Among the most accepted models that integrate a range of social, cultural, and cost-related factors are: UTAUT, the Theory of Reasoned Action (TRA), the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), the Combined-TAMTPB, and the Innovation Diffusion Theory (IDT). UTAUT is a technology acceptance model postulated by Venkatesh et al. (2003) through synthesizing the important components of the above-mentioned behavioral intentions models used in various technology acceptance contexts. UTAUT was recognized to be the most effective model with a high explanatory power that is capable of explaining about 70% of the variance in the users' technology acceptance (Raza et al., 2019; Venkatesh et al., 2003; Wrycza et al., 2017). The model's substantial power has been empirically tested and confirmed in the domain of higher education. Hence, this study adopts UTAUT as a main theoretical model to examine whether students are influenced by the adoption environment, and particularly their perception towards performance expectancy upon engaging with the system, and the societal influence and convenience/resources offered by the enrolling institutions. These would be considered as behavioral factors influencing m-learning success.

On the other hand, the updated DL&ML model has emerged as a valuable approach in understanding the IS success through examining user satisfaction and acceptance of technology based on a number of factors, namely the desirable characteristics of a system (i.e., system quality), the quality of support the student received from IT personnel (i.e., service quality), and its desirable content (i.e., information quality). These factors would be considered as quality factors influencing technology adoption.

This study is based on the work of Mohammadi (2015) who identified the determinants of user satisfaction and usage of elearning in Iranian universities, and Almaiah and Alismaiel (2019), who integrated the DL&ML and TAM models to evaluate the effects of the three quality factors with two individual factors on students' satisfaction and usage of m-learning in Jordanian universities. However, the TAM model has been shown to have a number of disadvantages (Chao, 2019), such as not offering adequate understanding of users' perspectives of novel systems. Therefore, this study is considered to be one step ahead in employing the UTAUT model through examining mediating roles of two dimensions and ascertaining its originality and value.

The UTAUT is a widely used popular model in the area of technology adoption that provides a clear understanding of people's behavior when using technology (Al-Saedi et al., 2020;). The theory comprises six constructs: (a) performance expectancy, (b) effort expectancy, (c) social influence, (d) facilitating conditions, (e) behavioral intention to use the system, and (f) usage behavior (Venkatesh et al., 2003). According to the UTAUT model, the first four constructs are considered to be the UTAUT key predictors in explaining user perception and acceptance behavior. Performance expectancy, effort expectancy, and social impact drive behavioral intention towards new technology; this in turn, and in addition to facilitating conditions, significantly affects user behavior (Dwivedi et al., 2020).

### *2.3 Extended UTAUT with DL&ML*

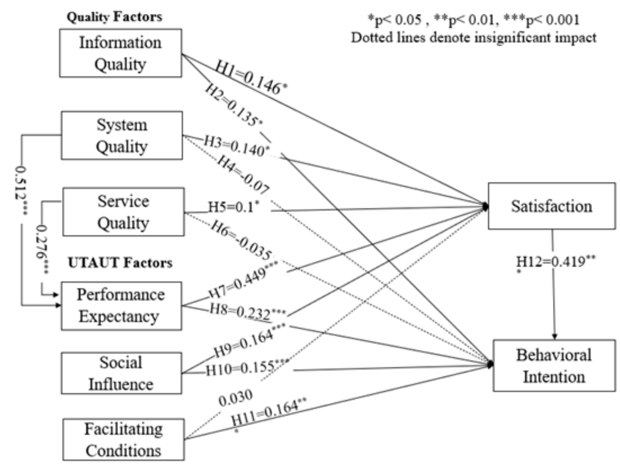
The DL&ML model was designed by Delone and McLean (2016) and is the most extensively used model in information systems today (Almaiah & Alismaiel, 2019). Following their extensive review of all IS scholar studies between 1970 and 1980, Delone and McLean synthesized the taxonomy of their IS framework that reveals six quality factors: information quality, system quality, service quality, system use, user satisfaction, and net benefits. The model poses that a system of reliable quality characteristics will lead to a pleasant experience that leads to high satisfaction levels upon usage and better intention to use (Delone & McLean, 2004). A number of scholarly studies (such as Albashrawi & Motiwalla, 2020; Almaiah & Alismaiel, 2019; Mohammadi, 2015) ascertained the importance of the role these quality factors play in the success of any novel information system. The DL&ML model is currently the most commonly applied theoretical framework in achieving IS/IT success (Almaiah & Alismaiel, 2019; Cheng, 2012), confirming the relevance of this framework to the current study and proposed research model.

The hypotheses brought forth in the study are based on a thorough understanding of the foundational underpinnings stemming from contemporary studies. To achieve the research aim and objectives, an integrative framework has been developed that expands the theoretical boundaries of IS success and acceptance models to better understand the system factors, along with individual behavioral factors that are specific to users, towards using a m-learning system. We believe that combining two complimentary IS adoption models should satisfy this aim and propose that the integration of IS success and UTAUT models should bring about a clearer perspective towards user satisfaction and usage of m-learning systems. IS success captures satisfaction and usage of the information system through quality factors related to the design and format of the learning content material and personalization and responsiveness of the system, among other system characteristics. On the other hand, UTAUT determines users' behavioral intention to use the system through performance expectancy, social influence, and facilitating conditions. In his pioneering study on expanding the UTAUT model to include a number of contextual predictors, Chao (2019) demonstrated the need to empirically test the influence of system design as a moderator of the relationship between behavioral intention and other factors/variables. Students' perceptions of performance expectancy and other key factors of UTAUT are changing over the course of time as experience and knowledge are accumulated, particularly amid and following the COVID-19 outbreak and the transition to remote learning. Therefore, our research study aims to fill the gap by integrating quality (namely information, system, and service quality) and behavioral factors (namely performance expectancy, social influence, and facilitating conditions) in predicting m-learning acceptance. While UTAUT has been empirically tested and modified in different ways, researchers utilizing the model have reported a number of limitations that may suggest reconsidering certain hypotheses and paths proposed by the model. For instance, two major observations could be denoted as follows: (a) The associated relationship between facilitating conditions and intention to use in the original model is absent, and (b) certain moderators specific to the individual characteristics of the users, such as attitude and satisfaction, were not theorized in the original model and hence should be presented. Venkatesh et al. (2012) confirmed that most of the studies incorporating UTAUT have only partially utilized the model and only a subset of it has been utilized. Whereas satisfaction is considered to be a positive attitude, the role of the latter in predicting technology acceptance and adoption has been well established in prior research (such as Bobbitt & Dabholkar, 2001; Taylor & Todd, 1995b; Yang & Yoo, 2004). However, Dwevidi et al. (2017) stated that their analysis reveals a sheer absence of attitude or satisfaction as a construct from the majority of emerging IS/IT acceptance models as it shows up in only five out of 16 explored theories. Hence, our research aims to fill this gap by including satisfaction as a main variable that can predict m-learning acceptance.

## 3 CONCEPTUAL FRAMEWORK AND HYPOTHESES

This section presents the research model, which incorporates eight main constructs and a number of hypotheses, as presented in Figure 1.

*Figure 1. Conceptual Framework*




### *3.1 Information Quality*

The success dimension Information Quality refers to the desirable characteristics of the m-learning system output (DeLone & McLean, 2016; Urbach 2011). This dimension captures a wide variety of factors such as accuracy, adequacy, availability, reliability, scope, etc. Researchers ascertained that choosing Information Quality measures should be specific to the addressed field and the context of the study (AlBashrawi & Motiwalla, 2020). Therefore, the current study adopted the definition provided by Cheng (2012) as the users' perception on the quality of the learning content and content design. Content Quality measures a user's perceptions of the content suitability including relevance, accuracy, reliability, and timeliness. Content design refers to the attributed type and format of the learning material and content. The richness of the learning material, presented as lectures, tasks, quizzes, courses, graphics, and so on, would reinforce user perception of system usefulness. The capacity of the content design to meet users' expectations and needs, through allowing for various formats while making it more accessible using audios, videos, animations, and text, makes the app useful and requires less user effort. Information Quality is often denoted as the main antecedent of IS acceptance, user satisfaction (Hassanzadeh et al., 2012), and intention to use the IS system (Hassanzadeh et al., 2012; Mohammadi, 2015). It also has a contributing significant positive influence over the users' beliefs on the performance expectancy and it being simple to use. Kim-Soon et al. (2018) observed that playfulness, accomplishment anticipation, and familiarity to students all have a beneficial, long-lasting effect on behavioral intention for utilizing m-learning. In addition, user satisfaction partially mediates the association between factors impacting learning and behavioral intention to use m-learning (Kim-Soon et al., 2018). Similarly, Mohammadi's (2015) findings indicated that information quality is the strongest predictor of satisfaction and behavioral intention. Based on the above, we propose the following hypotheses:

H1: Information Quality will have a positive significant influence on Satisfaction with m-learning.

H2: Information Quality will have a positive significant influence on the Behavioral Intention of university students to use m-learning.

*3.2 System Quality*

The success dimension System Quality refers to the desirable features of an IS (DeLone & McLean, 1992), particularly system functionality and performance. This construct is manifested in the capacity of the system to allow for adequate navigation and accessing of different and trustworthy services and is considered a main component of the success of an IS . A number of quality factors measure this dimension, such as access, convenience, interactivity, navigation, flexibility, reliability, etc. (Gable et al., 2008; Rahi et al., 2019). In a similar manner to Information Quality mentioned above, the choice of measures comprising the construct System Quality should be in relation to the IS/IT context of the study. Hence, the current study adopted factors identified in a study by Almaiah and Alismaeil (2019) based on a number of prior studies in the field of elearning systems, namely interactivity, simplified access, functionality, and user interface design. System quality is subject to the user's perception, hence, the better the quality of the system with an appealing user interface, the more enhanced is user perception of the flexibility, reliability, simplified access to learning material, and interactivity of the system with different stakeholders such as peers, faculty, administrative staff, and advisors (AlBashrawi & Motiwalla, 2018). Hassanzadeh et al. (2012) observed that the quality of technical systems is a major component involved in measuring the success of an elearning system, leading to higher user satisfaction and general success. Almaiah and Alismaiel (2019) further supported the positive influence of system quality on student satisfaction and behavior. To anticipate m-learning adoption on the basis of UTAUT and TAM, Al-Shihi et al. (2018) hypothesized that students' intentions for using m-learning were significantly impacted by the system quality, presented mainly through flexibility, efficiency, and appropriateness. Based on the above, we propose the following hypotheses:

H3: System Quality will have a significant positive influence on Satisfaction with m-learning.

H4: System Quality will have a significant positive influence on Behavioral Intention of university students to use m-learning.

*3.3 Service Quality*

Service Quality refers to the quality of services and support that the user receives upon from the hosting organization and IT support personnel when using the system (DeLone & McLean, 2016) and plays a principal role in the success of an information system. The literature offers numerous quality factors that are part of service that include security, dependability, reaction time, responsiveness, trust, personalization, and availability (Chang & King, 2005. The quality of services in a face-to-face environment that comprises all the in-facility interactions has traditionally been perceived as critical in the success of the service and is extendable to virtual learning platforms like m-learning channels (Albashrawi & Motiwalla, 2018). Prior IS research revealed that high quality of services can predict user satisfaction and behavior intention to use the system. For instance, Almaiah and Alismaiel (2019) observed that service quality had significant influence on student satisfaction and intention to use the m-learning app. Similarly, Cheng (2012) showed that service quality is an antecedent of system acceptance influencing intentions to use. Al-Nassar (2017) explained the role of this dimension as a key component influencing students' behavioral intentions toward the acceptance of elearning, which was later expanded to include m-learning (Bharati & Srikanth, 2018). Service quality appeared to enhance students' motivation to learn and acceptability of m-learning. Based on the above, we propose the following hypotheses:

H5: Service Quality will have a positive influence on Satisfaction with m-learning.

H6: Service Quality will have a positive influence on Behavioral Intention of university students to use m-learning.

*3.4 Performance Expectancy*

As part of the UTAUT model, Vankatesh et al. (2003) defined performance expectancy as the extent to which a user perceives that using the system is effective and will enhance performance in achieving positive gains. In the context of this study, this construct denotes students' beliefs regarding whether using m-learning will enhance their performance through better efficiency and productivity. Performance expectancy appears to be the most prominent determinant of attitude in elearning environments despite the introduction of new constructs. The role of this dimension as a strong predictor of satisfaction and intentions to adopt a technology is evident in many prior research studies ( Dweveidi et al., 2017; Šumak et al., 2017). Users' satisfaction and behavioral intention are shaped by the degree to which the technology is found useful. Given that the literature overwhelmingly finds that a user's perception towards the technology's performance expectancy influences satisfaction and intention to use, we propose the following hypotheses:

H7: Performance Expectancy will have a positive influence on Satisfaction with m-learning.

H8: Performance Expectancy will have a positive influence on Behavioral Intention of university students to use m-learning.

*3.5 Social Influence*

As an integral part of the UTAUT model, Venkatesh et al. (2003) defined social influence as the extent to which a person perceives it is critical that others believe one should adopt and be using a new IS. In an educational context, this construct refers to the opinion of other students, classmates, friends, faculty members, and members of their families on the use of the new innovative system (Khechine et al., 2020). As a standard norm, users may show high levels of satisfaction and acceptance once the system appears to be well accepted and recommended by their social network (Albashrawi & Motiwalla, 2018). Hence, it is expected that students will form an intrinsic motivation to comply with options suggested by people who are influential to them. The potential effect of social influence as a powerful explaining factor of a user's satisfaction and intention to use a new IS is evident in the literature (AlHujran et al., 2014; Shorfuzzaman & Alhussein, 2016). Researchers suggest that social influence is a direct predictor of an individual's behavioral intention to use a new technology (Abu-Al-Aish & Love, 2013; Khechine et al., 2020). Ali and Arshad (2018) observed that, among other variables, social influence was found to be significant predictor of behavioral intention to use m-learning. Following the above argument, we propose that:

H9: Social Influence will have a positive influence on Satisfaction with m-learning.

H10: Social Influence will have a positive influence on Behavioral Intention of university students to use m-learning.

*3.6 Facilitating Conditions*

The Facilitating Conditions construct is defined as the perception of the presence of a reliable organizational and technical infrastructure to support the system's users (Venkatesh et al., 2003). In the context of the current study, this dimension comprises the availability of human, organizational (IT personnel), and technical (IS personnel) support for using the new system. The association between the facilitating conditions construct and intentions to use has been found to be positive and strong in the extended UTAUT model by Venkatesh et al. (2012). Effects on the intent to utilize m-learning is evident in the literature (Ali and Arshad, 2018; Shukla, 2021). Khechine et al. (2020) further confirmed that in a similar manner to social influence, facilitating conditions predicted user behavior. Shukla (2021) argued that effects on student intent to utilize m-learning were found to be positively influenced by affective need and facilitating conditions; however cognitive need was found to be unimportant when projecting and explaining m-learning acceptance. Following the above argument, we propose that:

H11: Facilitating Conditions will have a positive influence on Behavioral Intention of university students to use m-learning.

### *3.7 Satisfaction*

The Satisfaction construct refers to the users' perception regarding the extent to which their needs and requirements were fully met by the IS (Sanchez-Franco, 2009). As a success dimension, satisfaction is an important measure of IS success and has been widely accepted as a predictor of both behavioral intention and actual usage of a system (Albashrawi & Motiwalla, 2020; Chao, 2019; Mohammadi, 2015). Success at sustaining the level of satisfaction upon using mobile learning systems will help in sustaining the level of usage. Moreover, having a pleasant experience in using the system will encourage users to further engage deeper in usage. Iqbal and Qureshi's (2012) results showed that usefulness, simplicity of use, and supportive conditions all have a considerable impact on students' desire to adopt m-learning, while perceived fun has a less significant impact. Following the above argument, we propose that:

H12: Satisfaction will have a positive influence on Behavioral Intention of university students to use m-learning.

## 4 RESEARCH METHODOLOGY

This section presents the data collection, instrumentation, survey approach, research sample, and methods adopted to analyze the data.

### *4.1 Data Collection and Participants*

This study seeks to understand the m-learning satisfaction and behavioral intention towards using mobile learning in the UAE. Data were collected in summer 2021, a period that is marked by the transition of most educational institutions to online and hybrid learning environments due to the outbreak of COVID-19 as a global pandemic. Committing to social distancing and other precautionary measures, the transition was unavoidable.

Empirical data were collected using a cross-sectional survey that was distributed electronically. A convenience sampling approach was adopted where 383 participants were recruited to take part in the study. The sample was taken from three large and reputable universities in the UAE: two from Dubai and one in Sharjah. To optimize survey response, a research assistant was hired to manage the survey distribution process and data collection. All subjects were informed about the research purpose and volunteered to participate without monetary incentive. They were also assured that their responses would be treated with total confidentiality and anonymity and that the collected data would be used solely for research purposes. The questionnaire required about 15–20 minutes to complete. The demographic results of the respondents are presented in Table 1.

*Table 1. Profile of Respondents (N=383)*

| Demographics/level | | N | Percentage |
|---|---|---|---|
| Gender | Male | 179 | 46.7 |
| | Female | 204 | 53.3 |
| Age | 17–24 | 329 | 85.9 |
| | 25–34 | 43 | 11.2 |
| | 35+ | 11 | 2.9 |
| Experience with m-learning | Beginner | 30 | 7.8 |
| | Intermediate | 117 | 30.5 |
| | Expert | 236 | 61.6 |
| Education (Year in College) | First Year | 60 | 15.7 |
| | Second Year | 171 | 44.6 |
| | Third Year | 89 | 23.2 |
| | Fourth Year | 48 | 12.5 |
| | Masters or PhD | 15 | 3.9 |

### *4.2 Instrument Development*

A questionnaire was used to collect data from respondents that was made up of two main sections. The first section contained five demographic items presented on a nominal scale, collecting basic information about respondents' age, marital status, experience with m-learning usage, and education status. The second section comprised 27 items measuring the eight constructs of the research model. The instrument (i.e., INQ, SEQ, SYQ, PE, SI, FC, SA, BI) was developed after thorough review of studies related to the DL&ML and UTAUT models with modifications to fit the context of the current study as follows:

The structured instrument was used to collect data using a five-point Likert scale to score questionnaire responses. Each construct was measured by multiple items. The Likert scale consisted of five answer options ranging from *strongly disagree (mapped to number 1) to strongly agree (mapped to number 5).* A pilot study was conducted to empirically examine and validate the reliability of the developed questionnaire by verifying the accuracy

*Table 2. Constructs and Indicators of Study*

| Construct | Indicator | Reference |
|---|---|---|
| Performance Expectancy | · Using m-learning would improve my learning performance.<br>· Using mobile learning increases my chances of achieving learning that is important to me.<br>· Using mobile learning would allow me to accomplish learning tasks more quickly.<br>· Using mobile learning would enhance my effectiveness in learning. | Chao (2019) |
| Behavioral Intention | · Assuming I had access to mobile learning, I intend to use it.<br>· Given that I had access to mobile learning, I predict that I would use it.<br>· I plan to use mobile learning in the future. | Chao (2019) |
| Satisfaction | · I was very content with mobile learning.<br>· I was very pleased with mobile learning.<br>· I was satisfied with mobile learning efficiency.<br>· I felt delighted with mobile learning.<br>· Overall, I was satisfied with mobile learning. | Chao (2019) |
| Information Quality | · Mobile learning provides information that is relevant to my needs.<br>· Mobile learning provides comprehensive information.<br>· Mobile learning provides me with organized content and information.<br>· Mobile learning provides up-to-date content and information.<br>· Mobile learning provides required content and information. | Lee et al. (2009)<br>Cheng (2012) |
| System Quality | · Mobile learning application makes it easy for me to interact with my teachers.<br>· Mobile learning application is compatible with different platforms.<br>· Mobile learning application allows me to download and upload files.<br>· For mobile learning to be useful, it is important for the size and resolution of the interface to be good.<br>· Mobile learning application has well-designed menus and icons. | Almaiah & Alismaiel (2019) |
| Service Quality | · Mobile learning application provides learning services anywhere.<br>· Mobile learning application provides learning services any time.<br>· Mobile learning application provides me with a prompt service.<br>· Mobile learning department staff responds in a cooperative manner. | Almaiah & Alismaiel (2019) |
| Social Influence | · People who influence my behavior think that I should use mobile learning.<br>· People who are important to me think that I should use mobile learning.<br>People whose opinions I value prefer that I should use mobile learning. | Kim et al. (2008) |
| Facilitating Conditions | · I have the resources necessary to use mobile learning.<br>· I have the knowledge/technical skills necessary to use mobile learning.<br>· I can get help easily from others when I have difficulties using the mobile learning system. | Marchekwa & Kostiwa (2007) |

and precision of all the measurement items (Hair et al., 2010).

The reliability of each construct was checked based on Cronbach's alpha, for which the cutoff score was set to be 0.7 (Hair et al., 2010). Responses were collected from students at two main universities in the UAE. The reliability scores ranged from 0.908 for SEQ to 0.972 for PE. The results indicated that the Cronbach's alpha values for all variables exceeded 0.7. After the appropriate level of reliability had been confirmed for all measurement items, the final questionnaire proved reliable and usable: INQ (5 items; $\alpha = .971$); SYQ (4 items; $\alpha = .908$); SEQ (4 items; $\alpha = .923$); PE (4 items; $\alpha = .972$); SA (5 items; $\alpha = .959$); BI (3 items; $\alpha = .948$); SI (3 items; $\alpha = .959$); FC (3 items; $\alpha = .932$).

## 5 DATA ANALYSIS

The Partial Least Squares (PLS) technique was applied to analyze the causal relationships between constructs using the software application Smart-PLS. The PLS approach was selected due to the exploratory nature of the research (Hair et al., 2011). The two-step approach was utilized in data analysis as suggested by Henseler et al. (2009). The first step involves the analysis of the measurement model, while the second step tests the structural relationships among the latent constructs. The two-step approach aims at establishing the reliability and validity of the measures before assessing the structural relationship of the model.

### *5.1 Measurement Model*

In this study, the convergent validity of the measures was tested. Convergent validity is the degree to which multiple attempts are made to measure the same concept in agreement. As recommended by Hair et al. (2010), the estimation of the convergent validity was achieved through examining the values of factor loading, average variance extracted (AVE), and composite reliability (CR). Confirmatory factor analysis (CFA) was used to examine the reliability and validity of the measures adopted from the literature. The results are presented in Table 3.

As shown in Table 3, the factor loadings of all items ranged from 0.829 to 0.971, exceeding the threshold of 0.5 as recommended by Hair et al. (2006). The average variance extracted, which represents the total amount of variance in the indicators of a latent construct, was in the range of 0.794 and 0.930, which was above the suggested value of 0.5 (Hair et al., 2010). Composite reliability, which describes the degree to which the indicators of a construct exhibit that construct, ranges from 0.939 to 0.976, which was higher than the suggested value of 0.6 (Hair et al., 2010). In the next step, the value of Cronbach alpha was used to measure the reliability of the measures. The values ranged from 0.913 to 0.962, which were above the threshold of 0.7 as suggested by Nunnally and Bernstein (1994). Table 4 presents means, standard deviations, correlations between constructs, and the results of discriminant validity, which refers to the issue of how truly distinct a construct is from other constructs (Fornell & Larcker, 1981; Hair et al., 2006).

*Table 3. Convergent Validity and Internal Reliability*

| Construct | Item | Convergent Validity | | | Internal Reliability Cronbach Alpha |
|---|---|---|---|---|---|
| | | Final Factor Loading | Average Variance Extracted (AVE) | Composite Reliability (CR) | |
| Information Quality (IQ) | IQ1 | 0.921 | 0.847 | 0.965 | 0.955 |
| | IQ2 | 0.934 | | | |
| | IQ3 | 0.932 | | | |
| | IQ4 | 0.905 | | | |
| | IQ5 | 0.911 | | | |
| System Quality (SYQ) | SYQ1 | 0.872 | 0.820 | 0.948 | 0.927 |
| | SYQ2 | 0.904 | | | |
| | SYQ3 | 0.906 | | | |
| | SYQ4 | 0.939 | | | |
| Service Quality (SEQ) | SEQ1 | 0.923 | 0.794 | 0.939 | 0.913 |
| | SEQ2 | 0.906 | | | |
| | SEQ3 | 0.903 | | | |
| | SEQ4 | 0.829 | | | |
| Performance Expectancy (PE) | PE1 | 0.920 | 0.845 | 0.956 | 0.939 |
| | PE2 | 0.944 | | | |
| | PE3 | 0.877 | | | |
| | PE4 | 0.935 | | | |
| Social Influence (SI) | SI1 | 0.962 | 0.930 | 0.976 | 0.962 |
| | SI2 | 0.971 | | | |
| | SI3 | 0.961 | | | |
| Facilitating Conditions (FC) | FC1 | 0.940 | 0.906 | 0.967 | 0.948 |
| | FC2 | 0.971 | | | |
| | FC3 | 0.944 | | | |
| Satisfaction (SA) | SA1 | 0.930 | 0.848 | 0.965 | 0.955 |
| | SA2 | 0.937 | | | |
| | SA3 | 0.918 | | | |
| | SA4 | 0.909 | | | |
| | SA5 | 0.909 | | | |
| Behavioral Intention (BI) | BI1 | 0.939 | 0.886 | 0.959 | 0.936 |
| | BI2 | 0.952 | | | |
| | BI3 | 0.933 | | | |

*Table 4. Discriminant Validity, Correlations, and Descriptive Statistics*

| | Construct | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Information Quality (IQ) | 3.84 | 0.88 | 0.920 | | | | | | | |
| 2 | System Quality (SYQ) | 3.87 | 0.96 | 0.812 | 0.906 | | | | | | |
| 3 | Service Quality (SEQ) | 3.82 | 0.89 | 0.741 | 0.720 | 0.891 | | | | | |
| 4 | Performance Expectancy (PE) | 3.57 | 0.96 | 0.766 | 0.711 | 0.645 | 0.919 | | | | |
| 5 | Social Influence (SI) | 3.21 | 0.96 | 0.507 | 0.465 | 0.537 | 0.531 | 0.964 | | | |
| 6 | Facilitating Conditions (FC) | 4.02 | 1.01 | 0.680 | 0.680 | 0.628 | 0.579 | 0.476 | 0.952 | | |
| 7 | Satisfaction (SA) | 3.53 | 0.91 | 0.781 | 0.746 | 0.705 | 0.829 | 0.609 | 0.624 | 0.921 | |
| 8 | Behavioral Intention (BI) | 3.62 | 0.93 | 0.747 | 0.675 | 0.645 | 0.787 | 0.628 | 0.656 | 0.836 | 0.941 |

Values in diagonal-bold display the square root of the average variance extracted

Standardized correlations reported $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

As shown in Table 4, the square root of the average variance extracted for each construct was higher than the correlations of that construct with other constructs (Hair et al., 2010). Further, the correlations between constructs were all less than the threshold of 0.85, ranging from 0.465 to 0.836, indicating satisfactory discriminant validity between the constructs (Kline, 2010).

Table 4 also represents the descriptive statistics of the constructs including the mean and standard deviation. The lowest mean value belonged to Social Influence (SI) (mean = 3.21), while Facilitating Conditions (FC) has the highest mean value (mean = 4.02). The lowest and highest standard deviation belonged to Information Quality (IQ) (SD = 0.880) and FC (SD = 1.01) respectively.

*5.2 Structural Model*

With the satisfactory results in the measurement model, the structural model was subsequently evaluated. The predictive accuracy of the model was evaluated in terms of the portion of variance explained (R-square) and Stone-Geisser cross-validated redundancy (Q-square) (Geisser, 1975; Stone, 1974;). The R-square value for Performance Expectancy (PE), Satisfaction (SA), and Behavioral Intention (BI) was 0.542, 0.779, and 0.769 respectively. All values were above the requirement for the 0.30 cut off value which indicated that the full model explains 77% of the variance in BI, 78% in SA, and 54% in PE. The Q-square value was 0.455, 0.648, and 0.668 for PE, SA, and BI respectively, and greater than zero, which implies the model has predictive relevance (Chin, 2010). The path coefficients and the results of examining hypothesized direct effects are displayed in Table 5.

*Table 5. Examining Results of Hypothesized Direct Effects of the Constructs in Structural Model*

| Path | Path Coefficient | Standard Error | T-value | P-value | Hypothesis Result |
|---|---|---|---|---|---|
| IQ → SA | $0.146^{*}$ | 0.059 | 2.469 | 0.014 | H1) Supported |
| IQ → BI | $0.135^{*}$ | 0.066 | 2.038 | 0.042 | H2) Supported |
| SYQ → SA | $0.140^{*}$ | 0.066 | 2.122 | 0.034 | H3) Supported |
| SYQ → BI | −0.070 | 0.058 | 1.214 | 0.226 | H4) Rejected |
| SEQ →SA | $0.100^{*}$ | 0.047 | 2.124 | 0.034 | H5) Supported |
| SEQ → BI | −0.035 | 0.049 | 0.718 | 0.473 | H6) Rejected |
| PE → SA | $0.449^{***}$ | 0.048 | 9.395 | 0.000 | H7) Supported |
| PE → BI | $0.232^{***}$ | 0.049 | 4.701 | 0.000 | H8) Supported |
| SI → SA | $0.164^{***}$ | 0.034 | 4.802 | 0.000 | H9) Supported |
| SI → BI | $0.155^{***}$ | 0.033 | 4.673 | 0.000 | H10) Supported |
| FC → BI | $0.164^{***}$ | 0.045 | 3.670 | 0.000 | H11) Supported |
| SA → BI | $0.419^{***}$ | 0.067 | 6.284 | 0.000 | H12) Supported |
| FC → SA | 0.030 | 0.043 | 0.687 | 0.493 | Rejected |
| SEQ → PE | $0.276^{***}$ | 0.067 | 4.132 | 0.000 | Supported |
| SYQ → PE | $0.512^{***}$ | 0.057 | 8.954 | 0.000 | Supported |

Note. N = 383; $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

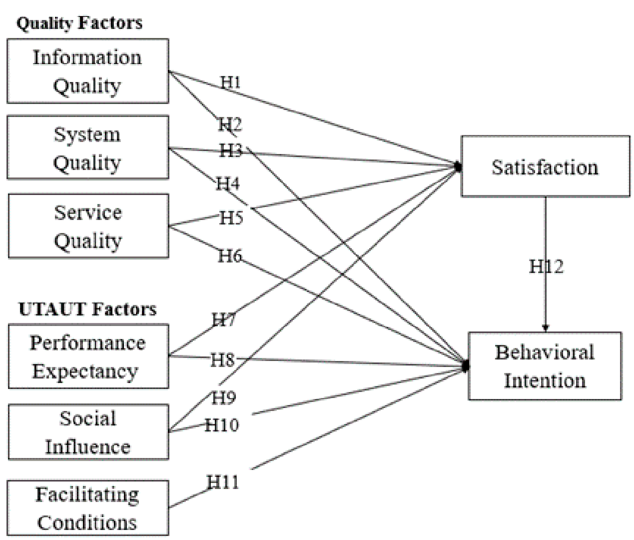
As shown in Table 5, all paths from IQ, System Quality (SYQ), Service Quality (SEQ), PE, and SI on SA as well as all paths from IQ, PE, SI, FC, and SA, on BI were statistically significant as the *p*-values were all below the standard significance level of 0.05. The direction of all paths was positive, meaning by an increase in each of the independent variables, the dependent variables will be increased too. The results supported hypotheses H1, H2, H3, H5, H7, H8, H9, H10, H11, and H12.

The results indicated that SA has the highest effect on BI with the path coefficient of 0.419, significant at the 0.001 level. PE was found to have highest effect on SA with a path coefficient of 0.449, $p < 0.001$.

It can be demonstrated that IQ, PE, and SI have significant positive indirect effects on BI through SA, referring to partial mediation effects of SA on these relationships. Moreover, it was found that SYQ and SEQ have significant positive indirect effects on Behavioral Intention (BI) through Performance Expectancy (PE) and Satisfaction (SA), referring to full mediation effects of Performance Expectancy (PE) and Satisfaction (SA) on these relationships.

2 presents the detailed results of the structural model to examine the research hypotheses.

*Figure 2. Structural Model Results*




## 6. DISCUSSION

This study seeks to propose an integrative model of the updated DL&ML and extended UTAUT. Specifically, it aims at examining the determinants affecting students' adoption of m-learning during the era of COVID-19 with special focus on quality and behavioral factors as the antecedents of students' satisfaction and their intention to use m-learning in the UAE in a future crisis and beyond. In the structural model, direct paths were hypothesized from quality factors (IQ, SYQ, and SEQ) and UTAUT factors (PE, SI, and FC) to users' SA and BI, with an additional path from SEQ and SYQ to users' PE.

The findings revealed that three types of information system quality factors (IQ, SYQ, and SEQ) have significant influence on the intentions to use m-learning indirectly through user satisfaction, with the view of the fact that user satisfaction is the main determinant of users' intention to use. IQ is found to have a significant effect on SA and intention to use (BI). Therefore, these results indicate that providing high quality learning content characterized by being complete and sufficient, and supporting various learning instructional activities such as lectures, courses, assignments, images, and quizzes, will lead to more useful instructional activities through the mobile learning application as more useful for learning. Therefore, mobile learning app designers are encouraged to provide services that take into consideration students' needs by providing them with up-to-date content that supports multiple media such as graphics, audios, animations, and the capacity to upload and download files, as this will lead to better usage intentions through higher satisfaction. This study also showed that SYQ and SEQ have significant effects on SA but insignificant direct impact of both constructs with users' BI, referring to full mediation of SA on the relationship between SYQ and BI. These two constructs, however, had a significant positive indirect effect on BI through users' PE and SA. This clearly suggests that learners' satisfaction is the main antecedent for the acceptance and use of m-learning whereas their intention to use the technology is indirectly dependent on the flexibility, efficiency, and appropriateness of the online system whenever it is perceived to be beneficial to students' performance. Contradictory to previous studies (i.e., Almaiah & Alismaiel, 2019; Al-Shihi et al., 2018; Cheng, 2012; Hassanzadeh et al., 2012) higher education students in the UAE consider that both SYQ and SEQ do not impact their intention to use the m-learning tool unless they see its outcomes on their performance. This is mainly because of the high quality of technological infrastructure that is offered in the UAE and as students have high confidence in the networks and connectivity provided (Murshidi, 2017; Tamer, 2014).

This study also found that behavioral factors such as individual beliefs regarding perceived usefulness and social influence have a significant effect on the intentions to use m-learning indirectly through user satisfaction, bearing in mind that user satisfaction is the main antecedent of users' intention to use. These results are consistent with findings from studies by Albashrawi and Matewalli (2018) . PE on the other hand had the highest effect on SA with a path coefficient of 0.449, $p < 0.001$. *This finding is also supported by a large body of research arguing the relationship between technology adoption and its benefits to learners' academic performance (Chao, 2019; D*wivedi et al., 2017 Šumak et al., 2017). As such, PE also had a direct effect on users' BI, referring to partial mediation of SA on the relationship between PE and BI. Participants in this study, like their worldwide peers, intend to use m-learning and are satisfied with it if they believe it will help them improve their academic efficiency and productivity.

SI is revealed to have a significant effect on SA and intention to use referring to partial mediation of SA on the relationship between SI and BI. These findings are consistent with those of Mohammadi (2015), where it was found to be a significant factor affecting users' intention to use m-learning. In this study, however, and despite having a low effect on users' SA and BI, it had the lowest mean among all constructs (M = 3.21). According to the UTAUT model, SI was identified as one of the most important factors for forecasting the BIs for adopting and using new m-learning systems (Dwivedi et al., 2020) and greatly influenced the development of m-learning among students and teachers (AlHujran et al., 2014; Shorfuzzaman & Alhussein, 2016). In the context of this study, learners who used m-learning during COVID-19 were mostly motivated to adopt and use the technology based on the extent of its impact on their performance and on the information quality it provides (such as management reports and web pages). This is also explained by the fact that during the pandemic the UAE forced quarantine for several months and students and teachers had to stay home where social contact was very limited. Hence, students were isolated in their houses, and they were rarely influenced by people's (i.e., peers' and teachers') opinions to use or adopt m-learning.

The findings of this study contribute to the proposed model suggested by Dwivedi et al. (2019) in measuring the associated relationship between FC and intention to use where a strong effect was found to be significant. This highlights the learners' need for having the resources, technical knowledge, and support to use the m-learning (Marchekwa & Kostiwa, 2007). Similar to the findings of Venkatesh et al. (2012), we argue that the presence of a reliable organizational and technical infrastructure impacts learners' perceptions and intentions to use m-learning. However, unlike the results of studies by Shukla (2021) and Ali and Arshad (2018), results of this study found no direct significant impact on users' SA.

## 7. RESEARCH IMPLICATIONS

This study has brought forth strong theoretical implications. First, as earlier mentioned, it was only during the COVID-19 outbreak that m-learning gained momentum and started being considered part of formal learning in academic institutions (AlEmran, 2020). In that sense, most of the studies reporting on m-learning acceptance in the past were empirical in nature and had not experienced its actual usage. Hence, the present study findings are valuable, as the study re-examines determinants of m-learning usage during and beyond the era of COVID-19, paying special attention to system-related quality aspects. Second, this study has enabled a better understanding of student acceptance and behavior towards m-learning usage through user satisfaction and intentions to use by developing and testing a parsimonious and yet comprehensive conceptual framework that combines system design quality constructs (IS success model) with non-system-related constructs (UTAUT model). Such an integrative framework contributes to expanding the foundational theoretical boundaries of the two prevalent models and advances the theory of technology acceptance and usage within the context of m-learning. Third, considering behavioral intentions as the main key outcome variable in this m-learning study, the integrative framework has performed highly and provided high explanatory power, which suggests that both system and user's behavioral influences are critical for m-learning acceptance and use. By achieving that, this integrative framework can be a robust theoretical base model to examine m-learning system use in future research studies or can even be generalized to other similar m-learning app settings that are perhaps external to the education industry. Finally, this study attempts to present a strong literature review of recent work around m-learning in the national UAE context and beyond.

## 8. CONCLUSION, LIMITATIONS, AND RECOMMENDATIONS

Smartphone devices are becoming increasingly popular among teachers and students all around the world because of their ease of use and low cost, among other factors. Research provides insight into how incorporating mobile technologies in a university setting offers a superior learning environment when compared to traditional classroom lectures. Hence, the purpose of this research is to determine the factors that influence university students' intentions to accept m-learning and to make recommendations. Combining the quality factors to the UTAUT model was tested through PLS and showed high explanatory power with strong convergent validity and internal reliability. Based on data collection, information quality, system quality, service quality, performance expectancy, and social influence all have significant influence on user satisfaction, and this in turn exhibits a strong impact on users' behavioral intentions to use m-learning. All the aforementioned constructs have direct significant effect on behavioral intentions, except for system quality and service quality, which indirectly affect behavioral intentions via satisfaction and performance expectancy and facilitating conditions that proved to directly, significantly impact behavioral intentions and not satisfaction. In the UAE, higher education students strongly perceive the benefit of m-learning to their performance expectancy, which in turn would impact their satisfaction and the latter showed to have the highest effect on behavior intention. To this end, the results of this study recommend that designers of m-learning apps enhance the efficiency and information quality provided to learners rather than focusing on the most cost-effective ones.

It is recommended that researchers test the proposed model post–COVID-19 to examine whether the social influence construct would make an impact on students' behavior intentions and satisfaction. Investigating this relationship would provide scientific evidence of the impact of the culture on the adoption of m-learning tools, particularly in a culture where individuals are more socially oriented than their counterparts in the west. Furthermore, it is suggested that additional paths be tested to investigate the potential moderating role of experience in IS usage that can serve as an internal intrinsic motivator.

This study is based on a cross-sectional survey that examines participants' perceptions at a single point in time. Further longitudinal studies are recommended to identify a clearer picture of users' behavioral patterns in using m-learning. Additionally, the sample was limited to three universities from two emirates out of seven in the UAE. A larger sample from all the emirates is needed to strengthen the generalizability of the results.

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