Developing an educational framework for using mobile learning during the era of COVID-19

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C H R O N I C L E	**A B S T R A C T**
	This paper focuses on the impact of fear emotion upon technology adoption by educators and students during Covid-19 pandemic. Mobile learning (m-learning) has been applied as the educational social platform within higher education institutes, public as well as private. The research hypotheses were associated with the Covid-19 influence on m-learning adoption with the rise of the coronavirus increasing types of fear. Such fears include fear caused by the education failure, family lockdown, and loss of social relationships. Teachers and students are mostly fearful of these aspects of the situation. An integrated model was established within the research, using theoretical models; the Planned Behavior theory, the Technology Acceptance Model, and the Expectation-Confirmation Model. The proposed integrated model (using PLS-SEM software) was analyzed using an online survey data, with 420 respondents from Zayed University, UAE. The findings indicated that attitude was the best predictor for using the m-learning system, followed by continuous intention, expectation confirmation, perceived usefulness, ease-of-use, perceived fear, behavioral control, and satisfaction. According to the research, during the coronavirus pandemic, if the m-learning system is adopted for educational reasons, the learning and teaching outcome proves quite promising. Yet there is a fear of the family being stressed, or of loss of friends, and also a fear of the results of future schooling. It is therefore necessary to assess the students efficiently during this pandemic so that the situation can be managed emotionally.

1. Background

Several efforts have been made by universities and colleges to establish a virtual teaching environment using appropriate platforms and resources (Salloum & Shaalan, 2021; Alhashmi, Salloum, & Abdallah, 2020; Alshurideh, Salloum, Al Kurdi, Monem, et al., 2019; Hantoobi et al., 2021; Salloum, Mhamdi, et al., 2018; Sultan et al. 2021). These educational institutions are constantly struggling to attain specific outcomes. Yet, due to COVID-19, the institutions are challenged (Alameeri, Alshurideh, & Al Kurdi, 2021; Amarneh et al., 2021; Al Khasawneh et al., 2021; Leo et al., 2021). Negative emotions have taken rise in the form of fears, worries and apprehension among students worldwide (Alameeri et al., 2020; Alshurideh et al., 2021; Alyammahi et al., 2020; Al Kurdi et al., 2021). The psychological well-being of students is influenced by fear of situations arising that will cause stigma. Covid-19 period has deteriorated and various psycho-social issues that have arisen e.g., discrimination and loss (Ahorsu et al., 2020; Al-Maroof, Alhumaid, Akour, et al., 2021; Lin, 2020; Pappas et al., 2009). Educational institutions have also been affected by fear, creating a hindrance to the learning and teaching process which deeply influences the e-learning process (Al-Maroof et al., 2021; Bettayeb, Alshurideh, & Al Kurdi, 2020; Turki, 2020). There are various forms of fear such as insecurity, missing out, failure and risk taking (Alt and Boniel-Nissim, 2018; Ellahi, 2017; Machů and Morysová, 2016; Morchid n.d.). Keeping the above-mentioned aspects in mind, it has been observed that fear could affect technology adoption. Various institutions have implemented online learning systems so that the dangerous and malicious influence of coronavirus can be reduced. Yet various colleges and universities are facing challenges related to

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teachers' knowledge of technology and their implementation ability. The ability of students to understand and the inability to convert from a normal class to a virtual class are also issues (Chen & Li, 2011; Li et al., 2018; Liang, Zheng, & Wang, 2011). The technology-effectiveness endorsement and the virtual classes depend mostly on technology adoption, considering this as an online learning resource (Akour et al., 2021; Alshamsi et al., 2020; Alshraideh, Al-Lozi, & Alshurideh, 2017; Alshurideh et al., 2015; Al Kurdi et al., 2020).

Some adoption research indicates that the adoption procedure is not easy as several aspects are affected, such as strategy, context (Salloum, Al-Emran, & Shaalan, 2016) and learning technology (Alshurideh, Salloum, Al Kurdi, & Al-Emran, 2019; Salloum et al., 2020; Salloum, Maqableh, et al., 2018). Since technology adoption has been researched by various researchers, it has been observed that, within extraordinary circumstances, innovative teaching methods are adopted, such as the m-learning application (AlSuwaidi et al., 2021; Nuseir et al., 2021; Suleman et al., 2021). However, until now, the coronavirus pandemic has not been assessed. M-learning platforms have been provided by Apple Store and Google Play for users and, through the Store, it is possible to download and update the application. The App Store extends a freemium strategy which positively influences the number of users (Liu, Au, & Choi, 2014; McIlroy, Ali, & Hassan, 2016). Much attention must be given to the psychological stance of teachers and learners in relation to the importance of using m-learning in unforeseen time. In Covid-19 situation, such a platform has been developed recently, which is why there has been little focus on the domain of higher education. Much research has examined the technology adoption. Yet, little is known about fear of the application adoption during this pandemic. Several studies have considered the technological developments, but not the psychological aspects. The role played by fear has not been understood clearly, which is why the opportunities to make use of technology in terms of education has not been completely understood (Agha, Alzoubi, & Alshurideh, 2021; Alzoubi, Alshurideh, and Ghazal, 2021; Naqvi et al., 2021). Considering the limitations mentioned above, the present research aims to establish an effective educational assessment of the type of technology that is most suitable even if fear is a dominant part of students' and teachers' lives. The new application is being followed by teachers and students for the first time, so that they may enhance their learning outcomes at this difficult time.

Academically, the literature suggests that the Technology Acceptance Model (TAM), Expectation-Confirmation Model (ECM) and Theory of Planned Behavior (TPB) are successfully applied as the technology adoption model to measure the motivation of users to understand (Liu, Geertshuis, & Grainger, 2020; Sami Alkalha et al., 2012; Tsai et al., 2020). Therefore, this current research is based on the TAM, TPB and ECM and adding two external elements: subjective norms and fear. This would help to assess the willingness of students to use m-learning systems. Two groups, students and teachers, maintain perceptions related to m-learning use during the pandemic, which would be analyzed using the TAM.

Previously, there has been no research carried out on the aspect of fear during the COVID-19 predicament and its association with the hybrid model (TAM, TPB, and ECM). The current model would analyze the various kinds of fear experienced by teachers and students during the period of the pandemic. Thus, we expect that our study will enhance the educational and technological input for teachers and application developers to understand the implementation method and to establish new technologies during the pandemic lockdown time.

The m-learning adoption conditions during the pandemic need to be understood as this would help to extract various educational aspects that are extraordinary in nature, and which would arise during such unique circumstances. The technology adoption field would be contributed, practically and theoretically.

2. Literature review

Earlier adoption research has analyzed the various kinds of fear. For example, anxiety is an essential factor within a certain section of research assessing technology adoption and anxiety. In the educational sector, anxiety is considered as an extraordinary aspect, which influences technology acceptance amongst students. Furthermore, apart from anxiety, if experience and skills are lacking, then this would limit interest in technology usage even further. Another factor present is fear of the actual use of technology. This integrates with literacy and anxiety to decrease technology adoption effectively. Hence, it is essential for educators and teachers to assess the psychological context and make sure that the students are well prepared to accept technology. In the educational sector, another cause of fear is limited preparedness and limited technical abilities. These two factors negatively influence the adoption / acceptance of technology (Callum & Jeffrey, 2014; Nchunge, Sakwa, & Mwangi, 2012; Thatcher & Perrewe, 2002). The fear of technology adoption is limited not only in the educational sector but also within the rest of the (Al-Dhuhouri et al., 2021; Al-Maroof, Alshurideh, et al., 2021; Alkitbi et al., 2021; Almazrouei et al., 2021; AlShehhi et al., 2021; Mehrez et al., 2021). In the health sector, health anxiety is present amongst patients, which leads to fear or apprehension of outcomes that show significant illness. The medical-sector research, therefore, stresses the negative influences of anxiety and perceived risk when technology is being used (Aburayya et al., 2020; Alhashmi, Salloum, and Mhamdi, 2019; Almansoori et al., 2021; Kamal, Shafiq, & Kakria, 2020; Meng et al., 2020; Mouzaek et al., 2021; Salloum et al., 2017). In the banking sector (Al-Khayyal et al. 2020; Alsuwaidi et al. 2021), various kinds of fear arise from attitudes towards, as well as perceptions of, technology (Al-Maroof, Alfaisal, & Salloum, 2020; Alsharhan, Salloum, & Shaalan, n.d.; Gaid & Salloum, 2021). Within the context of mobile payments (Alshurideh, Al Kurdi, & Salloum, 2021; Salloum et al., 2019; Salloum & Al-Emran, 2018), numerous consumers are afraid to present their data. Research also indicates that customers fear

they may be subject to fraud. In any household, it is found that when technology is feared, there is also a lack of interest in technology use, giving rise to family tasks. Lastly, mobile banking technology is also negatively influenced by lack of trust and experience (Ahmed et al., 2021; AlGhanem et al., 2020; Bailey et al., 2020; Makttoofa, Khalidb, & Abdullahc, n.d.).

Several studies have assessed technology acceptance and the fear issue. Many of these studies have relied on the TAM model (Alshurideh, Al Kurdi, & Salloum, 2020; Bailey et al., 2020; Bhattacherjee & Hikmet, 2007; Callum & Jeffrey, 2014; Kamal, Shafiq, & Kakria, 2020; Makttoofa, Khalidb, & Abdullahc, n.d.; Mhamdi, Al-Emran, & Salloum, 2018; Nchunge, Sakwa, & Mwangi, 2012; Al Suwaidi et al., 2021) and on other models (Aburayya et al., 2020; Al-Maroof et al., 2020; Al-Maroof, Alhumaid, Alhamad, et al., 2021; Al-Maroof et al., 2019; Alghizzawi et al., 2018; Alshurideh, 2018; Brown and Venkatesh, 2005; Elbasir et al., 2021; Habes et al., 2019; Johnston and Warkentin, 2010; Al Kurdi, Alshurideh, and Salloum, 2020; Meng et al., 2020; Salloum et al., 2021; Thatcher and Perrewe, 2002). The objective of these studies is to assess the influence of technology acceptance based on the fear of technology. There are various justifications provided by people as to why they fear using technology. Some stated that it was a lack of confidence. When a human functions, it is possible that he will make mistakes, which is why the fear factor is amplified (Gresham, 2020). On the other hand, some claim that when technology has not been used, the process consumes more time and tasks remain unaccomplished within the allotted time (Appavoo, 2020). Some acceptance studies state that there is a fear that data privacy will be breached, which is why so much focus is placed on privacy and on security awareness (Distler, Lallemand, & Koenig, 2020).

2.1 Knowledge gap

The current research carries out a bibliometric mapping analysis on the mobile learning technology literature so that the research gap presented in Fig. 1 can be addressed.
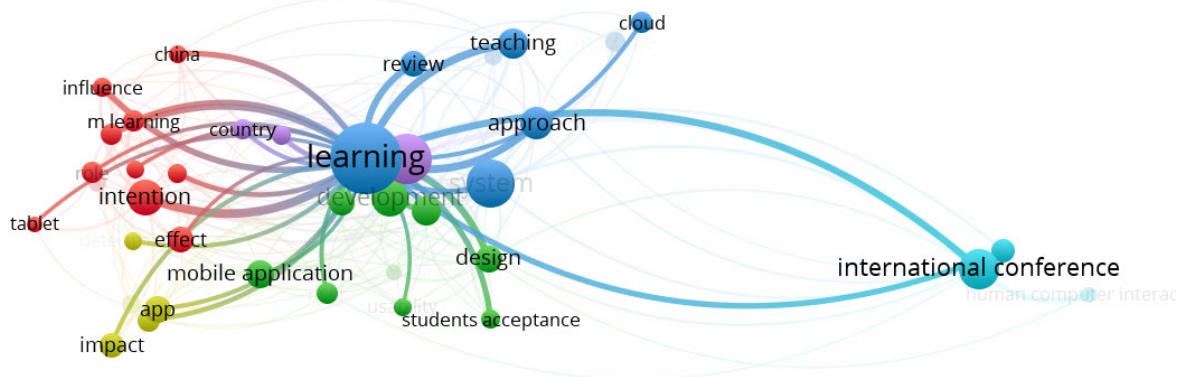

Fig. 1. Most used author keywords in mobile learning adoption/acceptance

The database has been searched as follows: "ACM Digital Library, Google Scholar, IEEE, SAGE Pub, ScienceDirect, and Springer". This was during the time period 2015-2020 in which nearly 1,393 papers made use of the keywords "mobile learning", "mobile learning adoption", and "mobile learning acceptance". The numbers were distributed in the following manner: ACM Digital Library engine search with 99 papers on mobile learning; 708 papers found in a Google Scholar engine search; 210 papers found in IEEE; SAGE Pub engine with about 65 articles; ScienceDirect with 147 papers; and 164 articles in the Springer engine. It is necessary to consider that various studies have assessed mobile learning adoption or acceptance. However, a few studies have addressed m-learning usage during the COVID-19 outbreak. There are 25 articles in total. Within the field, the earliest paper found was in the 2020 databases (Raza et al., 2020). This paper is the earliest and has then provided an entirely new procedure to create real information in m-learning during COVID-19. This was the first step in m-learning technology development in which scientists remained focused on those mobile devices which have an earphone, a front camera and signal processing units. Some earlier research studies have focused on mobile devices, as well as on mobile learning platforms. Out of these research studies, one considered mobile learning technology adoption and extracted the specific features motivating individuals to adopt smartphones. For functionality, the hands-free phone is highly influential (Adapa et al., 2018). The users become quite involved in using the smartphones. Furthermore, using the internet, the information can be quickly accessed, which is why time is saved and the adoption level rises. The adoption issue was considered by using a personal perspective. According to the research, if personal features, such as readiness and openness, are present, new experiences may happen and it is quite possible that the device may be adopted since there is a high perceived-usefulness level present for the device. Finally, the research by (Gasaymeh &Waswas, 2019) indicates that users positively consider the use of smartphones because of its ease of use and usefulness. However, fear has been raised by the research, along with the health concern brought forward by the users. Details of the research studies focusing on mobile technology acceptance are mentioned

below and the coronavirus**,** or COVID-19 pandemic, is included. The research has considered mobile learning acceptance since mobile learning is believed to be a technology that is unfamiliar in the Middle East. There are some students who consider its importance within the educational context. Hence, the current research would motivate educators, teachers and students in the future to use it within various educational environments.

3. Research model

The research model that has been developed is based upon integration of the subjective norm and the fear construct with three kinds of theoretical models: TAM, TPB, and ECM. The proposal made is that the subjective norm (SBJ) and perceived fear (PF) would significantly influence the m-learning system's perceived ease of use (PEU) and usefulness (PU). Additionally, regarding attitude (ATD), subjective norm (SBJ), and perceived behavioral control (PBC), they would affect the continuous intention (CON) to use m-learning systems (CON). It must also consider that CON influences the actual use (ACU) of m-learning perception (Fig. 2).

3.1 Perceived Fear (PF)

Some studies suggest that fear can also be perceived positively if there is some sort of real danger, which COVID-19 has. Different forms of fear related to COVID-19 can be highlighted such as uncertainty, health anxiety, and fear of losing loved ones. That is why there are two aspects which need consideration: worrying to a high degree and possibility that are affected by this disease (Ahorsu et al., 2020; Gerhold, 2020). The current research aims to analyze the association with technology adoption using TAM and perceived fear (PF) as an external factor. Hence, the research will try to resolve the issue of TAM-model limitation (Tarhini, Hone, and Liu, 2015). The influence of PF on the TAM model would be analyzed in terms of PU and PEU, in addition to the SBJ which is also an external factor. Keeping this assumption in mind, the following has been hypothesized:

H₁: *PF positively affects the PEU of m-learning.*
H₂: *PF positively affects the PU of m-learning.*

3.2 The Expectation confirmation (EXP)
EXP refers to someone's perceptions of the congruence in relation to the actual performance as the EXP is linked to actual performance (Bhattacherjee, 2001). Earlier research states that EXP significantly influences satisfaction (SAT) and the PU of the various mobile technologies (Al-Emran, Arpaci, and Salloum, 2020; Muhammad Alshurideh et al., 2020; Le et al. 2020; Nascimento, Oliveira, and Tam, 2018).

H₃: *EXP positively affects the PU of m-learning.*
H₄: *EXP positively affects SAT with m-learning.*

3.3 The TAM

The external factor validation of personal belief is measured by one fixed goal that is part of the TAM model. This is quite a powerful model which explains that individuals would accept technology if it was present in educational institutions (Al-Maroof & Al-Emran, 2018; Davis, 1989; Teo, 2012; Venkatesh & Bala, 2008). PU and PEU are dominant features according to TAM which can measure two kinds of perception. Based on the TAM, using a particular system (e.g., m-learning) in our life would be related to the PU that would enhance our job performance (Davis, 1989). Accordingly, PU maintains a significant influence upon the CON to use several mobile technologies (Alshurideh et al., 2020; Joo, Kim, and Kim, 2016; Le et al., 2020; Nascimento, Oliveira, & Tam, 2018). whereas PEU refers to someone's uses a particular system that needs little effort to use (Davis, 1989). Earlier research indicated that PEU significantly influences the CON to use m-learning (Alshurideh et al., 2020; Joo, Kim, and Kim ,2016; Le et al., 2020; Nascimento, Oliveira, & Tam, 2018). Keeping the earlier assumption in mind, if users think that technology can be used easily, they will develop positive attitudes towards m-learning. Therefore, their perceptions of this PU are observed. In this way, if technology is perceived as useful, then there is a higher probability that a positive attitude will be maintained towards adopting this technology, highlighting our hypotheses:

H₅: *PEU positively affects the PU of m-learning.*
H₆: *PU positively affects SAT with m-learning.*
H₇: *PEU positively affects the CON to use m-learning.*
H₈: *PU positively affects the CON to use m-learning.*

3.4 Satisfaction (SAT)

SAT refers to the users' attitude of using a particular system (e.g., m-learning) which they feel satisfied with such a system after usage (Doll, Hendrickson, & Deng, 1998). Earlier research stated that SAT significantly influenced the CON to use mobile technologies (Alshurideh et al., 2020; Le et al., 2020; Nascimento, Oliveira, & Tam, 2018; Tam, Santos, & Oliveira, 2018).

H9: *SAT positively affects the CON to use m-learning.*

3.5 Attitude (ATD)

ATD refers to someone's perception towards a particular system (Karjaluoto, Mattila, and Pento, 2002). Earlier m-learning studies stated that ATD maintained a relationship with CON. Research stated that ATD have a high influence on CON to adopting m-learning (Al-Emran, Arpaci, & Salloum, 2020; Cheon et al., 2012; Khanh & Gim, 2014; Prieto, Migueláñez & García-Peñalvo, 2014).

H10: *ATD positively affects the CON to use m-learning.*

3.6 Perceived Behavioral Control (PBC)

The PBC refers to someone's perception and experience of using a particular system in terms of ease or difficulty of performing the behavior of interest (Ajzen, 1991). Research shows that PBC significantly influences the CON to use m-learning (Al-Emran, Arpaci, and Salloum, 2020; Cheon et al., 2012; Cheong et al., 2012; Kim, 2010). Hence, the following is attained.

H11: *PBC positively affects the CON to use m-learning.*

3.7 Subjective norm (SBJ)

SBJ is a means that helps measure someone's perception in the presence of other individuals who share a similar attitude and who would (not) exhibit similar behavior towards technology. Socially, the TAM model has been strengthened by the SBJ since it helps the TAM to account for users' behavior when looking at various users (Fishbein & Ajzen, 1975). We perceive SBJ as the external factor that manages students' CON to accepting the m-learning system. Furthermore, PBC is influenced by SBJ, especially in the case of PU or PEU, which are applied in the literature research in an extensive manner regarding technology adoption or acceptance (Song & Kong, 2017; Venkatesh & Bala, 2008; Viswanath Venkatesh & Davis, 2000; Wong, Teo, & Russo, 2012). One item of recent research by (Huang, Teo, and Zhou 2020) used external factors TAM and SBJ, in which emphasis was placed on the association between the external factors and the rest of the included TAM factors for various earlier items of research. Yet it has been observed that the external SBJ factor would not be implemented in an effective or a deep manner within the research. Research shows that CON is linked to someone using m-learning platforms (Al-Emran, Arpaci, & Salloum, 2020; Cheon et al., 2012; Liu & Chen, 2008; Mtebe & Raisamo, 2014; Park, Nam, & Cha, 2012).

H12: *SBJ positively affects the CON to use m-learning.*

3.8 The Continuous intention (CON)

CON refers to a person's intention to continue using a particular system if they benefit to some extent from it (Bhattacherjee, 2001). Research indicates that CON significantly influences the ACU of m-learning systems (Al-Emran, Arpaci, & Salloum, 2020; Alshurideh et al., 2020; Joo, Kim, & Kim, 2016).

H13: *CON positively affects the ACU of m-learning.*

Fig. 2 revealed our proposed model. The theoretical model has been presented as the structural equation model and would be analyzed with the help of machine learning methods.
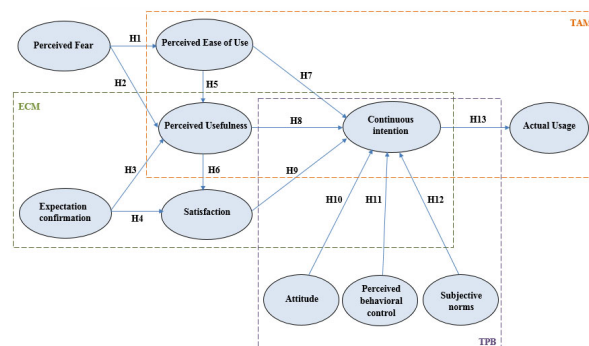

Fig. 2. The study model

4. Method

4.1 Data collection

Data were collected between October 25th and December 25th 2020 (fall semester), after carrying out online surveys which helped to target UAE university students. Target universities provided ethical clearance for this research. The research objective and survey links were emailed to the related students. The response rate was maximized by sending the survey link through the university's social media platforms. 500 questionnaires were handed out randomly by the student department and 420 questionnaires were replied, indicating an 84 percent response rate. There were some missing values, which is why 80 completed questionnaires were rejected. Hence, 420 questionnaires were considered by the survey team since these were complete and effective. Only students were included since it is believed that it is the students who are highly influenced by the research effectiveness. If the technology is insufficient to support the students, the colleges and universities can replace the tool. If the teachers have significant experience, they can easily adopt these technologies, unlike the students. Even though the students have knowledge regarding the application through social media, they have not had the chance to use it on their own. Krejcie & Morgan (Krejcie & Morgan, 1970) stated that the sample size estimated for the 1500 is 306 respondents. As compared with the trivial criteria, the 420-sample size is considerably higher.

4.2 Demographic data

Table 1 presents the sample demographic feature. The ratio of female to male students is 61%. A total of 62% of respondents were aged between 18 and 29 and 38% were aged over 29. Most respondents have an academic history with university degrees. A total of 77% have BA, 21% have MA and 2% have PhD. (Al-Emran and Salloum, 2017) suggests that a "purpose sampling approach" be applied and the respondents were interested in voluntarily participating in the research. Students from different colleges were included in the sample and their age groups are also diverse.

Table 1
The sample demographic feature

Criterion	Indictor	n	%
Gender	Female	255	61%
	Male	165	39 %
Age	18-29	261	62%
	30-39	97	23%
	40-49	62	15%
	50-59	0	2%
Education qualification	BA	322	77%
	MA	88	21%
	PhD	10	2%

4.3 The instrument

The research instrument is divided into two parts. First, the participant demographic data. Second, responses related to the conceptual model variables (29 items) were collected. Items from (Al-Emran, Arpaci, & Salloum, 2020; Davis, 1989) were used to assess the PEU and PU. Items from (Al-Emran, Arpaci, & Salloum, 2020; Bhattacherjee, 2001) were used to extract the items for analysis of EXP, SAT, and CON. SBJ items were used from (Al-Emran, Arpaci, & Salloum, 2020; Viswanath Venkatesh et al., 2003), but the actual-use indicators have been adopted using (Al-Emran, Arpaci, & Salloum, 2020; Mohammadi, 2015). Table 2 illustrates the constructs and its related items.

Table 2
Constructs and their sources

Constructs	Number of items	Source
Actual use (ACU)	2	(Al-Emran, Arpaci, and Salloum 2020; Mohammadi 2015)
Attitude (ATD)	3	(Al-Emran, Arpaci, and Salloum 2020; Cheon et al. 2012; Khanh and Gim 2014; Prieto, Migueláñez, and García-Peñalvo 2014)
Continuous intention (CON)	3	(Al-Emran, Arpaci, and Salloum 2020; Bhattacherjee 2001)
Expectation confirmation (EXP)	3	(Al-Emran, Arpaci, and Salloum 2020; Bhattacherjee 2001)
Perceived usefulness (PU)	3	(Al-Emran, Arpaci, and Salloum 2020; Davis 1989)
Perceived ease of use (PEU)	3	(Al-Emran, Arpaci, and Salloum 2020; Davis 1989)
Perceived behavioral control (PBC)	3	(Al-Emran, Arpaci, and Salloum 2020)
Perceived fear (PF)	3	(R.S. Al-Maroof et al. 2020)
Subjective norm (SBJ)	3	(Ahmad Aburayya and Salloum n.d.; Al-Emran, Arpaci, and Salloum 2020; Viswanath Venkatesh et al. 2003)
Satisfaction (SAT)	3	(Al-Emran, Arpaci, and Salloum 2020; Bhattacherjee 2001)

4.4 Pre-testing the questionnaire

Questionnaire-item reliability was tested through a pilot study. There were nearly 50 students out of 500 taking part in the pilot research, randomly picked from the population decided upon. The main results include the pilot research, in which pilot participants have been included within the main research; however, new data was extracted from these individuals. The pilot study's internal reliability was tested through the Cronbach alpha test and this showed acceptable results related to the measurement items. When such an analysis trend is observed within the research studies (Al-Maroof et al., 2021; Nunnally, 1978; Salloum, n.d.), it is acceptable to have 0.7 as the reliability coefficient. The Cronbach alpha values are presented in Table 3 for the next stated seven measurement scales.

Table 3
Cronbach's alpha test

Items	CA (≥ 0.70)	Items	CA (≥ 0.70)
ACU	0.847	PEU	0.798
ATD	0.879	PBC	0.715
CON	0.775	PF	0.847
EXP	0.769	SBJ	0.868
PU	0.758	SAT	0.786

4.5 Common method bias (CMB)

To ensure that there was no CMB in the collected data, the Harman's single-factor is applied, using 10 variables (ACU, ATD, CON, EXP, PU, PEU, PBC, PF, SBJ, SAT) (Podsakoff et al., 2003). One factor was loaded with the 10 factors. Accordingly, the largest variance present (23.21%) is lower than the 50% threshold value (Podsakoff et al., 2003). Therefore, there are zero concerns present regarding collected-data CMB.

5. Findings

The PLS-SEM was used to analyze the data. It was accompanied by the SmartPLS V.3.2.7 program (Ringle, Wende, and Becker, 2015). A two-stage assessment approach was implemented for collected data evaluation, along with the structural model and the measurement model (Hair et al., 2017). There are various explanations for the PLS-SEM within the analysis.

First, PLS-SEM has been used since it is most appropriate for the research if it has been based on an earlier one (Urbach &Ahlemann, 2010). Second, exploratory research that includes complex models should make use of PLS-SEM (Hair Jr et al., 2016). Third, the entire model is analyzed by PLS-SEM as a single unit and is not broken into parts (Goodhue, Lewis, &Thompson, 2012). Measurement is carried out through a concurrent analysis with the help of PLS-SEM, along with the structural model, which is why calculations are expected to be accurate (Barclay, Higgins, & Thompson, 1995).

5.1 Convergent validity

Hair et al. (2017) considers that construct reliability and validity must be observed for the measurement model evaluation. In this case, it includes composite reliability (CR), Dijkstra-Henseler's rho (pA), and Cronbach's alpha (CA) and validity includes convergent and discriminant validity (DV). According to Table 4, CA values were higher than the 0.7 threshold value and would lie within the 0.730 to 0.887 range, helping to state the construct's reliability. The CR ranges 0.734 to 0.890 and these are higher than the recommended 0.7 (Nunnally and Bernstein, 1994). CR can also be computed using the pA reliability coefficient (Kline 2015). Similar to CA and CR, for the reliability coefficient ρA, 0.7 or a greater value should be presented for the exploratory research. Values higher than 0.80 or 0.90 should be attained for the ρA if the research is carried out at an advanced level (Hair, Ringle, and Sarstedt, 2011; Henseler, Ringle, and Sinkovics, 2009; Nunnally and Bernstein, 1994). The measurement construct is able to present the reliability coefficient value or the ρA which is higher than 0.70. Based on these tests, verification of construct reliability is possible, stating that there is an accurate construct. After testing the Average Variance Extracted (AVE), convergent validity can be measured and factor loading (Hair et al., 2017). The 0.7 suggested value is lower as compared with the factor-loadings values. Apart from this, the values generated from AVE, 0.594 to 0.796, are higher than the 0.5 threshold value as stated in Table 4. Keeping these outcomes in mind, for each construct, it would be efficiently possible to evaluate convergent validity.

5.2 Discriminant validity

For the DV measurement (Hair et al., 2017), two parameters should be measured: Fornell-Larker and the Heterotrait-Monotrait ratio (HTMT) factors. The conditions are supported by the Fornell-Larker factor, according to the Table 5 findings, since each AVE value, added to the square root, would exceed the correlation value present with other constructs (Fornell & Larcker, 1981). The HTMT ratio attained values are shown in Table 6 and these show that 0.85, the threshold value, is higher than each construct value (Henseler, Ringle, & Sarstedt, 2015). Hence, there is confirmation for the HTMT ratio. Keeping these

findings in mind, it is possible to calculate discriminant validity. The data analysis showed that reliability and validity of the measurement model are smoothly assessed. Hence, collected data would be used further and testing done for the structural model.

Table 4
The convergent validity outcomes

Constructs	Items	Factor loading	CA	CR	PA	AVE
ACU	ACU1	0.726	0.887	0.834	0.845	0.661
	ACU2	0.886				
ATD	ATD1	0.846	0.840	0.890	0.886	0.789
	ATD2	0.805				
	ATD3	0.805				
CON	CON1	0.819	0.869	0.822	0.837	0.700
	CON2	0.795				
	CON3	0.883				
EXP	EXP1	0.822	0.730	0.883	0.879	0.663
	EXP2	0.873				
	EXP3	0.778				
PU	PU1	0.808	0.880	0.819	0.823	0.594
	PU2	0.845				
	PU3	0.866				
PEU	PEU1	0.872	0.870	0.857	0.850	0.644
	PEU2	0.832				
	PEU3	0.857				
PBC	PBC1	0.878	0.856	0.861	0.836	0.796
	PBC2	0.906				
	PBC3	0.848				
PF	PF1	0.795	0.845	0.803	0.815	0.756
	PF2	0.778				
	PF3	0.846				
SBJ	SBJ1	0.805	0.801	0.734	0.746	0.771
	SBJ2	0.819				
	SBJ3	0.795				
SAT	SAT1	0.883	0.806	0.834	0.839	0.772
	SAT2	0.805				
	SAT3	0.819				

Table 5
Fornell-Larcker scale

	ACU	ATD	CON	EXP	PU	PEU	PBC	PF	SBJ	SAT
ACU	**0.844**									
ATD	0.452	**0.840**								
CON	0.355	0.529	**0.867**							
EXP	0.536	0.452	0.503	**0.838**						
PU	0.457	0.429	0.241	0.160	**0.885**					
PEU	0.518	0.455	0.363	0.288	0.256	**0.887**				
PBC	0.326	0.399	0.454	0.428	0.476	0.521	**0.838**			
PF	0.266	0.469	0.445	0.208	0.566	0.401	0.422	**0.809**		
SBJ	0.445	0.561	0.230	0.638	0.455	0.452	0.477	0.403	**0.811**	
SAT	0.408	0.400	0.319	0.588	0.250	0.608	0.257	0.428	0.466	**0.888**

Table 6
Heterotrait-Monotrait ratio (HTMT)

	ACU	ATD	CON	EXP	PU	PEU	PBC	PF	SBJ	SAT
ACU										
ATD	0.430									
CON	0.433	0.651								
EXP	0.408	0.523	0.590							
PU	0.119	0.309	0.432	0.502						
PEU	0.169	0.218	0.334	0.504	0.150					
PBC	0.280	0.202	0.205	0.329	0.150	0.219				
PF	0.216	0.180	0.293	0.202	0.150	0.226	0.303			
SBJ	0.268	0.339	0.432	0.403	0.150	0.382	0.290	0.501		
SAT	0.123	0.240	0.600	0.505	0.150	0.200	0.133	0.404	0.269	

5.3 Model fit

The model fit measures for the SmartPLS are the following. The standard root means square residual (SRMR), exact fit criteria, d_ULS, d_G, Chi-Square, NFI, and RMS_theta indicate the model fit in PLS-SEM (Trial n.d.). The observed correlations and model implied correlation matrix (Hair Jr et al., 2016) is stated by the SRMR and values lower than 0.08 are found to be good model-fit measures (Hu and Bentler, 1998). A good model fit is present if the NFI values are over 0.90 (Bentler and Bonett, 1980). For the proposed model, the NFI is a ratio of Chi2 value to the null model or benchmark model (Lohmöller, 1989). If the parameters are large, the NFI would be large, which is why the NPI has not been recommended as the model-fit indicator (Hair Jr et al., 2016). Two metrics squared Euclidean distance d_ULS, and geodesic distance d_G indicate a discrepancy between the empirical covariance matrix and covariance matrix as stated by the composite factor model (Dijkstra and Henseler, 2015; Hair Jr et al., 2016). For reflective models, the RMS theta is applicable and assesses the degree of outer-model residuals correlation (Lohmöller, 1989). If the RMS theta is close to the zero value, the PLS-SEM model is better and there is a good fit if the value remains less than 0.12. If there is anything else, then the fit is lacking (Henseler et al., 2014). According to Hair Jr et al. (2016), a correlation between all constructs can be evaluated through the saturated model and the total effects and model structure are accounted for in the estimated model.

The RMS Theta value was 0.081 indicating that the related goodness-of-fit for the PLS-SEM model was enough to indicate the global PLS-model validity.

Table 7
Model-fit indicators

	Complete Model	
	Saturated model	Estimated model
SRMR	0.033	0.042
d_ULS	0.764	1.328
d_G	0.518	0.548
Chi-Square	454.647	463.476
NFI	0.839	0.827
Rms Theta	0.081	

5.4 Testing the Hypotheses

Our 13 hypotheses were verified using the PLS-SEM approach (Davis, Bagozzi, & Warshaw, 1992). The R^2 value for each path and each hypothesized connection's path significance within the research model was analyzed (Figure 3 and Table 8). The R^2 values for adoption of m-learning, ACU, CON, PEU, and PU ranged between 0.496 and 0.681. Hence, there is moderate predictive power present within these constructs (Liu, Liao, & Peng, 2005).

Table 8
The R^2 values

Constructs	R^2
ACU	0.668
CON	0.497
PEU	0.574
PU	0.496
SAT	0.681

The empirical data supports all our hypotheses (Table 9).

Table 9
The hypotheses tests

H	Relationship	Path	t-value	p-value	Direction	Decision
H1	PF -> PEU	0.867	23.280	0.000	Positive	Supported**
H2	PF -> PU	0.375	14.314	0.000	Positive	Supported**
H3	EXP -> PU	0.712	18.104	0.001	Positive	Supported**
H4	EXP -> SAT	0.469	5.825	0.023	Positive	Supported*
H5	PEU -> PU	0.438	5.551	0.016	Positive	Supported*
H6	PU -> SAT	0.591	4.703	0.032	Positive	Supported*
H7	PEU -> CON	0.688	20.448	0.000	Positive	Supported**
H8	PU -> CON	0.642	15.598	0.000	Positive	Supported**
H9	SAT -> CON	0.759	12.190	0.002	Positive	Supported**
H10	ATD -> CON	0.523	7.328	0.029	Positive	Supported*
H11	PBC -> CON	0.419	5.328	0.025	Positive	Supported*
H12	SBJ -> CON	0.653	16.698	0.000	Positive	Supported**
H13	CON -> ACU	0.742	18.478	0.000	Positive	Supported**
			p**=<0.01, p* <0.05			

The findings revealed that PF had impact on PEU (β= 0.867, P<0.001) supporting hypothesis H1, while PU significantly affected PF (β= 0.375, P<0.001); EXP (β= 0.712, P<0.001); PEU (β= 0.438, P<0.05); SAT (β= 0.591, P<0.05), supporting our H2, H3, H5 and H6 respectively. EXP had impact on SAT (β= 0.469, P<0.001) indicating H4 is supported. CON was affected by PEU (β= 0.688, P<0.001); PU (β= 0.642, P<0.001); SAT (β= 0.759, P<0.001); ATD (β= 0.523, P<0.05); PBC (β= 0.419, P<0.05); and SBJ (β= 0.653, P<0.05), supporting H7, H8, H9, H10, H11, and H12 respectively. Finally, CON to use m-learning platform significantly influenced ACU (β= 0.742, P<0.001), supporting H13.
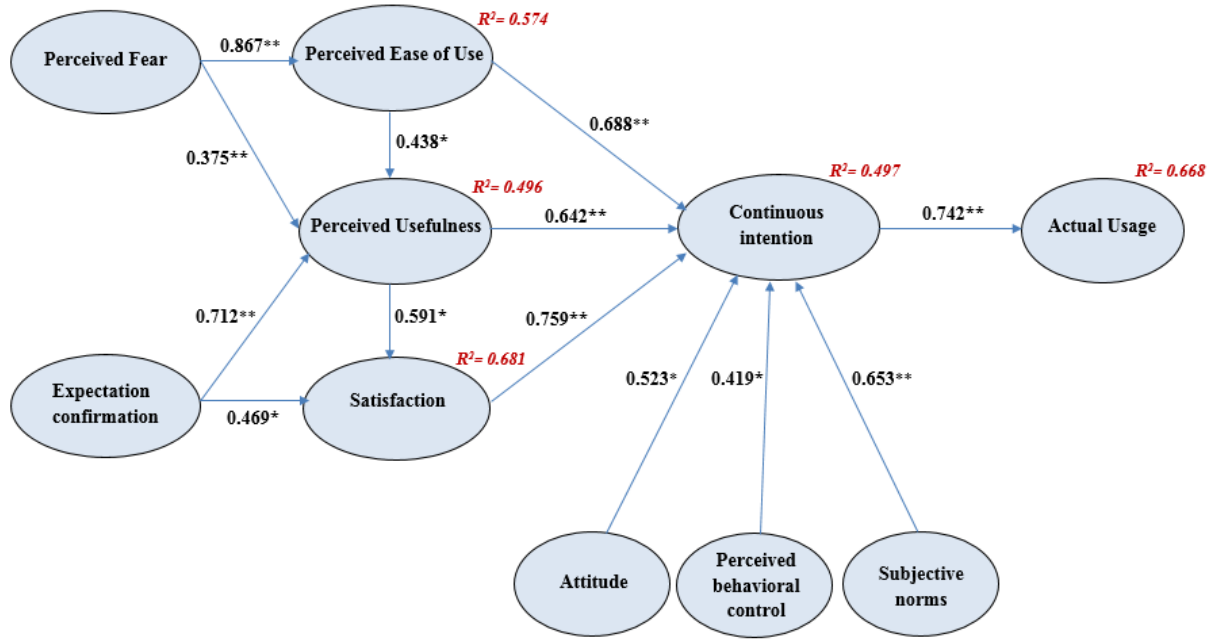
Fig. 3. Hypotheses testing results

6. Conclusion

The current research is consistent with early studies in terms of the TAM, TPB and ECM variables' importance (Davis, 1989; Teo, 2012; Venkatesh and Bala, 2008). The PU and PEU present and earlier results are also consistent since it is observed that the PU and PEU highly have impact on the m-learning acceptance of our respondents and place emphasis on the variables related to respondents' intention to use m-learning during the present extraordinary circumstances caused (COVID-19) (Habes et al., 2020). Likewise, the PU was highly affected by the PEU indicating that if someone perceived technology to be easy, then they would adopt it.

For SBJ, our results indicate a significant association between the SBJ and students' acceptance of m-learning, suggesting that students' acceptance of m-learning is highly affected by the behavior, existence, and reaction of classmates within the class using the m-learning. Earlier research (Song and Kong, 2017; Venkatesh and Bala, 2008; Viswanath Venkatesh and Davis, 2000; Wong, Teo, and Russo, 2012) have presented the same kind of relationship between the SBJ and students' acceptance of m-learning. Our respondents were significantly influenced by classmate behavior, which would increase their sense of security and comfort when in classes. This is why their sense of security is higher and their comfort is necessary during the pandemic. Respondents were found to be intrinsically motivated to make use of the m-learning if the same class is shared with other colleagues. Additionally, the PU and PEU variables highly influence the SBJ. Results indicate that m-learning use is promoted by the availability and attitude of instructors and peers. Since it is a tool used for learning during the pandemic, it is perceived as useful and enjoyable, as well as effort-free. The findings are like those in the earlier research (El-Gayar, Moran, & Hawkes, 2011) in which it was stated that peer and instructor feedback significantly affects students' attitudes towards perceived technology effectiveness.

After the spread of COVID-19, the fear factors that took rise indicate that one of these hypotheses is essential. The human population has been significantly influenced by the COVID-19 pandemic and there is a high transmission probability, which is why the lockdown and stay-at-home policies are applied (Zhang et al., 2020). A model has been adopted by the research which may be useful for research in the future after the COVID-19 influence during the pandemic is assessed. Keeping in mind the research results attained, the time of the fear factor is quite evident; however, with the help of the ML, it has been possible to reduce peer and instructor fears. Furthermore, the PF highly influences the PU and PEU. According to the research

responses, the PF can be seen at the time of the pandemic; however, the m-learning has a high PU and PEU degree which decreased the fear factor and helped respondents to attain their classes on schedule.

6.1. Research implications

Our study focused fear on three aspects: Theoretically, using the TAM, TPB and ECM; empirically testing the COVID-19 effect on mobile application users; and analyzing the COVID-19 influence on users' ability to use mobile application and on users' attitudes towards the usefulness of the m-earning platform. Within earlier research, fear has been analyzed from different perspectives such as technology (Bhattacherjee & Hikmet, 2007). There is an implication that a negative perception would influence PEU and PU in a direct or indirect manner. In this manner, the current implications, and the ones presented by Bhattacherjee and Hikmet, are similar in saying that fear would negatively influence technology use (Bhattacherjee & Hikmet, 2007). Hence, it is empirically stated that perceived fear during the pandemic would be a significant variable for any model being adopted.

6.2 Limitations and future research

Several limitations can be highlighted here. Initially, generalizing the results for the rest of the UAE's higher educational institutions, or for other countries, should be done with caution. This is due to two aspects: 1. The sample is based on a specific institution; 2. The convenience sampling technique has been applied for the participant selection. For results to be generalized, it is necessary to take these aspects into account. Second, the research sample was only students, suggesting the actual use of m-learning by others should be analyzed.

6.3 Recommendations

Based on our results m-learning system is highly recommended in unforeseen time and seen as a potential solution. M-learning availability allows teachers, peers, a sense of security, as well as an instant communication tool considering the contamination status of the city of Abu Dhabi. Compared with other means of communication, there are various advantages to the mobile learning platform. First, the application can be used on any mobile device and smartphones. Second, the links given during each class can be used several times and this allows easy student-teacher communication throughout the day. Finally, students gain higher confidence and minimum fear is experienced.

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