Predicting the intention to use mobile learning during Coronavirus Pandemic through Machine Learning Algorithms

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Abstract

Background: This paper investigates the use of mobile learning platforms for learning purposes among university students in UAE. An extended Technology Acceptance Model (TAM) and theory of planned behavior (TPB) are proposed to analyze the adoption of mobile learning platforms by university students for accessing course materials, searching the web for information related to their discipline, sharing knowledge, conducting assignments during COVID-19 pandemic. The total number of questionnaires collected was 1880 form different universities. Partial least squares-structural equation modeling (PLS-SEM) and machine learning algorithms (ML) were utilized to investigate the research model based on the student's data gathered through a survey. According to the results, each hypothesized relationship within the research model has been supported by the data analysis methods. It should also be noted that the J48 classifier mostly had the upper hand on other classifiers when it comes to the prediction of the dependent variable. As per the indication of our research, teaching and learning can greatly benefit from the adoption of machine learning as an educational tool at the time of this pandemic; nevertheless, its significance could be lowered because of the emotion of fear concerning poor grades, stressful family circumstances, and loss of friends. Accordingly, this issue can only be solved by evaluating the emotions of students during this pandemic.

Objective: This study is one of the earliest attempt to: (1) theoretically integrate the notion of fear within a hybrid model of Technology Acceptance Model (TAM) & Theory of Planned Behavior (TPB) (2) empirically test the effect of COVID-19 on the users of mobile application, and (3) explore the impact of the Coronavirus pandemic on users' ability to use the mobile application easily and users' attitude towards the usefulness of mobile learning platform.

Methods: The developed theoretical model has been evaluated using two different techniques in this research. The first one involves the usage of the partial least squares-structural equation modeling (PLS-SEM) alongside the SmartPLS tool. This research uses PLS-SEM mainly because both the structural and measurement model can be concurrently analyzed through PLS-SEM, which increases the preciseness of results. As for the second technique, the research predicts the dependent variables entailing the conceptual model with the help of machine learning algorithms via Weka.

Results: The present research has implemented a model that would be useful for future studies to be conducted since it helps assess the COVID-19 influence at the time of the pandemic period. Keeping the research results in mind, and the fear factor present during the period, the ML is considered to be a significantly useful tool which helps reduce the fear present within the peers and instructors. Similarly, the perceived fear (PF) highly affects the PU and PEU. According to the responses, during the pandemic period, the PF is quite evident; however, the ML maintains a high PU and PEU degree, which reduces the fear factor and encourages the students to participate in their scheduled class.

Conclusions: The current research results are similar to the ones presented in earlier research studies related to the TAM and TPB variable's importance (Ajzen, 1985; F. D Davis, 1989; Teo, 2012; V Venkatesh & Bala, 2008). It is observed that the students are much more acceptable towards technology is there is nothing but the ML technology available as the tool for

learning during the COVID-19 pandemic. The PU and PEU related results are also similar to the ones of the earlier PU and PEU related results that influence the student acceptance of ML. Hence, it should be considered as an indicator for the students intention to make use of the ML when the environment is infected with COVID-19. Furthermore, PU is highly affected by PEU, which indicates that if it is easy to use the technology, then it would be considered useful.

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Abstract

This paper investigates the use of mobile learning platforms for learning purposes among university students in UAE. An extended Technology Acceptance Model (TAM) and theory of planned behavior (TPB) are proposed to analyze the adoption of mobile learning platforms by university students for accessing course materials, searching the web for information related to their discipline, sharing knowledge, conducting assignments during COVID-19 pandemic. The total number of questionnaires collected was 1880 form different universities. Partial least squares-structural equation modeling (PLS-SEM) and machine learning algorithms (ML) were utilized to investigate the research model based on the student's data gathered through a survey. According to the results, each hypothesized relationship within the research model has been supported by the data analysis methods. It should also be noted that the J48 classifier mostly had the upper hand on other classifiers when it comes to the prediction of the dependent variable. As per the indication of our research, teaching and learning can greatly benefit from the adoption of machine learning as an educational tool at the time of this pandemic; nevertheless, its significance could be lowered because of the emotion of fear concerning poor grades, stressful family circumstances, and loss of friends. Accordingly, this issue can only be solved by evaluating the emotions of students during this pandemic.

Keywords—COVID-19 pandemic; Mobile Learning; Fear; Technology Acceptance Model; Theory of Planned Behavior.

1. Introduction

Colleges and universities actively aim to create a virtual teaching environment with the help of relevant platforms and resources. Attempts to achieve specific effective results are being made. With that being said, such institutions have encountered an obstacle in the form of COVID-19. Because of it, students have been facing negative emotions, like feelings, worries, and fears of apprehension globally. Students are mentally affected by fear, which results in stigma in several cases as well. Discrimination, loss, and other such psychosocial issues are emerging as COVID-19 has declared a pandemic (Ahorsu et al., 2020; Lin, 2020; Pappas, Kiriaze, Giannakis, & Falagas, 2009). The e-learning concept has experienced a massive impact because of fear, which caused the education institutes to halt their learning and teaching processes. Fear of taking risks, failure, missing out, and security are some of the types of fear that have manifested (Alt & Boniel-Nissim, 2018; Ellahi, 2017; Machů & Morysová, 2016; MORCHID, n.d.). As it was assumed earlier, fear could also start affecting technology adoption at the time of COVID-19, which has forced a lot of universities, colleges, and schools to implement distance learning for lessening the harmful Coronavirus effects.

Nonetheless, a significant percentage of colleges and universities have experienced some issues related to the knowledge of educators and using technology for implementation, the proficiency and understanding of the students, and the small virtual classes being conducted (Chen & Li, 2011; Li et al., 2018; Liang, Zheng, & Wang, 2011). Adopting the technology aimed at distance learning is important for validating the level of efficiency in the application of virtual classes and technology. According to the majority of adoption studies, there are complications in the adoption process since it could affect other aspects, like learning strategy, context, and technology. Although a number of researchers have focused on technology adoption in their research, there is yet to be any exploration of adopting creative teaching methods, such as mobile learning application, in the Coronavirus pandemic and other such cases. As of late, it has become quite easy to find mobile learning platforms on both Apple Store and Google Play. Users can access the application from the Store, which is responsible for automatically updating it as well. Users keep on increasing because of the freemium approach undertaken by the App Store (C. Z. Liu, Au, & Choi, 2014; McIlroy, Ali, & Hassan, 2016). What students and educators think about the implementing mobile learning platform at the time of this pandemic has to be considered. Accordingly, it would become possible to address the novelty of both the mobile learning platform and the Coronavirus pandemic. There has not been much time since the introduction of mobile learning platforms and thus, there is a lack of research on how they can influence the higher education. More importantly, the technology adoption domain has been researched quite a lot; nevertheless, there is a lack of attention on the emotion of fear concerning the technology adoption at the time of this pandemic. Apart from that, past studies have mostly dealt with the technological factors, without any attention to the psychological aspect. The impacts of fear are yet to be clearly understood in past research and this is why technology has not been used to its full potential when it comes to the education domain.

Taking into consideration these limitations, the current research aims to get more educational information on the most appropriate technology for cases where the life of learners and educators is influenced by fear. For providing better education at the time of this pandemic, both learners and educators have newly started using this application.

When it comes to the academic research adoption model, the literature has found success in making great use of the Technology Acceptance Model (TAM) and the theory of planned behavior (TPB) as a hybrid model for technology adoption. With their help, it became possible to find the willingness of users when it comes to accepting and using technology (Q. Liu, Geertshuis, & Grainger, 2020; Tsai, Lin, Chang, Chang, & Lee, 2020). Accordingly, this research focuses on understanding the willingness of students and educators in terms of adopting mobile learning systems (ML) by using TPB (Theory of Planned Behavior) and TAM (Technology Acceptance Model) in addition to two external factors, which include subjective norms and fear. What students and teachers think about machine learning utilization as this disease spreads has been investigated with the help of TAM & TPB models. On the other hand, there is a lack of exploration of fear at the time of the COVID-19 pandemic and how it directly affects the TAM & TPB models. Considering this, the current hybrid model aims at the different fears which could be faced by both learners and educators during this pandemic. Because of this, the research paper has better chances of providing both teachers and app developers with the technology and education-related information needed for developing and implementing new technologies during this lockdown period.

Some unique educational problems that emerge only in these unordinary times could be highlighted if more information is gathered on the conditions related to the machine learning adoption at the time of the COVID-19 pandemic. The related literature dealing with the technology adoption domain could benefit in terms of theory and practicality.

2. Literature Review

Earlier research studies, carried out upon adoption, focus upon various fear emotion forms. For example, anxiety is a significant factor that helps manage technology approval and anxiety. Within the education sector, the adoption of technology by students is influenced by anxiety. Furthermore, apart from anxiety, lack of experience and skills may also influence technology use. The fear of using technology, combined with literacy and anxiety, negatively affects the adoption of technology. Hence, it is essential for teachers as well as educators to focus on psychological development and help students accept the use of technology. Another reason for fear of using technology within the educational sector is technical readiness and preparedness. Technology adoption is negatively influenced by both of these aspects (Mac Callum & Jeffrey, 2014; Nchunge, Sakwa, & Mwangi, 2012; Thatcher & Perrewe, 2002). The education sector, along with other sectors, has also indicated the fear of technology adoption. Health anxiety is one of the significant concerns of the healthcare sector, which includes the apprehension of the patients or the fear of receiving results related to a severe illness.

Hence, the medical sector students usually emphasize the perceived risk and negative anxiety influences when technology is used (Kamal, Shafiq, & Kakria, 2020; Meng, Guo, Zhang, Peng, & Lai, 2020). As part of the banking sector, various kinds of fear are recognized regarding the perception and attitude of the customers towards technology. Customers do not want to use their data for mobile payments. The customers fear the use of technology in mobile banking and negatively influenced due to the frauds that occur. The experience and trust are both lacking (Bailey, Pentina, Mishra, & Ben Mimoun, 2020; Makttoofa, Khalidb, & Abdullahc, n.d.). Lastly, for the household sector, technology is not being used mainly due to the fear of using it and the increase in family tasks.

Various research studies have managed the technological acceptance and fear issues present. These research studies are based on the TAM (Bailey et al., 2020; Bhattacherjee & Hikmet, 2007; Kamal et al., 2020; Mac Callum & Jeffrey, 2014; Makttoofa et al., n.d.; Nchunge et al., 2012) and several other models (Brown & Venkatesh, 2005; Johnston & Warkentin, 2010; Meng et al., 2020; Thatcher & Perrewe, 2002). Most of the research studies assess how the fear of technology can influence technology acceptance. Various users have provided justifications related to the fear of technology use. Some have stated that it is related to self-confidence. Errors are made when a human is assigned to a job, and this belief enhances the fear factor (Gresham, 2020). Some suggest that technology is time-consuming and does not allow them to complete their tasks, which is why it is not being used

(Appavoo, 2020). Various acceptance studies assess the influence of fear upon the breach of data privacy, and this is why privacy and security awareness are emphasized (Distler, Lallemand, & Koenig, 2020).

The present literature does not have enough empirical research that deals with the utilization of mobile learning in UAE institutions by considering the factors influencing the actual use of students. When it comes to methodology, technology acceptance research analyzes the theoretical models generally by using the structural equation modeling (SEM) and machine learning algorithms (ML). Considering this, this research has two objectives: (1) examining how students utilize mobile learning by integrating TAM (Fred D Davis, 1989) and TPB (Ajzen, 1985), and (2) validating the created theoretical model with the help of ML and PLS-SEM algorithms.

3. Theoretical Model and Research Model

For the current research, the developed research model aims to integrate the subjective norm as well as the fear construct within two kinds of theoretical models, which are TAM and TPB. The proposal is that the subjective norm and fear would influence the perceived ease of use (PEOU) and perceived usefulness (PU) of m-learning systems. Additionally, attitude and perceived behavioral control are expected to be influenced by the continuous intention to use m-learning systems. The proposed theoretical model is presented in Figure 1.

3.1 TAM

One of the main objectives of the TAM model is to measure the external factor validation upon personal belief. The model is considered quite powerful since it helps explain the ability of the individuals to accept the technology at their educational institutions (Al-Maroof & Al-Emran, 2018; Fred D Davis, 1989; Teo, 2012; V Venkatesh & Bala, 2008). The two kinds of perceptions can be measured by perceived usefulness (PU) and perceived ease of use (PEOU) according to TAM. Through this aspect, the behavioral intention (INT) of the user can be influenced directly. The PU should be considered since this tool helps measure the degree to which technology must be evaluated by the individual, and if this technology is useful enough to be adopted and accepted. However, PEOU is the degree that allows the individual to believe that technology is manageable and attainable (Fred D Davis, 1989).

Attitude (ATT) has been stated as one’s desirability to use the system (Karjaluoto, Mattila, & Pento, 2002). The earlier m-learning studies indicated that INT and ATT maintain a relationship. Research also suggested that the intention to use m-learning systems is significantly influenced by the ATT (Mostafa Al-Emran, Arpaci, & Salloum, 2020; Cheon, Lee, Crooks, & Song, 2012; Khanh & Gim, 2014; Prieto, Migueláñez, & García-Peñalvo, 2014).

Keeping in mind the earlier assumptions, if the technology is considered to be easy to use then, it will retain a positive attitude. Therefore, user perceptions are quite essential. With this positive attitude, it is believed that the users would adopt the technology. The following hypotheses have been proposed applying the earlier assumptions to the current model.

H1: Perceived ease of use (PEOU) would predict the subjective norm (SN).
H2: Perceived ease of use (PEOU) would predict the perceived usefulness (PU).
H3: Perceived usefulness (PU) would predict attitude (ATT).
H5: Perceived usefulness (PU) would predict the subjective norm (SN).
H7: Attitude (ATT) would predict the intention to use mobile learning platform (INT).

3.2 Subjective norm

Individual perceptions can be measured using a tool called subjective norm (SN). This perception revolves around the presence of other individuals who have a similar attitude and would indicate similar behavior towards technology. Socially, the TAM model has been strengthened by the SN since the TAN is enabled to integrate the user behavior present within a user group (Fishbein & Ajzen, 1975). SN has been considered as an external factor that includes the intention of the students to adopt the ML technology for classmate group meetings.

The SN also influences behavioral intention, especially PU and PEOU, within various technology adoption or acceptance related literature researches (Song & Kong, 2017; V Venkatesh & Bala, 2008; Viswanath Venkatesh & Davis, 2000; Wong, Teo, & Russo, 2012). The SN and TAM have recently been used as an external factor within the (Huang, Teo, & Zhou, 2020), where it was stated that the TAM embedded factors of various earlier research studies and external factors maintain a significant-close relationship. Yet, it is found that the SN external factor has not been efficiently or deeply implemented within the research. Earlier research stated that intention of using m-learning platforms (IU) is significantly influenced by the subjective norm (Mostafa Al-Emran et al., 2020; Cheon et al., 2012; Y. Liu & Chen, 2008; Mtebe & Raisamo, 2014; Park, Nam, & Cha, 2012). Hence, the following hypothesis occurs.

H8: Subjective norm (SN) would predict the intention to use mobile learning platform (INT).

3.3 Perceived Fear

In China, December 2019, the novel coronavirus disease was observed, and with time it spread throughout the world. Keeping the recent studies in mind, the reaction that has been perceived towards this virus is fear. The Health Anxiety Inventory (HAI) scale has fear at the highest level (Nicomedes & Avila, 2020). Even though fear is perceived to be positive when there is real danger present, however, in the case of the Coronavirus, this fear may be burdensome and chronic. There are various forms of fear that is related to the COVID-19, like health anxiety, uncertainty, and risk associated with loved ones. Hence, two vital issues have developed, which is the high worrying degree and the high possibility that one would be affected by the disease (Ahorsu et al., 2020; Gerhold, 2020).

The present research aims to analyze the association between the adoption of technology through the use of TAM and the external factor of Perceived Fear (PF) The TAM model limitations need to be overcome within the research and this refers to the external factor implementation which are specific to the context (Tarhini, Hone, & Liu, 2015) through the analysis of the TAM model perceived factor (PF), that is PU and PEOU as well as the SN external factor. Hence, keeping these aspects in mind, the hypothesis developed is.

H4: Perceived fear (PF) would predict the perceived usefulness (PU).
H6: Perceived fear (PF) would predict the subjective norm (SN).

3.4 Perceived Behavioral Control (PBC)

Perceived Behavioral Control (PBC) is defined as “people’s perception of the ease or difficulty of performing the behavior of interest” (Ajzen, 1991). Earlier research shows that the intention to use m-learning platforms (INT) is significantly affected by the PBC (Mostafa Al-Emran et al., 2020; Cheon et al., 2012; Cheong, Lee, Crooks, & Song, 2012; Kim, 2010). Hence, the following hypothesis should be considered.

H9: Perceived behavioral control (PBC) would predict the intention to use mobile learning platform (INT).

The hypotheses have been used to carry out the proposed research model, as indicated in Figure 1. The theoretical model has been presented as a structural equation model and then analyzed using the machine learning methods.

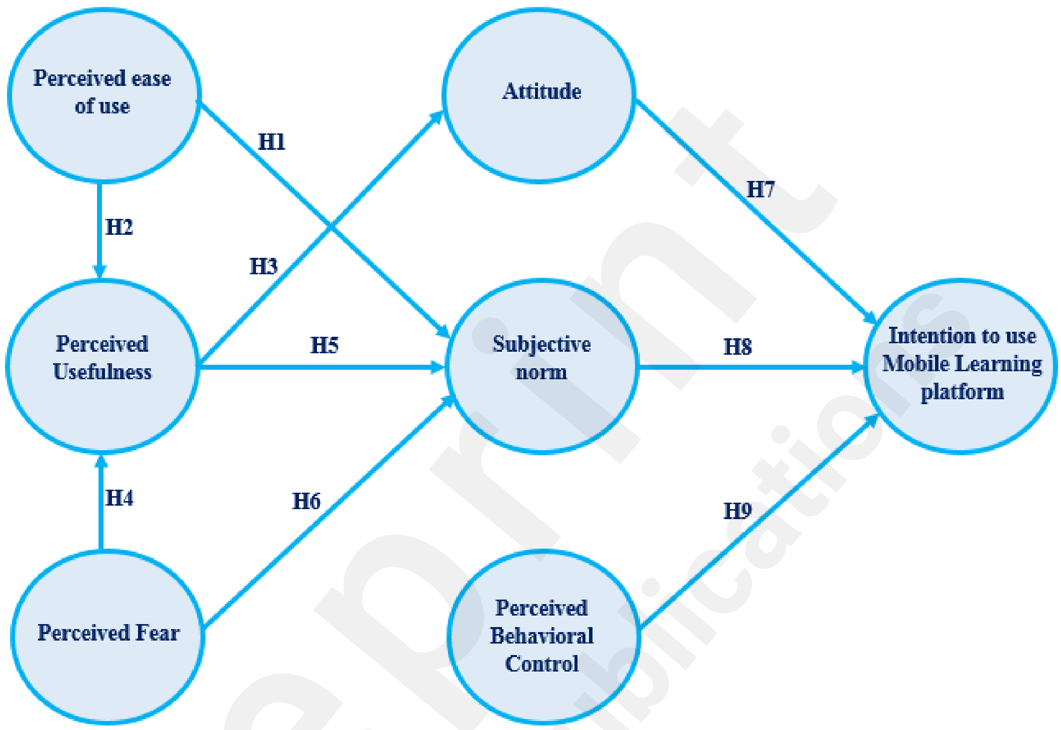

Figure 1. The study model.

4. Research Methodology

4.1 Context and subjects

University students were the target population for this research. The students from the universities of United Arab Emirates were given the questionnaire. Seven different universities were chosen for the study; these include University of Sharjah (UOS), Higher Colleges of Technology (HCT), The British University in Dubai (BUiD), United Arab Emirates University (UAEU), University of Fujairah (UOF), And American University in UAE (AUE) and Ajman University (AU), which are the well-known universities in UAE. With the help of an online survey, the collection of data lasted from May to June of 2020. The surveys were completed by the participants, who did not ask for any compensation as well. For data collection, the convenience sampling technique has been used in this research. There was a distribution of 2000 surveys, and a 94% response rate was recorded since 1880 students completed the whole survey. The number of men and women who completed the survey was 1102 and 778, respectively.

Moreover, the percentage of participants aged 18 to 29 was 40.3%, and the remaining 59.7% were older than 29 years. Finally, the participants consisted of 33.3% of undergraduate students, 45.2% master's students, 11.1% Ph.D. students, and 10.4% diploma students. A comprehensive view of the collected data is given in Tables 1 & 2.

Table 1. Participants details

University	No. of students
United Arab Emirates University (UAEU)	568
University of Sharjah (UOS)	439
Higher Colleges of Technology (HCT)	365
Ajman University (AU)	287
The British University in Dubai (BUiD)	103
University of Fujairah (UOF)	68
American University in UAE (AUE)	50
Total	1880

Table 2: Summary of Students' demographic characteristic

Variables	No. of Respondents	Percent %
Gender:		
• Male	1102	58.6%
• Female	778	41.4%
Age:		
• 18 to 29 years	758	40.3%
• 30 to 39 years	635	33.7%
• 40 to 49 years	367	19.5%
• 50 to 59 years	120	06.5%
Level of education:		
• Diploma	196	10.4%
• Bachelor's degree	626	33.3%
• Master	849	45.2%
• PhD	209	11.1%

4.2 Study Instrument

There are two parts of its research instrument. For the first part, the focus will be on collecting the participant's demographic data. While the second part is aimed at collecting responses related to the factors entailing the conceptual model "5-point Likert scale". For measuring the seven constructs (Attitude, Intention to use mobile learning platform, Subjective norm, Perceived Behavioral Control, Perceived Fear, Perceived ease of use, and perceived usefulness) in the questionnaire, 20 items were included in the survey. The sources of these constructs are presented in Table 3.

Table 3: Constructs and their sources.

Construct	Number of items	Source
ATT	3	(Mostafa Al-Emran et al., 2020; Cheon et al., 2012)
INT	2	(Mostafa Al-Emran et al., 2020; Bao et al., 2013; Tan et al., 2014)
SN	3	(Mostafa Al-Emran et al., 2020; Cheon et al., 2012)
PBC	3	(Mostafa Al-Emran et al., 2020; Cheon et al., 2012)
PF	3	Developed in this study
PEOU	3	(Mostafa Al-Emran et al., 2020; Bao, Xiong, Hu, & Kibelloh, 2013; Tan, Ooi, Leong, & Lin, 2014)
PU	3	(Mostafa Al-Emran et al., 2020; Bao, Xiong, Hu, & Kibelloh, 2013; Tan, Ooi, Leong, & Lin, 2014)

Note: ATT, Attitude; INT, intention to use mobile learning platform; SN, subjective norm; PBC, Perceived Behavioral Control; PF, Perceived Fear; PEOU, perceived ease of use; PU, perceived usefulness.

4.3 Pre-test of the questionnaire

Before conducting the final survey, it was made sure whether the questionnaire items are reliable by carrying out a pilot study for which there was a random selection of 100 students out of the target population. With the help of Cronbach's alpha, the items of the constructs were measured in terms of their internal reliability. (Nunnally & Bernstein, 1978) suggests an acceptable reliability coefficient be 0.70 at a minimum. From Table 4, it can be seen that this study's constructs had a minimum of Cronbach's alpha value of 0.7. So, there was reliability in each construct, and thus, the final research can use them.

From the table mentioned above, the reliability of the questionnaire's five measurement scales can be seen, and thus, the study could use them.

Table 4: Cronbach's Alpha values for the pilot study (Cronbach's Alpha ≥ 0.70).

Construct`	Cronbach's Alpha
ATT	0.736
INT	0.755
SN	0.864
PBC	0.859
PF	0.847
PEOU	0.887
PU	0.803

Note: ATT, Attitude; INT, intention to use mobile learning platform; SN, subjective norm; PBC, Perceived Behavioral Control; PF, Perceived Fear; PEOU, perceived ease of use; PU, perceived usefulness.

5. Findings and Discussion

5.1 Data Analysis

The developed theoretical model has been evaluated using two different techniques in this research. The first one involves the usage of the partial least squares-structural equation modeling (PLS-SEM) alongside the SmartPLS tool (Ringle, Wende, & Becker, 2015). This research uses PLS-SEM mainly because both the structural and measurement model can be concurrently analyzed through PLS-SEM, which increases the preciseness of results (Barclay, Higgins, & Thompson, 1995). As for the second technique, the research predicts the dependent variables entailing the conceptual model with the help of machine learning algorithms via Weka (Arpaci, 2019).

5.2 Measurement model assessment

The validity and reliability are tested for assessing the measurement model (Hair Jr, Hult, Ringle, & Sarstedt, 2016). Afterward, the reliability was tested by using the Cronbach's alpha and composite reliability (CR) measures. It has been suggested that these measures can only have a minimum of 0.70 (Hair Jr et al., 2016). As per Table 5 results, there was confirmation of reliability as satisfactory values were attained for both measures.

According to (Hair Jr et al., 2016), the discriminant and convergent validities can be evaluated to test validity. There was the testing of the factor loadings and average variance extracted (AVE) in terms of convergent validity. It has been suggested that the AVE and factor loadings values can only have a minimum of 0.50 (Fornell & Larcker, 1981), and 0.70 (Hair, Black Jr, Babin, & Anderson, 2010), respectively. According to Table 5 results, there was confirmation of the convergent validity as accepted values were attained for both measures. (Henseler, Ringle, & Sarstedt, 2015) suggests that the "Heterotrait-Monotrait ratio (HTMT)" of correlations can be tested in the case of discriminant validity. Only the HTMT values below 0.85 are acceptable. According to Table 6 readings, there is confirmation of discriminant validity since accepted values were attained.

Table 5: Convergent validity results which assures acceptable values (Factor loading, Cronbach's Alpha, composite reliability ≥ 0.70 & AVE > 0.5).

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	AVE
Attitude	ATT1	0.726	0.798	0.823	0.760
	ATT2	0.886			
	ATT2	0.800			
Intention to use mobile learning platform	INT1	0.846	0.739	0.789	0.703
	INT2	0.805			
Subjective norm	SN1	0.819	0.758	0.811	0.716
	SN2	0.795			
	SN3	0.883			
Perceived Behavioral Control	PBC1	0.822	0.843	0.771	0.652
	PBC2	0.873			
	PBC3	0.778			
Perceived Fear	PF1	0.808	0.779	0.798	0.593
	PF2	0.845			
	PF3	0.866			
Perceived ease of use	PEOU1	0.872	0.769	0.746	0.633
	PEOU2	0.832			
	PEOU3	0.857			

Perceived usefulness	PU1	0.878	0.715	0.750	0.785
	PU2	0.906			
	PU3	0.848			

Table 6: Heterotrait-Monotrait Ratio (HTMT).

	ATT	INT	SN	PBC	PF	PEOU	PU
ATT							
INT	0.480						
SN	0.519	0.299					
PBC	0.377	0.583	0.516				
PF	0.330	0.514	0.460	0.602			
PEOU	0.549	0.350	0.393	0.657	0.263		
PU	0.651	0.504	0.511	0.542	0.494	0.333	

Note: ATT, Attitude; INT, intention to use mobile learning platform; SN, subjective norm; PBC, Perceived Behavioral Control; PF, Perceived Fear; PEOU, perceived ease of use; PU, perceived usefulness.

5.3 Hypotheses testing and coefficient of determination

The nine hypotheses mentioned earlier are tested using the structural equation modeling (SEM) procedure (Fred D Davis et al., 1992). Analysis has been carried out for the variance, which was described (R^2 value) through each path and the research model each hypothesized path significance association. Table 7 and Figure 2 indicate the standardized path coefficients and path significances.

The R^2 values for the adoption of ML, Attitude, intention to use mobile learning platform, subjective norm, and perceived usefulness present within the range of 0.391 and 0.575 are indicated in Table 6. Hence, a Moderate predictive power is present within these constructs (Liu, Liao, & Peng, 2005). Keeping in mind the data analysis hypotheses, empirical data has supported H1, H2, H3, H4, H5, H6, H7, H8, and H9.

Table 8 and Figure 2 present a summarized result, which indicates that subjective norm (SN) significantly influenced perceived ease of use (PEOU) (β= 0.756, P<0.001), perceived usefulness (PU) (β= 0.227, P<0.05), and perceived fear (PU) (β= 0.480, P<0.05) supporting hypothesis H1, H5, and H6 respectively. Perceived usefulness (PU) has significant effects on attitude (ATT) (β= 0.801, P<0.001); hence H3 is supported. Finally, the results revealed that intention to use mobile learning platform (INT) significantly influenced attitude (ATT) (β= 0.707, P<0.001), subjective norm (SN) (β= 0.553, P<0.001), and perceived behavioral control (PBC) (β= 0.148, P<0.05) supporting hypothesis H7, H8, and H9 respectively. Subjective norm (SN) (PU) was determined to be significant in affecting perceived ease of use (PEU) (β= 0.553, P<0.001), and perceived fear (PF) (β= 0.480, P<0.05) supporting hypothesis H1, H5, and H6 respectively.

Table 7: R^2 of the endogenous latent variables.

Constructs	R^2	Results
PU	0.473	Moderate
ATT	0.391	Moderate
SN	0.575	Moderate
IN	0.534	Moderate

Note: ATT, Attitude; INT, intention to use mobile learning platform; SN, subjective norm; PU, perceived usefulness.

Table 8: Summary of hypotheses tests at p**=<0.01, p* <0.05Significant at p**=<0.01, p* <0.05.

H	Relationship	Path	*t*-value	*p*-value	Direction	Decision
H1	PEOU -> SN	0.756	18.179	0.001	Positive	Supported**
H2	PEOU -> PU	0.264	10.203	0.002	Positive	Supported**
H3	PU -> ATT	0.801	19.093	0.000	Positive	Supported**
H4	PF -> PU	0.358	4.936	0.038	Positive	Supported*
H5	PU -> SN	0.227	4.660	0.027	Positive	Supported*
H6	PF -> SN	0.480	5.892	0.042	Positive	Supported*
H7	ATT -> INT	0.707	15.337	0.000	Positive	Supported**
H8	SN -> INT	0.553	19.485	0.000	Positive	Supported**
H9	PBC -> INT	0.148	18.089	0.000	Positive	Supported**

Note: ATT, Attitude; INT, intention to use mobile learning platform; SN, subjective norm; PBC, Perceived Behavioral Control; PF, Perceived Fear; PEOU, perceived ease of use; PU, perceived usefulness.

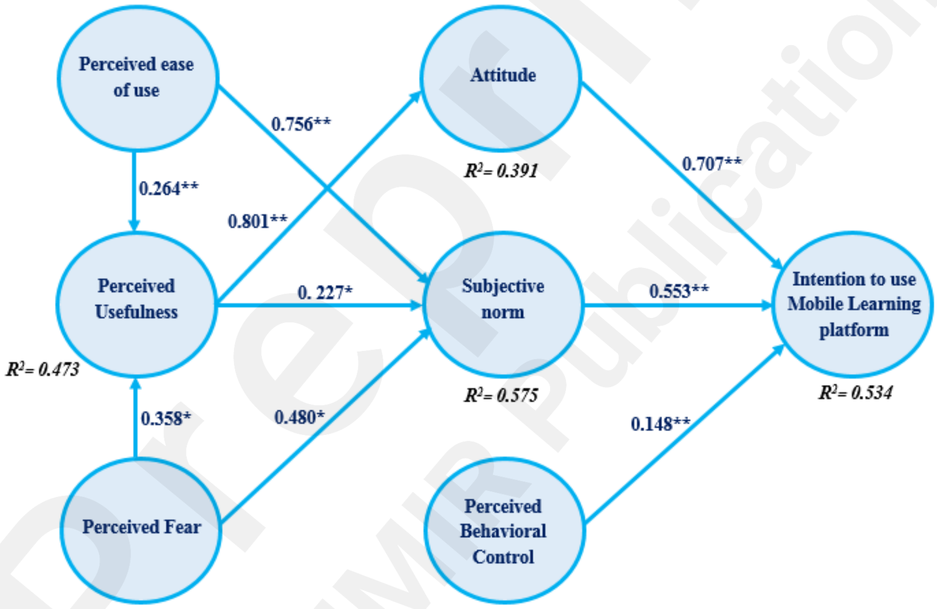

Figure 2. Hypotheses testing results (significant at p** < = 0.01, p* < 0.05).

4.4 Hypotheses testing using machine learning algorithms

This study takes help from ML classification algorithms through the application of various methodologies, such as neural networks, if-then-else statements, decision trees, and Bayesian networks, so that the relationships entailing the suggested theoretical model can be predicted (Arpaci, 2019). With the help of Weka (ver. 3.8.3), the predictive model was tested on the basis of different classifiers, such as OneR, J48, Logistic, LWL, AdaBoostM1, and BayesNet (Frank et al., 2009). When it comes to the prediction of PU of m-learning systems, J48 got the upper hand on other classifiers as it can be seen from Table 9 results. In terms of the 10-fold cross-validation, the J48 showed 83.76% accuracy when predicting the PU. Accordingly, there is support for H2 and H4. This classifier had the upper hand on the other ones because of its TP rate (.837), precision (.803), and recall (.838).

Table 9. Predicting PU by PEOU, and PF.

Classifier	CCI1 (%)	TP[2] Rate	FP[3] Rate	Precision	Recall	F-Measure
BayesNet	80.11	.801	.295	.721	.801	.790
Logistic	81.02	.810	.308	.735	.810	.798
LWL	80.54	.805	.339	.705	.810	.801
AdaBoostM1	82.10	.821	.338	.732	.821	.819
OneR	81.66	.816	.337	.712	.820	.816
J48	83.76	.837	.634	.803	.838	.828

[1]CCI: Correctly Classified Instances, [2]TP: True Positive, [3]FP: False Positive.

In terms of the classification performance, the J48 also had the upper hand on other ones for ATT prediction, which can be seen from the results. The J48 considered the attributes relation to PU for predicting the ATT with 80.13% accuracy. Accordingly, there was support for H3.

Table 10. Predicting ATT by PU.

Classifier	CCI1 (%)	TP[2] Rate	FP[3] Rate	Precision	Recall	F-Measure

BayesNet	78.02	.780	.229	.735	.781	.726
Logistic	77.22	.772	.205	.737	.723	.728
LWL	76.79	.767	.269	.700	.768	.687
AdaBoostM1	78.11	.781	.289	.745	.782	.776
OneR	79.61	.796	.301	.754	.800	.798
J48	80.13	.801	.480	.787	.801	.800

Table 6 results suggest that the J48 classifiers had the upper hand on other classifiers when it comes to SN through PEOU, PU, and PF. With their help, there was a prediction of the SN alongside 89.37% accuracy. Henceforth, there was support for H1, H5, and H6.

Table 11. Predicting SN by PEOU, PU, and PF.

Classifier	CCI1 (%)	TP[2] Rate	FP[3] Rate	Precision	Recall	F-Measure
BayesNet	80.76	.807	.311	.760	.810	.758
Logistic	80.63	.806	.369	.762	.810	.759
LWL	80.06	.800	.299	.756	.801	.748
AdaBoostM1	81.37	.813	.378	.763	.814	.760
OneR	82.79	.827	.409	.772	.833	.772
J48	89.37	.893	.598	.788	.894	.782

According to Table 7 results, the J48 classifier had the upper hand on the other ones when it comes to INT via attributes related to ATT, SN, and PBC. In the prediction of INT, the J48 was accurate by 86.66%, and thus, there was support for H7, H8, and H9.

Table 12. Predicting INT by ATT, SN, and PBC.

Classifier	CCI1 (%)	TP[2] Rate	FP[3] Rate	Precision	Recall	F-Measure
BayesNet	81.10	.811	.303	.753	.812	.750
Logistic	81.23	.812	.371	.758	.813	.752
LWL	80.73	.807	.389	.751	.812	.750
AdaBoostM1	81.44	.814	.369	.762	.815	.761
OneR	83.76	.837	.396	.770	.841	.768
J48	86.66	.866	.595	.802	.872	.798

5. Discussion

For testing the proposed model, the research undertakes a complementary approach utilizing PLS-SEM and machine learning classification algorithms. There are not many studies that aim to predict the actual use of m-learning systems through machine learning algorithms. Accordingly, if a complementary multi-analytical approach is undertaken, this research could play a major role in the information systems (IS) literature. Moreover, it should also be noted that PLS-SEM can help to predict a dependent variable and validate a conceptual model aimed at extending an existing theory (M. Al-Emran, Mezhuyev, & Kamaludin, 2018). Similarly, a dependent variable can be predicted with the help of supervised machine learning algorithms (which have a pre-defined dependent variable) through independent variables (Arpaci, 2019). Another thing to be noted is that the research involves various classification algorithms alongside a number of methodologies, including if-then-else rules, neural networks, association rules, Bayesian networks, and decision trees. The J48 decision tree mostly had the upper hand on other classifiers, as it can be seen from the findings. Apart from that, there was the utilization of the decision tree (non-parametric) to classify both categorical and continuous (numerical) variables as it makes homogeneous sub-samples out of the sample on the basis of the main independent variable (Arpaci, 2019). With that being said, a non-parametric technique called PLS-SEM tested the significant coefficients alongside the sample replacements for drawing numerous sub-samples on a random basis.

Current research studies are assessing the influencing of the coronavirus pandemic upon modern technology. This is specifically for the technology used for learning and teaching. Technology is considered an effective tool that has helped attain victory upon the disease and established a new method for teaching (Kumar, Gupta, & Srivastava, 2020). The current research is aimed to analyze the influence of COVID-19 upon the teaching process using ML. The research model emphasizes the perceived fear factor (PF), and this is an extraordinary influence upon the measurement of the COVID-19 influence over the student and teacher groups. Similarly, analysis should be conducted upon the influence of the pandemic over the ML and technologies that are used for teaching at this point of time. Hence, with the help of this research, it would be possible to remove all gaps and establish a basis for future research.

6. Conclusion

The current research results are similar to the ones presented in earlier research studies related to the TAM and TPB variable's importance (Ajzen, 1985; F. D Davis, 1989; Teo, 2012; V Venkatesh & Bala, 2008). It is observed that the students are much more acceptable towards technology is there is nothing but the ML technology available as the tool for learning during the COVID-19 pandemic. The PU and PEU related results are also similar to the ones of the earlier PU and PEU related results that influence the student acceptance of ML. Hence, it should be considered as an indicator for the students intention to make use of the ML when the environment is infected with COVID-19. Furthermore, PU is highly affected by PEU, which indicates that if it is easy to use the technology, then it would be considered useful.

Keeping in mind the subjective norm (SN), according to the research results, there is a significant association present between the ML acceptance of the students and the subjective norm. It has also been indicated that the behavior within the classroom, existence, and reactions using ML of the students highly affects the acceptance of the students for the ML. Earlier research studies like (Song & Kong, 2017; V Venkatesh & Bala, 2008; Viswanath Venkatesh & Davis, 2000; Wong et al., 2012) also state that SN and students' acceptance of ML are associated. Within the UAE, the students are observed to be significantly influenced by the classmate behaviors which increases the security sense as well as comfort for those who attend the classrooms at the time of the pandemic. Intrinsic motivation is present within the students to make use of the ML when the same class is to be shared with the rest of the colleagues or classmates. Additionally, there are several variables that influence the SN in a significant manner. These are the PEU and PU. According to the research results, the attitudes of the instructors and the peers would help promote the ML to be used as a learning tool throughout the pandemic period. This tool would be perceived as being useful, enjoyable as well as effort-free. These research findings are observed to be consistent with the ones mentioned in the earlier research studies by (El-Gayar, Moran, & Hawkes, 2011). In this case, it has been stated that peers and instructors provide useful feedback, which affects the students' attitude towards perceived technology effectiveness.

Due to the COVID-19, the fear factor has been on the rise, and this would be considered an essential hypothesis for the current research. The human population has been severely influenced by the COVID-19 pandemic. There is a high transmission probability, which is why there is a need for complete lockdown and stays at home strategy throughout the world (Zhang, Wang, Rauch, & Wei, 2020). The present research has implemented a model that would be useful for future studies to be conducted since it helps assess the COVID-19 influence at the time of the pandemic period. Keeping the research results in mind, and the fear factor present during the period, the ML is considered to be a significantly useful tool which helps reduce the fear present within the peers and instructors. Similarly, the perceived fear (PF) highly affects the PU and PEU. According to the responses, during the pandemic period, the PF is quite evident; however, the ML maintains a high PU and PEU degree, which reduces the fear factor and encourages the students to participate in their scheduled class.

6.1 Implications for research

The current research is considered to be an early attempt towards the following aspects: 1. The fear notion should be theoretically included within the TAM & TPB hybrid model. 2. The COVID-19 influence should be empirically tested, maintaining the context of mobile application users. 3. The Coronavirus pandemic influence should be analyzed considering the ability of the users to make use of the mobile application and attitudes of the users towards the usefulness of the mobile learning platform.

Research conducted earlier considered the concept of fear from various perspectives and its importance—for instance, the fear of technology (Bhattacherjee & Hikmet, 2007). The implication generated is that negative perception would directly or indirectly influence the ease of use and perceived usefulness. Hence, it is believed that the implications are similar to the ones presented by Bhattacherjee & Hikmet, which is that technology use would be negatively influenced by fear. It can now be stated that empirically, perceived fear, during the pandemic time period, would be the most significant and dominant variable for the adoption of any model.

6.2 Limitations and future research

It is necessary to report various key limitations. Firstly, caution needs to be taken when generalizing the results to other institutes in the UAE or other parts of the world. This could be attributed to the fact that only one institute has been concentrated on collecting data, and the respondents have been selected on the basis of a convenience sampling technique. If these problems are considered, future research can contribute to results generalization. Secondly, the research only considered students when evaluating them-learning systems' actual usage. When it comes to future research, it should also focus on the actual use of m-learning systems by teachers so that more information on the influencing factors and systems implementation can be found.

6.3 Recommendations

Within online teaching, the mobile learning platform is considered to be a safe environment. At the time of the pandemic, this system is recommended. During the lockdown, this can be considered to be a temporary solution. The ML availability allows the peers and teachers with a self-sensing security and communication tool that is immediate. Sharjah city has been contaminated, and this tool would prove to be quite useful. Various benefits are present for using this mobile learning platform as compared to other communication procedures. Firstly, this application can be used on laptops and smartphones. The students of the University of Sharjah can join classes and participate in using their smartphones. Secondly, the links for each class time should be used various times, and the students can communicate with teachers at any point in time during the day. Lastly, the students are observed to be much more confident, and fear feeling is reduced to the minimum.

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Appendix A

Instrument development

Intention to Use the M-Learning platform

- I intend to increase my use of mobile learning platforms in the future.
- Assuming that I had access to the mobile learning platforms, I intend to use it.

Perceived Ease of Use

- M-learning is understandable and clear.
- I found it easy to get the m-learning system to do what I want it to do.
- Overall, the m-learning system is easy to use.

Perceived Usefulness

- Using m-learning can improve my learning performance.
- Using m-learning increases my productivity
- I find the m-learning system to be useful in my study.

Attitude

- I would like my coursework more if I used m-learning.
- Using m-learning in my coursework is a pleasant experience.
- Using m-learning in my coursework is a wise idea.

Subjective norm

- Most people who are important to me think that it would be fine to use a mobile device for university courses.
- I think other students in my classes would be willing to adapt a mobile device for learning.
- Most people who are important to me would be in favor of using a mobile device for university courses.

Perceived Behavioral Control

- I have a sufficient extent of knowledge to use m-learning.
- I have a sufficient extent of control to make a decision to use m-learning.
- I have a sufficient extent of self-confidence to make a decision to use m-learning.

Perceived Fear (PF)

- I can’t concentrate on my class through m-learning because of COVIC-19.
- M-learning reduces my fear.
- M-learning provides a chance to be away from the lockdown.
- M-learning provides chances of learning instead of being afraid.