Examining the Factors Influencing the Mobile Learning Usage During COVID-19 Pandemic: An Integrated SEM-ANN Method

KHADIJA ALHUMAID[1], MOHAMMED HABES[2], AND SAID A. SALLOUM[3,4]

[1]College of Education, Zayed University, Abu Dhabi, United Arab Emirates
[2]Department of Radio and Television, Faculty of Mass Communication, Yarmouk University, Irbid 21163, Jordan
[3]School of Science, Engineering, and Environment, University of Salford, Manchester M5 4WT, U.K.
[4]Machine Learning and NLP Research Group, University of Sharjah, Sharjah, United Arab Emirates

Corresponding author: Said A. Salloum (ssalloum@sharjah.ac.ae)

ABSTRACT The way in which the emotion of fear affects the technology adoption of students and teachers amid the COVID-19 pandemic is examined in this study. Mobile Learning (ML) has been used in the study as an educational social platform at both public and private higher-education institutes. The key hypotheses of this study are based on how COVID-19 has influenced the incorporation of mobile learning (ML) as the pandemic brings about an increase in different kinds of fear. The major kinds of fear that students and teachers/instructors are facing at this time include: fear because of complete lockdown, fear of experiencing education collapse and fear of having to give up social relationships. The proposed model was evaluated by developing a questionnaire survey which was distributed among 280 students at Zayed University, on the Abu Dhabi Campus, in the United Arab Emirates (UAE) with the purpose of collecting data from them. This study uses a new hybrid analysis approach that combines SEM and deep learning-based artificial neural networks (ANN). The importance-performance map analysis is also used in this study to determine the significance and performance of every factor. Both ANN and IPMA research showed that Attitude (ATD) are the most important predictor of intention to use mobile learning. According to the empirical findings, perceived ease of use, perceived usefulness, satisfaction, attitude, perceived behavioral control, and subjective norm played a strongly significant role justified the continuous Mobile Learning usage. It was found that perceived fear and expectation confirmation were significant factors in predicting intention to use mobile learning. Our study showed that the use of mobile learning (ML) in the field of education, amid the coronavirus pandemic, offered a potential outcome for teaching and learning; however, this impact may be reduced by the fear of losing friends, a stressful family environment and fear of future results in school. Therefore, during the pandemic, it is important to examine students appropriately so as to enable them to handle the situation emotionally. The proposed model has theoretically given enough details as to what influences the intention to use ML from the viewpoint of internet service variables on an individual basis. In practice, the findings would allow higher education decision formers and experts to decide which factors should be prioritized over others and plan their policies appropriately. This study examines the competence of the deep ANN model in deciding non-linear relationships among the variables in the theoretical model, methodologically.

INDEX TERMS Artificial Neural Network Architecture, hybrid-model, mobile learning, Structural Equation Modeling, subjective norm.

I. INTRODUCTION

The focus of the adoption studies carried out in the past was on the distinct types of fear. For example, in various

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studies pertaining to technology adoption, anxiety was found to be a critical factor. Concerning the educational matters, anxiety is a significant component that influences the technology adaption by students. Another factor that may lead to inadequate attention being given to technology adoption is scarcity of skills and experience. In addition, there is

the fear of technology itself, which plays an influential role alongside anxiety and literacy in reducing the likelihood of adequately adopting technology. Hence, it is important for teachers and educators to be attentive towards the psychological aspect and to increase the readiness of students to accept technology. Another reason for the presence of fear in the educational domain is inadequate preparedness and technical readiness, both of which negatively affect the adoption of technology [1]–[3]. Fear of technology adoption is also seen in other fields apart from education. In the health sector, patients are mainly worried about health and this signifies the apprehension or fear of patients regarding any results that suggest serious conditions. Hence, studies carried out in the field of medicine place greater emphasis on how anxiety and perceived risk negatively influence the use of technology [4], [5]. Various kinds of fear are also present in the banking sector and these emerge from the attitude of customers towards technology. In terms of mobile payment, customers are scared of providing their data. It has been demonstrated in other studies that customers' fear of experiencing fraud and their inadequate skills negatively influence the adoption of mobile banking [6], [7]. Lastly, with respect to the household, the main reason why there has been a lack of attention paid towards technology usage is the fear of technology, as well as an increase in the number of family responsibilities.

Fear and technology acceptance have been examined in the past few studies. The TAM model [2], [3], [5]–[8], as well as other models [1], [4], [9], [10], are used in the majority of these studies. The focus of the studies is on how the fear of technology itself influences technology acceptance. Different reasons have been provided by users as to why they are apprehensive about using technology. According to a few of them, it is all about self-confidence. Humans are prone to make errors whenever they work and this leads to an increase in the fear factor [11]. However, other users assert that they prefer not to work with technology as it takes up too much time and does not allow them to fulfil their tasks in a timely manner [12]. The impact of the fear of violating the privacy of data has been evaluated in other acceptance studies and this leads to greater emphasis on aspects of privacy and security [13].

As per the literature present, the implementation of Mobile Learning (ML) in the educational environment of the UAE does not have sufficient empirical research as well as a lack of understanding of the factors influencing students' actual use. The structural equation modeling (PLS-SEM) approach is employed by the majority of the technology acceptance studies with regards to the methodology for assessing the theoretical models. Hence, this research aims at two-fold. Firstly, the acceptance of ML will be assessed by integrating the Technology Acceptance Model (TAM), the Expectation-Confirmation Model (ECM), and the Theory of Planned Behavior (TPM). Secondly, to authenticate the created theoretical model by employing (PLS-SEM) and deep learning-based artificial neural networks (ANN).

The rest of this paper is organized as follows: Section 2 provides a summary about the relevant studies that were carried out concerning ML. Section 3 shows the research framework & hypotheses. Section 4 illustrates the research methodology. Section 5 describes the results obtained after constructs and model validation. Finally, Section 6 demonstrates the discussion, conclusion, and future work.

II. LITERATURE REVIEW

Previous adoption research has centered on various types of fear emotion. Many longitudinal findings on the adoption of technology and anxiety, for example, regard anxiety to be a critical factor. Anxiety, which is a component of the academic field, is a significant factor that influences students' adoption of technology. A deficit of competence and experience in excess of anxiety can contribute to a deficit of enthusiasm in using technology. Another notable aspect is distrust of technology, which, when combined with anxiety and literacy, reduces the likelihood of effectively adopting technology. As a result, teachers and educators must consider the psychological impact of technology and educate students to accept it. Another source of fear in the academic system is a scarcity of preparedness and technical competence, both of which harm technology adoption [1]–[3]. The academic system is not an outlier, and fear of technology adoption can be seen in other fields as well. Patients' biggest concern in the healthcare services is uncertainty regarding the provision of suitable services. Consequently, healthcare stakeholders pay a special consideration to alleviate these concerns to facilitate their patients and also to remove their technology related uncertainties [4], [5]. Various forms of apprehension can be observed in the banking industry, many of which derive from clients' behavior and perception towards technology. When it comes to mobile payment, most people are hesitant to use their data. Customers' fear of being a fraud, as well as a scarcity of experience and trust, have been found in other findings to hurt mobile banking adoption [6], [7]. Eventually, it appears that fear of technology is the driving force behind a decrease of enthusiasm in adopting technology, as well as a growing number of household tasks. Fear and technology acceptance has also been addressed in recent research. The TAM model [2], [3], [5]–[8] and other models [1], [4], [9], [10] are used in the majority of these analyses. Much of the previous studies focused on the technology acceptance due to increased trust on technological advancements. Also there are many other dynamic factors increasing the technology usage and dependency. Here self-assurance is one of the prominent phenomenon, which can be exemplified in terms of fear of making mistakes and increased uncertainty leading to restricted technology usage and acceptance [11]. Previous studies also witness technology avoidance as a result of unawareness and insufficient capabilities to utilize the technology [12].

However, privacy concerns is one of the major factor that may hinder technology usage among the individuals [13]. It also notable that, several studies only focused on
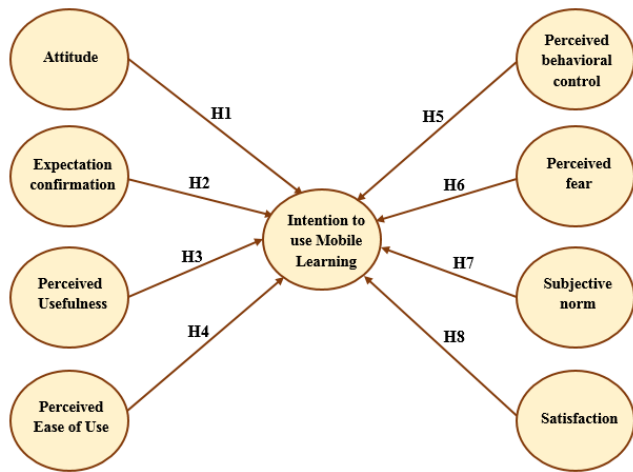
FIGURE 1. Conceptual framework of current study.

single-stage, one-way data that mainly involved Structural Equation Modelling in their methodology [14]. However, this single-stage, one-way relationship between the variables remained insufficient to examine the in-depth details of the complicated decision-making stages [15]. Despite many researchers also resorted to Artificial Neural Network to dig out multi-faceted results, they remained unsuccessful as the method was online one-layered, incapable of focusing on the other different dimensions [16]–[19]. In this context, an in-depth Artificial Neural Network Architecture helps to validate the accuracy and suitability of non-linear models by digging out more than just single layer. Thus, to further support these propositions, we utilized a hybrid Structural Equation Modelling- Artificial Neural Network to assess the deep learning [20]. Although, previous research mainly relied on Technology Acceptance Model, but this research will examine the Mobile Learning by using the hybrid research model.

III. THEORETICAL SUPPORT & RESEARCH FRAMEWORK
We used Technology Acceptance Model, the Expectation-Confirmation Model and Theory of Planned Behavior by integrating fear construct and subjective norm to propose the research model. The research assumptions anticipate that fear has a significant influence of Perceived Ease of Use and Perceived Usefulness of Mobile Learning system. We also assume that, both Subjective norm and Perceived Behavioral Control have a significant influence on the continuous intent to use Mobile Learning systems. Figure 1 gives a graphical illustration of the proposed study model.

A. ATTITUDE
Attitude (ATD) means "one's desire to use the system" [21]. It was determined in the m-learning studies carried out in the past that there is a significant relationship between ATD and CIT. According to previous studies, ATD significantly

influences the intention to use mobile learning systems [22]–[25]. Thus, the following hypothesis is proposed:

H1: Attitude (ATD) positively affects the intention to use mobile learning platforms (CIT).

B. EXPECTATION-CONFIRMATION
Expectation-confirmation signifies "users' perceptions of the congruence between the expectation of information system usage and its actual performance" [26]. According to previous studies, there is a significant effect of expectation-confirmation on satisfaction and on the CIT of various mobile technologies [24], [27]–[29]. Therefore, the following research hypotheses assume that:

H2: Expectation-confirmation (EC) positively affects the intention to use mobile learning platforms (CIT).

C. TECHNOLOGY ACCEPTANCE MODEL
Technology Acceptance Model helps to examine the external factors regarding personal beliefs. Researchers and critics consider Technology Acceptance Model as a potential source of describing the mechanisms behind accepting and integrating technology, especially in educational institutions [30]–[34]. Technology Acceptance Model emphasizes Perceived usefulness (PU) and perceived ease of use (PEOU) as the most significant factors to determine the two distinct perceptions. Perceived usefulness (PU) is "the extent to which an individual believes that using a particular system would improve their work performance" [31]. Previous studies witness that there is a significant impact of Perceived Usefulness is significantly influential on the continuous intention to execute different mobile technologies [27], [28], [29], [35]. Perceived ease of use (PEOU) also means "the extent to which an individual that using a particular system would require less effort" [31]. Previous investigations determined that the Perceived Ease of Use significantly influences the continuous intent to utilize Mobile Learning [27], [28], [29], [35]. Here we can assume that when individuals find a technology ease of use, they are more likely to accept and use it as complication cab be a barrier between technology acceptance and usage. Likewise, when individuals find technology as useful, capable of bringing out beneficial outcomes, they are more likely to accept the technology. Thus, in the light of these arguments, we propose the following hypotheses:

H3: Perceived usefulness (PU) positively influences the intention to use mobile learning platforms (CIT).

H4: Perceived ease of use (PEOU) positively influences the intention to use mobile learning platforms (CIT).

D. PERCEIVED BEHAVIORAL CONTROL (PBC)
Perceived Behavioral Control (PBC) means "people's perception of the ease or difficulty of performing the behavior of interest" [36]. The results of earlier studies witnessed a significant influence of PBC on the intention of using Mobile use learning platforms [24], [25], [37]. Based on this, the following is hypothesized:

H5: Perceived behavioral control (PBC) positively affects the intention to use mobile learning platforms (CIT).

E. PERCEIVED FEAR

During the December, 2019 emergency of Covid-19 led to several fears among the masses which gradually spread to all parts of the globe. It has been found in the latest studies that the most frequent reaction extensively experienced during this disease is the sense of fear. In the Health Anxiety Inventory (HAI) scale, fear has obtained the highest rating [38]. It has been asserted in studies that, when encountering actual danger, the feeling of fear can be perceived in a positive light. There are different types of fear experienced due to COVID-19, for example the feeling of uncertainty, concern for the risk faced by loved ones and health anxiety. In addition, it has given rise to two main issues: significant apprehensions and the high likelihood of getting infected by the virus [39], [40].

The current analysis aims to investigate how technology adoption is linked to the external factor of Perceived Fear (FR) by employing TAM. This study is an attempts to examine the news dimensions of the Technology Acceptance Model, which involves the use of external mechanism determining the technology adoptability and usage [41], by examining how perceived fear (FR) influences the TAM model, i.e. PU and PEOU in addition to subjective norm (SUB) [41], which is another external factor. Based on the relevant assumption, the following hypotheses are postulated:

H6: Perceived fear (FR) positively affects the intention to use mobile learning platforms (CIT).

F. SUBJECTIVE NORM

Subjective norm (SUB) stands for a tool used for determining individuals' perception regarding whether individuals, who share similar perceptions, will or will not exhibit similar attitude towards technology usage. The TAM model has been socially reinforced due to SUB because it allows the TAM to consider users' behaviors in terms of a group of users [42]. SUB has been considered as an external factor in this study, which can take into account the students' intention to adopt the ML technology in various meetings conducted in classrooms.

Various past studies on the acceptance or adoption of technology have examined the impact of SUB on behavioral intention, particularly on PEOU and PU [34], [43]–[45]. A study carried out recently [46] employed TAM and SUB as an external factor. It was shown in this study that the external factors are closely linked to other factors of the Technology Acceptance Model included in the earlier studies. Nevertheless, it is visible that these studies have not utilized the external factor of SUB extensively or efficiently. It has been suggested in the earlier studies that there is an integral influence of subjective norm on the intention to use mobile learning platforms (IU) [24], [25], [47]–[49]. Hence, the following can be hypothesized:

H7: Subjective norm (SUB) positively affects the intention to use mobile learning platforms (CIT).

G. SATISFACTION

Satisfaction stands for "the affective attitude towards a particular computer application by an end user who interacts with the application directly" [50]. It was determined in earlier studies that there is a strong influence satisfaction on the continuous intention to use various mobile technologies [27]–[29], [51]. Hence, we put forward the following hypotheses:

H8: Satisfaction (SAT) positively affects the intention to use mobile learning platforms (CIT).

The basic research model for current study is given below in the Figure 1 below.

IV. METHODOLOGY

The researchers distributed structured questionnaires among the student of Zayed University, UAE. The researchers randomly distributed n = 300 questionnaires however, the response rate was 93.3% as 7.3% of questionnaires were partially filled and returned [52]. Hence, n = 280 respondents were sufficient for conducting structural equation modeling as the sample size used to validate the study hypothesis [53]. It should be noted here that the researchers postulated the hypotheses on the basis of existing theories and also adapted to the context of e-learning. The measurement model was carefully scrutinized through structural equation modeling (SEM), after which it was treated using the final path model.

A. PERSONAL/DEMOGRAPHIC INFORMATION

There were 55% of female respondents and 45% male respondents. It was noted that 72% of respondents were in the 18-29 age group, whereas 44% of respondents were aged over 28. Regarding education, 30% of the students were enrolled in Business Administration programs, whereas 25%, 19%, 15%, and 11% respectively were enrolled in different programs such as Social Sciences, Arts, Engineering and Information Technology. Most of the participants were university degree holders as 59.0% of participants had bachelor's degree, 26.0% were holding Masters, and 15.0% of respondents were holding Doctorate. Notably we used purposive sampling method, as students were easily accessible for us without any personal bias [54]. So we randomly selected the participants from different institutions from diverse gender and age groups.

B. A PILOT STUDY OF THE QUESTIONNAIRE

We examined the research tool by evaluating their reliability during the pilot study. We selected n = 30 individuals as the total sample size was 300, so using 10% of the sample size was obligating the research standards. We also used IBM Statistical Package for Social Sciences to analyze the internal validity of research tool. We found that, all the research items were successfully higher than the threshold value of 0.7 [55].

Table 1 contains the detailed summary of the Cronbach Alpha values:

C. STUDY INSTRUMENT

We constructed a structured instrument for affirming the proposed hypotheses, containing 27 questions. Table 1 above also contains the sources of each construct. We also revised, and improved the questionnaire to further strengthen its validity and reliability:

Our research questionnaire had three primary sections, including [54]:

- The first section was focused on obtaining demographical data of respondents
- The second section contained, six items concerning mobile-learning systems (attitude, and continuous intention) are discussed.
- The final section comprises 21 items pertaining to expectation confirmation, perceived usefulness, perceived ease of use, perceived behavioral control, subjective norm, satisfaction, and perceived fear.

D. COMMON METHOD BIAS (CMB)

We utilized Harman's single factor assessment to ensure that the data did not have Common method bias [59]. Later, we loaded 10 factors into a single factor, which was comparatively less than the designated value of 0.5 (50%) as the newly created factor contained.24 (24%) of the difference. Consequently, we did not have any Common method bias in the gathered data.

V. STATISTICAL ANALYSIS AND DISCUSSION ON RESULTS

A. STATISTICAL ANALYSIS

We used Partial-Least Square Structural Equation Modeling for the data analysis that was supported by SmartPLS program [60]. Using PLS-SEM helped us to examine the strengthen our structural model and measurements model through gathered data [61]. Notably, we prefer using PLS-SEM due to several reasons.

The first reason is that PLS-SEM it is most effective when the basis of the study is previous research [62]. Second, it is possible to use PLS-SEM efficiently in exploratory studies that consist of complex models [63]. Third, the overall model is analyzed by PLS-SEM as one unit rather than being disintegrated into parts [64]. Finally, concurrent analysis is provided by PLS-SEM hence, it gives us accurate measurements [65].

As we mentioned earlier, this study used a hybrid model for deep learning analysis that adds to the novelty of the current research. Here we followed two primary stages:

First, we utilized SmartPLS to examine the proposed study model through the Partial Least Square-SEM. Due to the introspective nature of our proposed study model we preferred using Partial Least Square-SEM. Also we used Partial Least Square-SEM due to general recommendations

TABLE 1. Measurement items.

Constructs	Items	Instrument	Cronbach's alpha	Sources
Attitude	ATD1	Using ML is a wide idea	0.856	[24], [26], [56]
	ATD2	Like coursework when using ML		
	ATD3	Using ML is a good experience		
Continuous intention	CIT1	Continue using ML	0.801	[24], [26], [27], [56]
	CIT2	Intend to resume using ML		
	CIT3	Not preferring any alternatives		
Expectation confirmation	EC1	Services are better than expected	0.829	[24], [26], [27]
	EC2	My experiences of using ML		
	EC3	Expectations are fulfilled		
Perceived usefulness	PU1	Improved performance	0.783	[24], [26], [27], [56]
	PU2	Accomplishment of tasks		
	PU3	Enhanced efficiency		
Perceived ease of use	PEOU1	Easy and user-friendly	0.863	[24], [26], [27], [56]
	PEOU2	Clear and understandable Interaction		
	PEOU3	Mobile learning is easy to use.		
Perceived behavioral control	PBC1	sufficient self-confidence	0.808	[24], [56]
	PBC2	Sufficient knowledge about mobile learning.		
	PBC3	Sufficient control to use mobile learning.		
Perceived fear	FR1	Lacking concentration during COVID-19.	0.895	[56], [57]

TABLE 1. *(Continued.)* **Measurement items.**

	FR2	Reduced fear due to ML		
	FR3	Chance to cope the lockdown challenges		
Subjective norm	SUB1	Most people are fine to use ML platforms	0.803	[24], [27], [56], [58]
	SUB2	Students would be willing to use ML		
	SUB3	Most people would be in favor of using ML		
Satisfaction	SAT1	I am satisfied with multimedia instructions	0.796	[24], [26], [27]
	SAT2	Satisfied with utilizing learning-assisted tool.		
	SAT3	Satisfied with using ML platforms functions		

of using the relevant technique in the Information Systems inquires [66].

Previous studies recommend twostep process to assess the proposed study model [67]. We used importance performance map analysis to analyze the significance of constructs in the proposed conceptual model. Secondly, we utilized Artificial Neural Network to conducted, examine and validate the impacts of Independent Variables in dependent variables and Partial Least Square-SEM analysis. It is also worthwhile to mention that; Artificial Neural Network works as function approximation tool where the relationship between variables is non-liner and complicated. Artificial Neural Network is comprised of three modalities that involve: transfer function, network architecture, and learning rule, that are further categorized into feed-forward multilayer perceptron (MLP) network, radian basis, and recurrent network [15].

Here MLP network is one of the most preferred methods, which is made up of both inputs and outputs (layers) that are associated by hidden nodes. There are several neurons in the input layer that send raw to the hidden layers known as "synaptic weights". The activation function selected determines the output of every layer and here sigmoidal function is the most preferred active function [68], [69]. Consequently,

the Mobile Learning Platform neural network helps to train and test the proposed conceptual model in this study.

TABLE 2. **Results of convergent-validity analysis.**

Constructs	Items	Factor Loading	CA	CR	PA	AVE
Attitude	ATD1	0.868	0.760	0.782	0.799	0.622
	ATD2	0.826				
	ATD3	0.828				
Continuous intention	CIT1	0.830	0.769	0.810	0.832	0.603
	CIT2	0.706				
	CIT3	0.808				
Expectation confirmation	EC1	0.849	0.806	0.853	0.864	0.590
	EC2	0.884				
	EC3	0.799				
Perceived usefulness	PU1	0.887	0.823	0.826	0.858	0.588
	PU2	0.868				
	PU3	0.888				
Perceived ease of use	PEOU1	0.886	0.808	0.824	0.839	0.732
	PEOU2	0.864				
	PEOU3	0.887				
Perceived behavioral control	PBC1	0.890	0.865	0.831	0.856	0.755
	PBC2	0.800				
	PBC3	0.815				
Perceived fear	FR1	0.756	0.866	0.879	0.881	0.768
	FR2	0.856				
	FR3	0.868				
Subjective norm	SUB1	0.836	0.853	0.829	0.891	0.782
	SUB2	0.830				
	SUB3	0.841				
Satisfaction	SAT1	0.855	0.828	0.844	0.850	0.772
	SAT2	0.850				
	SAT3	0.826				

B. CONVERGENT VALIDITY

According to [61], construct reliability and validity help to assess the internal consistency of the proposed research model. In order to examine the construct reliability, we assess the composite reliability and Cronbach alpha, validity comprises divergent and convergent reliability. Table 2 below shows the details results of composite reliability, which shows its value are ranging between 0.782 and 0.879, which is higher than the threshold values 0.7 [70]. Researcher also consider using Dijkstra-Henseler's rho (pA) reliability coefficient to examine the construct reliability [71]. Table 2 below also exhibits that the reliability coefficient value which is higher than 0.7. Thus the construct validity affirms that all the constructs are validated. We can measure the convergent validity through Factor Loading and Average Variance Extracted (AVE) [61]. As visible in the Table 2, 0.7 is less than all the obtained values. Likewise, apart from this, values in the range of 0.588 to 0.782 were obtained from the AVE, which

are higher than the proposed threshold values. Thus, relying on the findings, we can obtain convergent validity regarding each construct.

C. DISCRIMINANT VALIDITY

It was suggested that the measurement of discriminant validity would require measuring one criteria, i.e. the Heterotrait-Monotrait ratio (HTMT) [61]. The HTMT-ratio findings are presented in Table 3 and it can be seen clearly that the value of every construct is less than 0.85, the threshold value [72]. Hence, the HTMT ratio is confirmed. The discriminant validity is also confirmed with these findings. It is proved by the analytical findings that no issues were found concerning measurement model assessment for its validity and reliability, and therefore the structural model can also be examined using the collected data.

TABLE 3. Heterotrait-Monotrait ratio (HTMT).

	ATD	CIT	EC	PU	PEOU	PBC	FR	SUB	SAT
ATD									
CIT	0.629								
EC	0.399	0.595							
PU	0.228	0.280	0.600						
PEOU	0.202	0.328	0.455	0.120					
PBC	0.328	0.420	0.427	0.284	0.219				
PR	0.399	0.442	0.322	0.165	0.428	0.539			
SUB	0.402	0.566	0.208	0.620	0.566	0.532	0.502		
SAT	0.449	0.657	0.505	0.559	0.385	0.688	0.424	0.552	

D. MODEL FIT

Fit measures are easily available in the Smart-PLS that is exhibited by Chi-square, exact fir criteria, RMS that and others [73]. Standardized Root Mean Square Residual represents the difference between model inferred correlations and observed correlation matrix, where if the value is less than .85, it indicates good fit measures [74], [75]. Normed Fit Index values indicate the Goof Fit Model when they are greater than 0.90 [76].

However, Normed Fit Index is not a Mode Fit predictor due to the larger parameters [74]. It I also notable that, geodesic distance d G and the squared Euclidian distance, are two primary matrices that indicate a difference between empirical covariance by using composite factor model [74], [75].

Standardized Root Mean Square Residual determines the degree of outer model residuals correlation and is according to the reflective models. If the Standardized Root Mean Square Residual that value is zero, to less than 0.12, it indicates a good fit [74], [77].

Table 4 summarizes that RMS theta value is 0.075 INDICTAING the Goodness of Fit is high and sufficient to exhibit the PLS model authenticity.

E. HYPOTHESES TESTING & COEFFICIENT OF DETERMINATION

We utilized used Structural Equation Modelling to assess the proposed study assumptions [78]. SEM facilitated us to assess

TABLE 4. Indicators of model fit.

	Complete Model	
	Saturated Model	Estimated Mod
SRMR	0.049	0.049
d_ULS	0.662	1.373
d_G	0.543	0.543
Chi-Square	471.041	471.041
NFI	0.810	0.810
Rms Theta	0.075	

TABLE 5. R^2 of the endogenous latent variables.

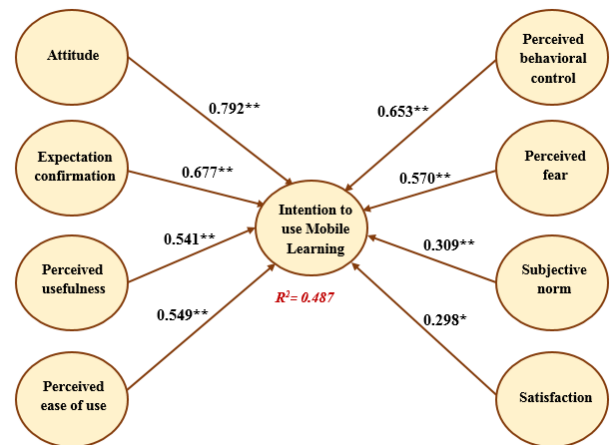| Constructs	R^2	Results
Continuous intention	0.487	Moderate

FIGURE 2. Results of hypotheses testing.

the R^2 value, path and significance values regarding the relationships between the study variables. Table 5 and Figure 2 show the path coefficients and significance. Here we found the coefficient of determination R^2 value for the Continuous Intention is .487 (48.7%), indicating a moderate yet significant predictive power of the research model [30], [79], [80]. Statistical analysis also showed that are proposed hypotheses are strongly significant. We found Data analysis indicated that all the proposed hypotheses are highly significant. The results showed that Intention to Use Mobile Learning has a significant influence on Attitude (ATD) ($\beta = 0.792$, P < 0.001), Expectation Confirmation ($\beta = 0.677$, P < 0.001), Perceived Usefulness (($\beta = 0.541$, P < 0.001), Perceived Ease of Use $\beta = 0.549$, P < 0.001), Perceived Behavioral Control ($\beta = 0.653$, P < 0.001), Perceived Fear (FR) ($\beta = 0.570$, P < 0.001), Subjective Norm (SUB) ($\beta = 0.309$, P < 0.001), and Satisfaction (SAT) ($\beta = 0.298$, P < 0.05). Thus, we found that all the hypotheses are strongly supported. Table 6 and Figure 2 below summarize the hypotheses testing:

F. ANN RESULTS

We used IBM Statistical Package for Social Sciences to conduct the ANN assessment. For the ANN analysis, the SUB,

TABLE 6. Summary of hypotheses validation.

H	Relationship	Path	*t*-value	*p*-value	Decision
H1	ATD -> CIT	0.792	19.598	0.000	Supported**
H2	EC -> CIT	0.677	21.015	0.000	Supported**
H3	PU -> CIT	0.541	8.220	0.003	Supported**
H4	PEOU -> CIT	0.549	6.136	0.004	Supported**
H5	PBC -> CIT	0.653	14.432	0.001	Supported**
H6	FR -> CIT	0.570	18.901	0.000	Supported**
H7	SUB -> CIT	0.309	9.369	0.004	Supported**
H8	SAT -> CIT	0.298	3.226	0.022	Supported*

FIGURE 3. Results of hypotheses testing.

SAT, PU, PEOU, PBC, FR, EC, and ATD variables are taken into account. The ANN model, as seen in Figure. 3, has one output neuron (e.g., intention to use mobile learning) and many input neurons (i.e., SUB, SAT, PU, PEOU, PBC, FR, EC, and ATD). We used one-hidden layer deep Artificial Neural Network to transpire for every output neuron node [81]. The sigmoid function helps to activate the function for both output and hidden neurons in the current research. We also defined the range between input and output neurons between [0, 1]. We further utilized cross-validation methodology (ratio 80:20) for testing and training the gathered data to avoid overfitting in the Artificial Neural Network [68]. The Root Mean Square results of the Artificial Neural Network model of the data are 0.1505 and 0.1617, respectively (see Figure 3). Since the Root Mean Square figures and Standard Deviation for

the data are so minuscule variance (i.e., 0.0057 and 0.0087), along-with the Artificial Neural Network usage, it is possible to conclude that the proposed research model achieves greater efficiency.

TABLE 7. Independent variable importance.

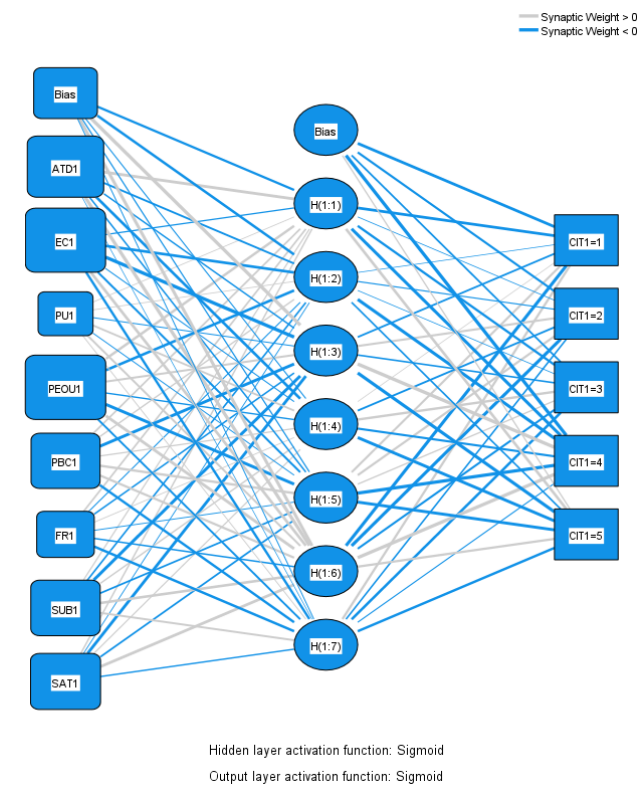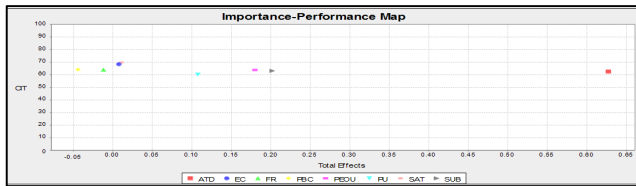|	Importance	Normalized Importance
ATD	.183	100.0%
EC	.182	99.0%
PU	.044	24.0%
PEOU	.162	88.2%
PBC	.121	66.0%
FR	.058	31.8%
SUB	.123	67.1%

G. SENSITIVITY ANALYSIS

We mentioned normalized and mean importance of all the predictors related to Artificial Neural Network in the Table 7 below. Findings of the sensitivity analysis indicated that, ATD is the most prominent determinant of the designated behavioral intention. Further, we examined the goodness of fit, to affirm the performance and accuracy of Artificial Neural Network and found that with the R^2 of 81%, is greater than that of $R^2 = 48.7\%$. Thus, these results showed that, Artificial Neural Network technique articulated endogenous constructs more consistently than the PLS-SEM technique. Moreover, the despairing variances are due to deep learning Artificial Neural Network's dominance in indicating non-linear relationship between the research variables.

H. IMPORTANCE-PERFORMANCE MAP ANALYSIS

We utilized Importance-Performance Map Analysis in Partial-Least Square- Structure Equation Modelling alongwith the behavioral intention as the main variable in the current research. According to [82], Importance-Performance Map Analysis helps to describe the comprehensive details about the Partial-Least Square- Structure Equation Modelling-based research [82]. In this study, we assessed the performance and significance of the eight primary variables (See Figure 4 for detailed overview). As visible that, the ATD has the highest scores regarding the significance and performance measures, SUB has he second highest scores, PEOU attains the third highest score, that is the lowest score uptill now. However, despite the lowest sore, PEOU is highly compatible with the EC, PBC, FR, and PN.

VI. DISCUSSION

The present study's findings appear to be consistent with prior studies on the significance of TAM and TPB variables [31], [33], [34], [83]. During the propagation of COVID-19, it appears that students' willingness to consider technology is greater as there are no other alternatives open than ML

FIGURE 4. IPMA results.

technology as a study tool. The findings related to PU and PEU are aligned with prior studies in that both PU and PEU have a major impact on students' acceptance of ML, stressing their significance as measures for students' intention to use ML in a particular situation such as the propagation of COVID-19. Furthermore, PEU has a major impact on PU, implying that once a technology is rated as simple, it is implicitly deemed useful.

In terms of the subjective norm (SN), the findings show that there is a clear connection between subjective norm and student acceptance of ML. Students' acceptance of ML is said to be affected substantially by their classmates' responses, presence, and actions in class as a result of ML. The connection between SN and students' acceptance of ML is consistent with previous research [34], [43]–[45], which found that UAE students are highly influenced by their classmates' conduct, which may provide a feeling of security and relaxation in joining classes throughout the pandemic period. When the same class is shared with a group of colleagues, students are more profoundly inspired to use ML. Moreover, the factors PEU and PU have an important impact on SN. The findings reveal that classmates' and teachers' behaviors and accessibility can help to encourage ML as a medium for learning during the pandemic period, as they are more likely to see it as valuable, low-effort, and exciting. These results appear to be in line with former research [84], which found that input from teachers and classmates has a significant impact on students' attitude towards perceived technology's efficacy.

One of the most important hypotheses in the present study is that the fear factor emerges as a result of the propagation of COVID-19. COVID-19 is a pandemic that has wreaked havoc on human societies. Since the risk of propagation is very significant, the lockdown and stay-at-home policy [85] has been implemented. This research used a model that is thought to be beneficial for future studies because it gives an insight into COVID-19's impact throughout the pandemic. The fear factor is noticeable at this time, according to the study's findings, but ML is a good tool for reducing the fear of teachers and students. As a result, perceived fear (PF) has a big impact on the factors PEU and PU. The results indicate that the PF is present during the pandemic, but that ML has a high level of PEU, and PU has lowered the fear factor and enabled students to join regular classes.

A. MANAGERIAL IMPLICATIONS OF THE STUDY

This is one of the initial attempts to: (1) theoretically incorporate the concept of fear into a hybrid model of TAM, ECM and TPB, (2) empirically examine the effect of COVID-19 on mobile application of users, and (3) investigate the influence of the Coronavirus pandemic on users' potential to use the mobile application easily and attitude towards the usefulness of mobile learning platforms. Prior studies have looked at the role of fear from various angles, like fear of technology [8], and found that negative perceptions can affect the ease of use and perceived usefulness directly or indirectly. This means that our implications are the same as Bhattacherjee and Hikmet's implications, and fear would have a detrimental impact on technology use. As a result, we show empirically that the perceived fear during an illness should be a primary variable in any adoption model.

B. THEORETICAL IMPLICATIONS

In terms, of methodology, unlike prior empirical studies that mainly depended on SEM analysis, this study uses a hybrid SEM-ANN technique developed on deep learning to add to the literature in general and the m-learning domain in particular. The ANN model has a much higher predictive power than the PLS-SEM model. The higher predictive power achieved by ANN analysis, we conclude, stems from the deep ANN architecture's potential to identify non-linear associations between the factors in the theoretical model.

C. LIMITATIONS AND FUTURE RESEARCH

Despite major contributions, our research has some notable limitations as well. First, we collected the data only from one institution that a major question when the same variables would be used in other situational contexts. Second, we used convenience sampling technique, which is another major limitation. However, by keeping these relevant limitations under consideration, we suggested more studies to examine the Mobile Learning by using the proposed hybrid-study model.

D. RECOMMENDATIONS

In online teaching, a mobile learning platform is deemed as a secure platform, during the healthcare crisis. It's being suggested as a promising teaching option during the lockdown. When the city of Abu Dhabi is in a state of contamination, the accessibility of ML has provided both teachers and students with a sense of security and an urgent communication channel. The benefits of a mobile learning platform over other modes of communication are numerous. First and foremost, it is a smartphone and laptop application. This fact allows students at Zayed University to conveniently attend classes through their mobile phones. Another most significant factor is that the provided links can be used many times that help the students to stay connected with their instructors anytime they want. Lastly, students feel more confident and fear is decreased to the lesser level.

Therefore, it seems that the results are consistent with those obtained in earlier studies in terms of the significance of TAM, ECM, and TPB variables [31], [33], [34]. The students' intention to adopt technology appears to be greater when no other sources are available, apart from ML technology,

as tools for studying while COVID-19 is spreading. The results attained with respect to PU and PEOU compatible with earlier research which showed a significant impact of PU and PEU on accepting Mobile Learning, which lays greater stress on their significance as determinants of students' intention to use ML, particularly when COVID-19 is spreading. In addition, there is a strong significant influence of PEOU on PU, which suggests that, when technology is considered easy to use, it is implicitly implied.

With respect to subjective norm (SUB), it is shown in the findings that this is strongly related to students' acceptance of ML. This acceptance is considered to be affected to a significant extent by the reactions, behavior and existence of their classmates within classrooms. SUB and students' acceptance of ML are found to have the same relationship as that determined in earlier studies such as [34], [43]–[45], where UAE students are found to be significantly affected by the way in which their classmates behave, as this may provide a feeling of comfort and safety regarding attending classes during the Covid-19 outbreak. There is higher intrinsic motivation among students to employ ML when they share the same class with their colleagues. In addition, the variables PEOU and PU have a significant impact on SUB. It has been shown in the findings that the use of ML as a learning instrument during the pandemic period may be promoted by the peers' and instructors' attitude; for example, when they exhibit greater readiness to consider it as being useful and effortless, as well as enjoyable. It seems that these findings are similar to those obtained in an earlier study [84] which confirmed that the students' attitude towards perceived usefulness of technology can be significantly affected by feedback from teachers and peers. One of the critical hypotheses in the present study is the fear factor which emerges because of the spread of COVID-19. This virus is a type of pandemic that has had a severe impact on humans. There is very high likelihood of the virus spreading, which has led to the implementation of lockdown and stay-at-home orders [85], [86]. A model has been used in this study that is considered to have potential for subsequent research because it concentrates on the impacts of COVID-19. On the basis of the findings of this study, it is clear that the fear factor exists; however, ML has been found to be an effective technique for decreasing the fear experienced by educators and peers. There is a significant impact of perceived fear (FR) on the variables PEOU and PU. It has been determined in the responses that PF is clearly present in the pandemic period; however, as ML has significant PEOU and PU, the fear factor has decreased and students are encouraged to participate in scheduled lectures. It is important to discuss various limitations that exist. First, one should be careful about generalizing the current results to the other educational institutions in the United Arab Emirates and other countries. This is because of two reasons: (1) only two institutions were used to obtain the samples; and (2) the researcher used convenience sampling technique to choose the participants. More studies should focus on the relevant issues to improve generalization of the results. Second, the focus was

on evaluating the use of mobile -learning systems by the young students only. Additional studies should determine the instructors' use of mobile learning systems so that more information can be obtained on the influencing factors and a complete picture obtained regarding the implementation of these systems.

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KHADIJA ALHUMAID received the Ph.D. degree in curriculum development from the University of Kansas, KS, USA. She joined Zayed University as an Assistant Professor with the Humanity and Social Sciences, in 2014. She held a position of the Chair of Department of Arabic Language, in 2016. She is currently an Assistant Professor with the College of Education, Zayed University. She has taught a wide range of undergraduate courses in both H&SS and Education Colleges. She has joined as a Mentor for the participants in Ta'alouf Teacher Training Program and mentorship sponsored by Al Jalila Foundation, in 2020. She has participated in national and international conferences, where she presented her research work. She has also published her work in several prestigious journals. Her research interests include the development of novel teaching strategies and curriculum design, and integrating technology into the learning and teaching methods. She has served as a member for the Curriculum Development Committee, Ministry of Education, United Arab Emirates, from 2015 to 2018. She has recently granted an Award of Sheikh Saud Bin Saqr AlQasmi Foundation for Policy Research Grand.

MOHAMMED HABES received the B.Sc. and M.Sc. degrees in mass communication (radio and television) from Yarmouk University, and the Ph.D. degree in television and digital media from the Faculty of Applied Social Sciences, Universiti Sultan Zainal Abidin (UniSZA), Kuala Terengganu, Malaysia. He does research in digital media, social media marketing, media studies, social TV, television studies, and academic development. His research interests include quantitative research methods and partial least squares-structural equation modeling (PLS-SEM).

SAID A. SALLOUM received the bachelor's degree in computer science from Yarmouk University, and the M.Sc. degree (Hons.) in informatics (knowledge and data management) from The British University in Dubai. He is currently working with the Research Institute of Sciences and Engineering (RISE), University of Sharjah, as a Researcher. He works in different research areas in computer science, including data analysis, machine learning, knowledge management, and Arabic language processing. Since 2013, he has been an oracle expert with several internationally recognized certificates.

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