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Investigating students' behavioral intention to use mobile learning in higher education in UAE during Coronavirus-19 pandemic

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A B S T R A C T

The study explores the impacts of fear emotions on technology adoption by teachers and students during the COVID-19 pandemic. Mobile learning (ML) has been considered an educational, social platform in private and public higher education institutes. Since several fears are connected with COVID-19, this study's key hypotheses are related to how COVID-19 influences Mobile Learning (ML) adoption. Educators, teachers, and students may face some common types of fear in the course of the coronavirus pandemic, such as fear of losing social relationships, fear of educational loss and failure, and fear because of the lockdown of the family in the prevailing circumstances. Different theoretical models, named Expectation-Confirmation Model (ECM) and Technology Acceptance Model (TAM), are combined to develop an integrated model for this study. The proposed model was analyzed with the development of a questionnaire survey. The survey served as a data collection instrument to collect data from students of the University of Sharjah in Sharjah city in the United Arab Emirates (UAE). Three hundred twenty undergraduate students participated in the study. The collected data was evaluated using the partial least squares-structural equation modeling (PLS-SEM). The significant predictors revealed by experimental results included perceived fear, perceived ease of use, expectation confirmation, satisfaction, and perceived usefulness, explaining the intention to use the mobile learning platform. According to our study, teaching and learning can be benefitted to a great extent by the adoption of mobile learning (ML) during this pandemic for educational purposes; however, this process may be negatively affected by the fear of future educational results, fear of losing social relations and fear of stressful family situations. Therefore, appropriate student evaluation may be conducted to overcome the emotional distress caused by the pandemic effectively.

1. Introduction

Various forms of fear emotions have been focused on by different earlier studies related to adoption. Anxiety, for example, is perceived as a key factor in many research studies that challenge the adoption of technology. In the educational sector, anxiety influences the adoption of technology by students. The dearth of experience and expertise, as well as anxiety, can contribute to the lack of interest in technology use. The fear associated with the use of technology is another key factor that affects the usage of technology or technology adoption which in turn is affected by anxiety and literacy. Thus, instructors and tutors need

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to concentrate on this physiological aspect and equip students with the skills and knowledge to allow them to willingly accept the technology. Additional underlying factors within the educational sector are the lack of technical readiness and preparedness which harm the adoption of technology (Mac Callum & Jeffrey, 2014; Nchunge et al., 2012; Al Hamad, 2016; AlHamad et al., 2014; Elshamy et al., 2017; Thatcher & Perrewe, 2002; Al Kurdi et al., 2020; Alsharari & Alshurideh, 2020). Other than the educational sector, other domains also demonstrate fear of technology adoption. In the health sector, the primary concern of patients is health anxiety which refers to the anticipation or uncertainty of patients regarding certain consequences that reflect serious illness. Due to this reason, studies in the health sector are focused on the negative impacts of perceived risk and anxiety on using technology (Kamal et al., 2020; Meng et al., 2020). In the banking industry, there are various kinds of concerns that originate from the mindset and perception of consumers towards technology. Most consumers show reluctance and hesitation in using their data while using the mobile payment option. Different studies have indicated that in addition to lack of trust and experience, the customers' fear about facing a fraudulent situation adversely affects the adoption of mobile banking (Bailey et al., 2020; Makttoofa et al., n.d.). Moreover, considering the use of technology within the household, people are not willing to resort to the use of technology in household tasks due to the fear associated with technology and a greater number of household tasks. Various kinds of fears experienced in various sectors as well as the models adopted have been shown in Table 1. The challenges of fear and technology acceptance have been discussed in recent research. These recent studies are based on TAM model (Bailey et al., 2020; Bhattacherjee & Hikmet, 2007; Kamal et al., 2020; Mac Callum & Jeffrey, 2014; Makttoofa et al., n.d.; Nchunge et al., 2012) as well as other models (Brown & Venkatesh, 2005; Johnston & Warkentin, 2010; Meng et al., 2020; Thatcher & Perrewe, 2002). Most of these studies evaluate the impact of the factor of fear of using technology on technology acceptance. Different users have given varying justifications on the point of fear of using technology. A few users indicated that fear of using technology is dependent on an individual's self-confidence. It is obvious that a working human is likely to make errors which is acceptable, but this contributes towards the fear factor (Gresham, 2020). While some do not prefer to use technology because in their opinion, it is time consuming, and they fail to finish the task in the required time (Gerhold, 2020). On the other hand, the factor of fear of breach of data privacy was focused on other acceptance studies which further highlights security and privacy concerns (Distler et al., 2020). The individual's intentions to engage or perform a behaviour have been described extensively in the literature (Ajzen, 2020). Many psychological theories and models were developed to describe the factors that would influence a person intention to engage or perform a behavior (Alhamad & Donyai, 2020; Alshamsi et al., 2020; Bettayeb et al., 2020; Alhamad & Donyai, 2021; Alhamad et al., 2018). The selection of a model that can fulfil the research objective can be determined based on whether the behaviour is health related or not. In this study, TAM model was selected to capture student's behavioural intentions to use mobile learning in higher education in UAE during Coronavirus-19 pandemic.

2. Theoretical model and research model

In this study, the research model is developed by integrating the perceived fear construct with the theoretical models of ECM and TAM. This study also suggested the major impact of perceived fear on perceived ease of use (PEOU) as well as perceived usefulness (PU) of m-learning systems. Moreover, it is recommended that expectation confirmation would influence satisfaction. It is also supposed that the continuous intention of using m-learning systems would be influenced by perceived usefulness, perceived ease of use, and satisfaction. The proposed theoretical model can be seen in Fig. 1.

2.1 Perceived Fear

In December 2019, the first case of novel coronavirus disease appeared in China, and then the entire world was in the grip of this outbreak that affected millions of people. According to recent studies, in this pandemic period, the most significant reaction that prevailed extensively was the feeling of fear. As per the scale of the Health Anxiety Inventory (HAI), the greatest score was attained by the fear factor (Nicomedes & Avila, 2020). While different researches suggest that in case of a real risk, the sense of fear can be seen as a favorable perception, however, the fear factor associated with Coronavirus has become a source of constant stress and anxiety. The fear factor associated with COVID-19 may be evident in the form of health anxiety, a sense of uncertainty, and the risk of loved ones getting infected and it has posed two important concerns: the high possibility of being infected by the virus and the high degree of worry (Ahorsu et al., 2020; Gerhold, 2020).

This study is focused to examine the association of the external factor namely the Perceived Fear (PF) with the adoption of technology using TAM. Hence, this study tries to control the limitation of the TAM model which involves the execution of context-specific external factors (Tarhini et al., 2015). This TAM limitation is controlled by evaluating impacts of factors like perceived fear (PF) as well as PU, PEOU, and SN. The following hypothesis is proposed based on this assumption:

H_1: Perceived fear (FR) positively affects the perceived ease of use of mobile learning platforms (PEOU).
H_2: Perceived fear (FR) positively affects the perceived usefulness of mobile learning platforms (PU).

2.2 Expected-confirmation

The "users' perceptions of the congruence between the expectation of information system usage and its actual performance " is termed as the expectation-confirmation (Bhattacherjee, 2001). According to earlier research, expectation-confirmation has a substantial effect on PU and satisfaction of numerous mobile technologies (Al-Emran et al., 2020; Alshurideh et al., 2020; Le et al., 2020; Nascimento et al., 2018). Thus, the subsequently mentioned recommendations are put forward:

H$_3$: Expectation-confirmation (EC) positively affects the perceived usefulness of mobile learning platforms (PU).
H$_4$: Expectation-confirmation (EC) positively affects the satisfaction of mobile learning platforms (SAT).

2.3 TAM

The TAM model measures several elements and one of them is the confirmation of an external factor on personal beliefs. Since the model can elucidate how people tend to accept technology specifically within the educational institutions, it is considered as the most influential model (Al-Maroof & Al-Emran, 2018; Fred D Davis, 1989; Teo, 2012; Venkatesh & Bala, 2008). As per TAM, two diverse perceptions may be evaluated through the mutual key factors of perceived ease of use (PEU) and perceived usefulness (PU).

"The degree to which a person believes that using a particular system would enhance his or her job performance" is referred to as the perceived usefulness (PU) (Fred D Davis, 1989). The previous studies suggested that PU has a substantial impact on the continuous intention to make use of numerous mobile technologies (Alshurideh et al., 2020; Joo et al., 2016; Le et al., 2020; Nascimento et al., 2018). Whereas, "the degree to which a person believes that using a particular system would be free of effort" is referred to as perceived ease of use (PEU) (Davis, 1989). The previous studies indicated that PEU has a substantial impact on the continuous intention to use m-learning systems (Alshurideh et al., 2020; Joo et al., 2016; Le et al., 2020; Nascimento et al., 2018).

Based on prior assumptions, in case the consumers consider technology to be easy to use, there is a high probability for them to have a favorable attitude about the technology; thus, the perceptions of the user about the usefulness and effectiveness of technology are important. Likewise, when consumers perceive technology as beneficial, there is a high probability for them to show a willingness to adopt the technology. The subsequently mentioned hypothesis is proposed for executing prior assumptions in the current model.

H$_5$: Perceived ease of use (PEOU) positively affects the perceived usefulness of mobile learning platforms (PU).
H$_6$: Perceived usefulness (PU) positively affects the satisfaction of mobile learning platforms (SAT).
H$_7$: Perceived ease of use (PEOU) positively affects the intention to use a mobile learning platform (CIT).
H$_8$: Perceived usefulness (PU) positively affects the intention to use a mobile learning platform (CIT).

2.4 Satisfaction

"The effective attitude towards a particular computer application by an end-user who interacts with the application directly" is termed as satisfaction. The previous studies indicated a substantial impact of satisfaction on the continuous intention to use numerous mobile technologies (AlHamad & Al Qawasmi, 2014; AlHamad et al., 2012; Alshurideh et al., 2020; Alshurideh et al., 2021; Alshurideh et al., 2018; Alshurideh, 2019; Le et al., 2020; Alshurideh et al., 2012; Nascimento et al., 2018; Tam et al., 2018; Alshurideh et al., 2021). Hence, we hypothesize that:

H$_9$: Satisfaction (SAT) positively affects the intention to use a mobile learning platform (CIT).

Fig. 1 shows the hypotheses on which the proposed research model is based. First, the theoretical model is shaped into a structural equation model and after that, it is evaluated through machine learning methods.

3. Research methodology

3.1 Data collection

The data for the study was obtained from the students enrolled in winter semester 2020/2021 of the United Arab Emirates between 10-January 2020 and 04-February 2020 using a randomly distributed online-survey. The total response rate of 80% was achieved as 320 respondents out of 400 submitted the filled questionnaire. Out of these filled questionnaires, 80 were rejected because they had missing information thus making a total of 320 questionnaires effective as they were filled properly. According to (Krejcie & Morgan, 1970), the number of effective questionnaires (320) to be used in the study for evaluation of collected data is adequate as the suggested sampling size is 306 respondents in a population of 1500. In this case, Structural Equation Modeling (SEM) is acceptable because the sample size of 320 is much higher than the minimum requirements of 306 (Chuan & Penyelidikan, 2006). Therefore, this sample size was used for hypothesis testing. Although the hypotheses used were found on current theories, they also proved to be efficient in the m-learning context. To evaluate the measurement model, Structural Equation Modeling (SEM) was used while the final path model was applied subsequently.

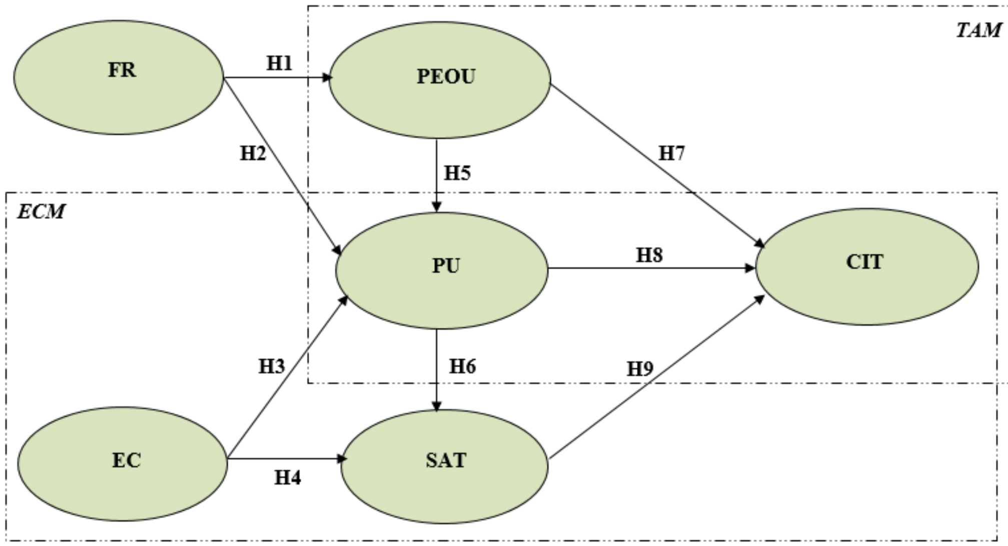

Fig. 1. The study model

3.2 Students' personal information / Demographic Data

The percentages of male and female students who participated in the study were 43% and 57% respectively. Out of all respondents, 82% belonged to the age group from 18 to 29 whereas the rest of the respondents i.e. 18% had ages above 29. As far as the educational background is concerned, students enrolled in Business Admiration were found to be 33% whereas 23%, 19%, 15%, and 10% of the students were enrolled in Engineering, Mass Communication and Public Relations, Arts, Social Sciences; Humanities, and Information Technology respectively. In the case of voluntary participation of the respondents, (Mostafa Al-Emran & Salloum, 2017) suggested using the "purposive sampling approach". This is an appropriate approach as it involves students having different ages, enrolled in different programs of different colleges at different levels. The demographic data for the study was measured using IBM SPSS Statistics ver. 23.

3.3 Study instrument

A questionnaire survey was prepared and distributed among students (Mostafa Al-Emran & Salloum, 2017). The following three sections make up the survey.

- The first section of the survey collects the participant's data.
- The second section of the survey focuses on the 8 questions that investigate mobile-learning systems (continuous intention, perceived usefulness, and perceived ease of use).
- The third and last section of the survey comprises 9 elements that signify expectation confirmation, perceived fear, and satisfaction.

All 17 items have been measured using a five-point Likert Scale composed of the following 5 scales: strongly agreed (5), agree (4), neutral (3), disagree (2), and strongly disagree (1).

4. Findings and discussion

4.1 Data Analysis

A software named SmartPLS V.3.2.7 and its partial least squares-structural equation modeling (PLS-SEM) was used to commence the data analysis of this study (Ringle et al., 2015). The assessment model based on two structural and measurement models was employed to analyze the collected data (Hair et al., 2017). Various reasons led to the employment of PLS-SEM for this study. First, PLS-SEM is considered to be the ideal option when it comes to the development of an existing theory (Urbach & Ahlemann, 2010). Second, when complex models need to be analyzed in the study, PLS-SEM works effectively (Hair et al., 2016). Third, PLS-SEM does not involve fragmentation of model rather it involves the analysis of complete model (Goodhue et al., 2012). Lastly, PLS-SEM provides more precise estimations by conducting simultaneous analysis for both structural model and measurement model (Barclay et al., 1995).

4.2 Convergent validity

According to Hair et al., (2017), the validity including discriminant and convergent validity and; construct reliability including composite reliability (CR), Cronbach's alpha reliability (CA), and Dijkstra Henseler's (PA) should be estimated in order to assess the measurement model. The data illustrated in Table 1 can help evaluate the construct reliability. According to the results, Cronbach's alpha values are between 0.788 and 0.851; hence, exceeding the 0.7 threshold value. The results in Table 1 also indicate that the values of composite reliability (CR) ranged between 0.759 to 0.889 which were all above the recommended value of 0.7 (Nunnally & Bernstein, 1994). The construct reliability can also be calculated using Dijkstra-Henseler's rho (pA) reliability coefficient (Kline, 2015). In the case of exploratory levels of research, a recommended value of 0.7 just like CA and CR must be attained for the reliability coefficient ρA whereas, in the case of advanced research levels, values exceeding 0.80 or 0.90 must be attained for ρA (Hair et al., 2011; Henseler et al., 2009; Nunnally & Bernstein, 1994). The data illustrated in Table 1 shows that the reliability coefficient ρA value for each construct is greater than 0.70. In accordance with these results, all the constructs were observed to be sufficiently error-free; thus, confirming construct reliability. In order to measure convergent validity, it is recommended to test the Average Variance Extracted (AVE) and the factor loading (Hair et al., 2017). According to the results of factor loadings given in Table 1, the values exceed the threshold value of 0.7. Moreover, the AVE values depicted in Table 1 were between 0.606 and 0.783; hence, exceeding the 0.5 threshold value. Under these results, it is concluded that the convergent validity for all constructs might be evaluated efficiently.

4.3 Discriminant validity

To measure the discriminant validity one parameter i.e., the Heterotrait-Monotrait ratio (HTMT) was recommended to be measured (Hair et al., 2017). The results in Table 2 reveal that the HTMT ratio value of each construct is below the threshold of 0.85 (Henseler et al., 2015); hence confirming the HTMT ratio. The discriminant validity is determined using all of these results. These outcomes reveal that the reliability and validity of the measurement model were effectively assessed; thus, the structural model can be assessed based on the collected data.

Table 1
Convergent validity results which assure acceptable values (Factor loading, Cronbach's Alpha, composite reliability, Dijkstra-Henseler's rho ≥ 0.70 & AVE > 0.5).

Constructs	Items	Factor Loading	Cronbach's Alpha	CR	PA	AVE
Continuous intention	CON1	0.722	0.788	0.759	0.782	0.714
	CON2	0.780				
Expectation confirmation	EXP1	0.804	0.851	0.835	0.846	0.665
	EXP2	0.866				
	EXP3	0.784				
Perceived usefulness	PU1	0.894	0.814	0.799	0.803	0.606
	PU2	0.801				
	PU3	0.856				
Perceived ease of use	PEU1	0.860	0.866	0.779	0.786	0.630
	PEU2	0.853				
	PEU3	0.839				
Perceived fear	PF1	0.823	0.802	0.889	0.892	0.783
	PF2	0.800				
	PF3	0.828				
Satisfaction	SAT1	0.801	0.841	0.803	0.810	0.767
	SAT2	0.799				
	SAT3	0.858				

Note Continuous intention; EXP, Expectation confirmation; PU, Perceived usefulness; PEU, Perceived ease of use, Perceived fear; SAT, Satisfaction.

Table 2
Heterotrait-Monotrait Ratio (HTMT).

	CON	EXP	PU	PEU	PF	SAT
CON						
EXP	0.353					
PU	0.169	0.211				
PEU	0.127	0.205	0.353			
PF	0.126	0.587	0.251	0.440		
SAT	0.339	0.663	0.555	0.533	0.632	

Note Continuous intention; EXP, Expectation confirmation; PU, Perceived usefulness; PEU, Perceived ease of use, Perceived fear; SAT, Satisfaction.

4.3 Hypotheses testing and coefficient of determination

To test the aforementioned 9 hypotheses altogether, the structural equation modeling (SEM) was utilized (Davis et al., 1992). The path significance of each hypothesized connection and the variance (R^2 value) described by every path in the research model were evaluated. The standardized path significance and path coefficients are represented in Table 4 and Figure 2. The data given in Table 3 reveals that the R^2 values for the adoption of ML, continuous intention, perceived usefulness, perceived ease of use, and satisfaction lie in between 0.733 and 0.817 exhibiting high predictive power of these constructs (Liu et al., 2005). According to the data analysis, the empirical data supported hypotheses H1, H2, H3, H4, H5, H6, H7, H8, and H9.

The results showed that perceived fear (FR) significantly influenced perceived ease of use (PEOU) (β= 0.453, P<0.001) supporting hypotheses H1. Perceived usefulness (PU) has significant effects on perceived fear (FR) (β= 0.369, P<0.001), expectation confirmation (EC) (β= 0.441, P<0.05), and perceived ease of use (PEOU) (β= 0.538, P<0.05) supporting hypothesis H2, H3, and H5 respectively. Expectation confirmation (EC) has significant effects on satisfaction (SAT) (β= 0.211, P<0.05); hence H4 is supported. Perceived usefulness (PU) was determined to be significant in affecting satisfaction (SAT) (β= 0.218, P<0.05), supporting hypotheses H6. Finally, continuous intention (CIT) was determined to be significant in affecting perceived ease of use (PEOU) (β= 0.751, P<0.05), perceived usefulness (PU) (β= 0.507, P<0.05), and satisfaction (SAT) (β= 0.240, P<0.05), supporting hypothesis H7, H8, and H9 respectively. A summary of the hypotheses testing results is shown in Table 4.

Table 3
R^2 of the endogenous latent variables.

Constructs	R^2	Results
CIT	0.739	High
PEOU	0.733	High
PU	0.817	High
SAT	0.755	High

Note CIT, Continuous intention; PU, Perceived usefulness; PEOU, Perceived ease of use; SAT, Satisfaction.

Table 4
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	FR -> PEOU	0.453	10.471	0.002	Positive	Supported**
H2	FR -> PU	0.369	9.133	0.001	Positive	Supported**
H3	EC -> PU	0.441	3.876	0.025	Positive	Supported*
H4	EC -> SAT	0.211	2.358	0.022	Positive	Supported*
H5	PEOU -> PU	0.538	4.264	0.041	Positive	Supported*
H6	PU -> SAT	0.218	4.029	0.033	Positive	Supported*
H7	PEOU -> CIT	0.751	5.100	0.013	Positive	Supported*
H8	PU -> CIT	0.507	14.157	0.022	Positive	Supported*
H9	SAT -> CIT	0.240	4.152	0.025	Positive	Supported*

Note CIT, Continuous intention; EC, Expectation confirmation; PU, Perceived usefulness; PEOU, Perceived ease of use; SAT, Satisfaction; FR, Perceived fear.

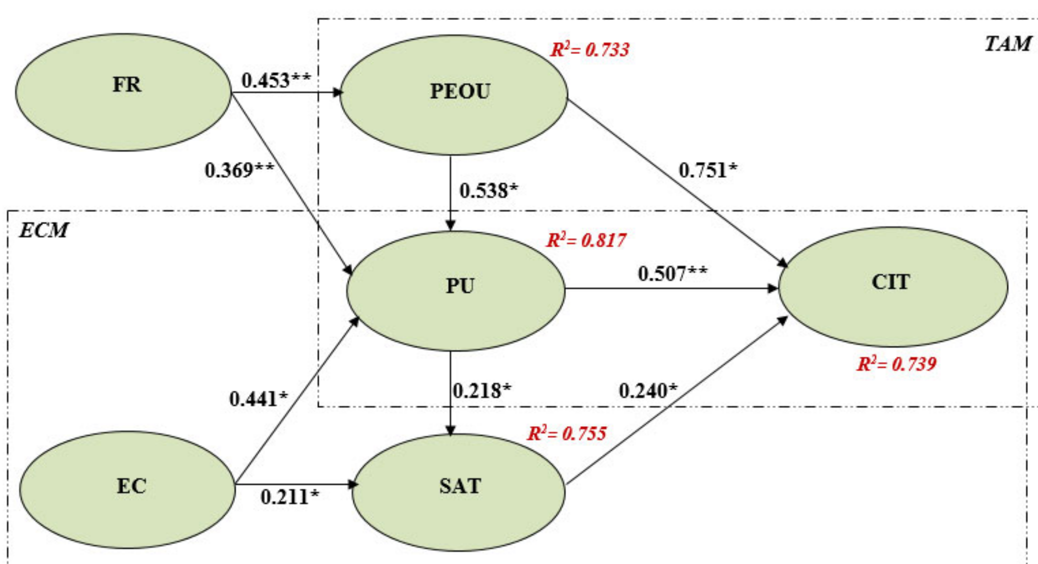

Fig. 2. Hypotheses testing results (significant at p** < = 0.01, p* < 0.0

6. Conclusion and discussion

The findings of the current study tend to show agreement with prior studies in terms of the significance of TAM and ECM variables (Davis, 1989; Teo, 2012; Venkatesh & Bala, 2008). Due to the absence of learning resources other than ML technology, the students have no option but to use ML technology, and hence their intention towards the adoption of ML is higher during the COVID-19 scenario. From previous studies, it was found that the results of PU and PEU are consistent i.e. both substantially affect the acceptance of ML by students. Both these factors indicate the intention of students regarding the use of ML during the spread of COVID-19. Furthermore, PU is significantly affected by PEU, which suggests that in case people perceive a technology to be easy-to-use, they are more likely to deem it as useful for them. In this study, a crucial hypothesis was represented by the fear factor that emerges due to the risk of COVID-19. The human population is severely affected by the COVID-19 pandemic and the high possibility of the spread of this virus has led to the enforcement of lockdown and stay-at-home strategies (Hamza Alhamad et al., 2020). (Zhang et al., 2020). The model used in this study is significant for future research because it highlights the impact of the COVID-19 pandemic period. According to the findings obtained from the study, the fear factor is apparent during the COVID-19 scenario, however, the fear of the learners and instructors was suppressed to a great extent because of the availability of ML teaching methods. Consequently, the perceived fear (PF) significantly impacted the variables PU and PEU. The findings reveal that despite the widespread prevalence of the PF throughout COVID-19 pandemic, the high extent of PU and PEU offered by ML was successful in suppressing fear factor to great extent and motivated students to appear in the classes as per schedule. Several significant limitations were also identified. The foremost limitation is that the study findings cannot be easily generalized to higher educational institutes other than the participating ones and similarly cannot be easily generalized to other international institutes. This is due to 2 reasons: (a) the inclusion of participants from only 2 institutes, and (b) the use of convenience sampling technique for selecting the participants. Future research must address these limitations so that generalized results can be obtained. Second, only students were focused in this study for evaluating the actual use of m-learning systems. In order to get detailed insights into the impacting factors and achieve a comprehensive result of these systems' implementation, future attempts are highly encouraged to evaluate the actual use of the m-learning system from the perspective of instructors and teachers as well.

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