International Journal of Data and Network Science 6 (2022). 669–682

Contents lists available at GrowingScience

International Journal of Data and Network Science

homepage: www.GrowingScience.com/ijds

An empirical study of e-learning post-acceptance after the spread of COVID-19

Ashraf Elnagar[a], Noha Alnazzawi[b] , Imad Afyouni[a], Ismail Shahin[c], Ali Bou Nassif[d] and Said Salloum[d]

[a]*Computer Science Department, University of Sharjah, Sharjah, United Arab Emirates*
[b]*Department of Computer Science and Engineering, Yanbu University College, Royal Commission for Jubail and Yanbu, Yanbu Industrial City, Saudi Arabia*
[c]*Electrical Engineering Department, University of Sharjah, Sharjah, United Arab Emirates*
[d]*Computer Engineering Department, University of Sharjah, Sharjah, United Arab Emirates*
[d]*School of Science, Engineering, and Environment, University of Salford, Manchester,, United Kingdom*

C H R O N I C L E

Article history:
Received: October 10, 2021
Received in revised format: November 20, 2021
Accepted: April 5, 2022
Available online: April 5 2022

Keywords:
Acceptance of e-learning platform
Fear of vaccination
Perceived routine use
Perceived enjoyment
Perceived critical mass
Self-efficiency

A B S T R A C T

There are various reasons why vaccine fear has resulted in public rejection. Students have raised concerns about vaccine effectiveness, leading to hesitation when it comes to vaccination. Vaccination apprehension impacts students' perceptions, which has an impact on the acceptability of an e-learning platform. As a result, the goal of this study is to look at the post-acceptance of an e-learning platform using a conceptual model with several factors. Every variable makes a unique contribution to the e-learning platform's post-acceptance. In the current study, TAM variables were combined with additional external factors such as fear of vaccination, perceived routine use, perceived enjoyment, perceived critical mass, and self- efficacy, all of which are directly associated with post-acceptance of an e-learning platform. Here, a hybrid conceptual model was used to evaluate the newly widespread use of e-learning platforms in this area in this study in the UAE. In the past, empirical investigations primarily used Structural Equation Modeling (SEM) analysis; however, this study used a developing hybrid analysis approach that combines SEM with deep learning–based Artificial Neural Networks (ANN). This study also employed the Importance–Performance Map Analysis (IPMA) to determine the significance and performance of each element. Through the findings, it was found that fear of vaccination, perceived ease of use, perceived usefulness, perceived routine use, perceived enjoyment, perceived critical mass, and self-efficiency all had a significant impact on students' behavioral intention to use the e-learning platform for educational purposes. It was also shown in the analysis of ANN as well as IPMA that the perceived ease of use of the e-learning platform is the most important indicator of post-acceptance. The proposed model, in theory, provides appropriate explanations for the elements that influence post-acceptance of the e-learning platform in terms of internet service factors at the individual level. In the practical sense, these findings will help decision-makers and practitioners in higher education institutions identify the factors that should be given extra care and plan their policies accordingly. The ability of the deep ANN architecture to identify the non-linear relationships between the factors involved in the theoretical model has been determined in this research. The implication offers extensive information about taking effective steps to decrease the fear of vaccination among people and increase vaccination confidence among teachers and educators and students, consequently impacting society.

1. Introduction

Various challenges were experienced by higher education institutions during the COVID19 pandemic, even after vaccination availability. Due to these challenges, a major change was required in the field of teaching and learning. During the pandemic, the majority of the schools and universities shifted to virtual classrooms, which was the only way teaching methods and goals

* Corresponding author.
E-mail address: S.A.S.Salloum@edu.salford.ac.uk (S. Salloum)

doi: 10.5267/j.ijdns.2022.4.005

could be applied (Crawford et al., 2020; Nuere & de Miguel, 2020; Watermeyer et al., 2020). University students shifted to an entirely different setting, where they experienced several issues (Alhassan et al., 2021; MacQuarrie et al., 2021). When the challenges experienced by students are comprehended, the method that can be used to evaluate students' understanding, success, and accomplishment during the second wave of Coronavirus can be established (Aguilera-Hermida, 2020).

It should be noted that this challenge continues to be experienced, even after vaccination, due to the rejection of vaccination by the population. Vaccination hesitancy is a critical factor that impacts the world in general, and the education system in specific. Vaccination hesitancy refers to the hesitation shown by people toward different vaccines in several countries worldwide. This suggests that a delay is experienced in the acceptance or the altogether rejection of vaccines, even though the vaccine has become available. This view differs across locations and changes over time, and it is closely linked to confidence and convenience. It is also influenced by contextual factors, group impact, individuals' beliefs, and people's faith in health services. There are differences in vaccination hesitancy from a specific user to another, based on their self-imposed perception, perceived risk, and workplace. Therefore, vaccine hesitancy is the key issue related to COVID-19 vaccine uptake, which means that several hurdles will be experienced by the vaccine against COVID-19 in a post-crisis scenario (Ogbuabor & Chime, 2021; Peretti-Watel et al., 2015; Piedrahita-Valdés et al., 2021). Opposing vaccination hesitancy is vaccination confidence, which refers to something that can be done "all by itself". Vaccine confidence is based on both faith in the healthcare system and trust in a sociopolitical setting. Because of the perceived hazards involved with immunization, users may lack consistent confidence in vaccination. Instead, it could lead to a reduction in vaccination coverage and a loss of immunity.

Based on these assumptions, the objective of this research is to examine how vaccination hesitancy or fear affects the post-acceptance degree of an e-learning platform, where the challenge continues to be critical and obvious because of vaccination rejection. A conceptual framework was formulated to attain the study objective, which caters to the two factors being discussed, i.e., post-acceptance and fear of vaccination. A few external variables are included in the conceptual model because they have a direct relationship with post-acceptance, which are perceived enjoyment, perceived routine use, self-efficiency, and fear of vaccinations (Bandura, 1982; Kwon, 2018; Mahler & Rogers, 1999; Saga & Zmud, 1993). Consequently, the precise contribution of the present study can be summed up in the following: the study first examines the impact of vaccination fear or hesitancy in the educational sector. For this, an integrated research model is used to examine the impact of vaccination fear on e-learning platforms. A conceptual model was formulated, in which the TAM acceptance model (Davis, 1985a) was integrated with the Flow Theory (Nakamura & Csikszentmihalyi, 2009; Shernoff et al., 2014), to show the importance and predictableness of the findings. Secondly, in contrast with the earlier empirical studies that mainly depended on Structural Equation Modeling (SEM) analysis. The method offers a new hybrid analysis strategy that combines SEM and deep learning–based Artificial Neural Networks (ANN). This study also used the Importance–Performance Map Analysis (IPMA) to determine the significance and performance of each element. Third, vaccination fear and hesitancy is a critical factor and has different effects based on the financial status of the country, age, and gender. It was shown in a recent study that there is greater vaccine hesitancy in low-income countries and among young females and older adults. Lastly, the model has been extended in this study to consider external variables that have a close relationship with the post-acceptance stage (Shen et al., 2013), which include critical mass and daily routine. We believe that this is the first study that seeks to examine the post-acceptance of e-learning platforms based on an integrated model in which fear of vaccination is the key variable, with the aim of filling a major research gap in the relevant literature.

2. Literature Review

The influence of COVID-19 on various educational e-learning platforms has been explored in previous studies, according to the literature review. Moodle, Zoom Microsoft Teams, Google Classroom, virtual reality applications, and other platforms were among them. The studies showed that all these platforms were effective while the pandemic was spreading and offered a viable solution to the issue (Bhatt et al., 2020; Jimenez et al., 2021; Pal & Vanijja, 2020). In most of the previous studies, TAM has been the most influential model used. The focus of the majority of the studies was on two of the most influential constructs, i.e., perceived usefulness and ease of use. The studies examined the effective part played by the two constructs in ensuring that the students' adoption or acceptance is on-demand (Bhatt et al., 2020; Karkar et al., 2020; Mad et al., 2020; Sukendro et al., 2020). UTAUT, which is an extended model of TAM, has also been employed as a model to determine how effective the constructs have been during the pandemic. Different technology acceptance models were used in the studies carried out in India. However, the model was extended by (Pal & Vanijja, 2020) by including SUS, which is vital for examining perceived usability. The same trend was followed in the study by (Jimenez et al., 2021), in which a few external factors were included to extend the TAM model, such as innovativeness, computer self-efficacy, computer anxiety, social norm, perceived enjoyment, content, and system quality.

The impact of the pandemic has extended to various parts of the world, which is why the study is varied in its location. Different studies were carried out in Indonesia, China, Vietnam, and Malaysia. In all of these studies, the impact of e-learning platforms during the pandemic was explained with the help of surveys or online questionnaires that were distributed to students of undergraduate educational institutions (Ho et al., 2020; Lazim et al., n.d.; Muqtadiroh et al., 2020; Sukendro et al., 2020). The studies conducted in Romania and Europe also used surveys or online questionnaires distributed among either students or farmers.

They had a distinct sample because of the distinct objectives of their study. The study in Europe has the objective of describing the farmers' readiness to use new technology during the pandemic, while that in Romania focuses on examining how the online platform affected a sample of students during the pandemic (Jimenez et al., 2021; Maier et al., 2020). The impact of COVID-19 on the educational environment of different cities in India was examined by various researchers. It was deduced in these studies that e-learning platforms were effective in maintaining direct and indirect means of communication between the various participants in educational institutions (Bhatt et al., 2020; Pal & Vanijja, 2020).

According to the used methodology, only single-stage linear data analysis, notably the Structural Equation Modeling (SEM) technique, was applied in the majority of earlier research works. It was only possible to identify the linear correlations between the factors in the theoretical model using the single-stage of SEM analysis, and this was not sufficient to predict the complex decision-making process (Sim et al., 2014). A few researchers conquered this issue by employing the Artificial Neural Network (ANN) approach as the second stage of analysis. (Al-Emran et al., 2021; Khan & Ali, 2018; Leong et al., 2013).

On the contrary in this approach, only a single hidden layer is present and considered as a shallow type of ANN (Huang & Stokes, 2016). It was found that the deep ANN architecture should be favored over the shallow ANN since it has the potential of enhancing the accuracy of non-linear models by employing over a single hidden layer (J.-G. Wang et al., 2017). Therefore, this research uses a hybrid SEM-ANN technique that is based on a deep ANN approach which offers deep learning. The previous studies (Bhatt et al., 2020; Ho et al., 2020; Jimenez et al., 2021; Karkar et al., 2020; Lazim et al., n.d.; Mad et al., 2020; Maier et al., 2020; Muqtadiroh et al., 2020; Nai, 2020; Pal & Vanijja, 2020; Saxena et al., 2020; Sukendro et al., 2020; Tiwari, 2020) have clearly shown that the majority of the studies are carried out in educational institutions where the teaching and learning process is mainly carried out through e-learning platforms. Hence, it ensures that the shift from the traditional classroom to the e-learning environment occurs safely and effectively (Crawford et al., 2020; Watermeyer et al., 2020). In the end, this would enable all the educational institutions to accomplish their aims and objectives (Lazim et al., n.d.; Mad et al., 2020).

3. The Conceptual Model and Hypotheses

3.1 Perceived Vaccination Fear (FV)

Within various populations, the COVID-19 vaccine fear and hesitancy is quite high, mainly due to the increase in the Coronavirus conspiracy theory. Hence, the vaccination is rejected and there is a constant increase in the vaccination hesitancy percentage (Salali & Uysal, 2020). Generally, vaccination acceptance is influenced by the risk theory. There are risk regulation and cultural assessments associated with risk theory. The risk response is quite deep considering the emotions present due to cultural developments. Risk information is evaluated in a way that expected utility is maximized (Douglas & Wildavsky, 1982; Posner, 1993; Starr, 1969; Viscusi, 1983). For different genders, the vaccination perceived fear differs. For women, the vaccine is associated with healthcare institutions' negative experiences, but the men's attitude is associated with the immune system. It is believed that their immune system would be weakened (Kakinami et al., 2008; Waithanji et al., 2019). It is observed that vaccine rejection is quite influenced by health literacy. Research indicates that the vaccine may be rejected by the students, specifically female students, considering their health literacy. Health protective behavior is adopted since their fear toward the COVID-19 vaccine is quite high. The perceived fear of the vaccine is what leads to the COVID-19 infection spread (Paakkari & Okan, 2020; Sentell et al., 2020; Shaukat et al., n.d.). Keeping in mind the earlier assessments, the vaccination fears' hypothesis is developed.

H_1: *FV has a positive and significant impact on POA.*

3.2 TAM Theory

Fred Davis developed the "Technology Acceptance Model (TAM)," which contributed to the concepts of technology adoption, acceptance, and post-acceptance. The constructs of this model include perceived ease of use and usefulness, assumed to be conceptual aspects that lead to the post-acceptance of the technology. The perceived ease of use variable is related to the effectiveness of the ease factor on users' performance, whereas perceived usefulness is concerned with the concept of "effort-free" that increases users' performance. (Davis, 1985b). This led to the following hypotheses:

H_2: *PU has a positive and significant impact on POA.*

H_3: *PE has a positive and significant impact on POA.*

3.3 Perceived Daily Routine (PR)

The idea of daily routine means the degree to which technology is a part of the routine tasks and the inclusion of technology into the standard work routine of users. The daily routine use of technology is described as the use of technology such that it enters into the daily pattern and is considered as a standard element in the life of users (Saga & Zmud, 1993; Schwarz, 2003; Sundaram et al., 2007). The daily routine is a significant factor that affects the post-acceptance model. The effectiveness and the use of outcomes have an impact on the daily routine. This suggests that the technology users may consider it as a part of their daily routine should it enhance their extrinsic motivation. Moreover, it can enhance technology integration with work processes (Saga & Zmud, 1993). However, the impact of daily routine is different for different users. These differences are caused by the presence of distinct work situations related to the users, and they may have different views about the integration of technology in their routine work (Barki & Hartwick, 1994). The following hypothesis was developed accordingly:

H4: *PR has a positive and significant impact on POA.*

3.4 Self-Efficiency (SE)

Albert Bandura was the first to present the idea of self-efficiency, suggesting that the concept was a crucial prerequisite for effective learning behavior and was part of the social cognitive theory. Self-efficiency investigates users' perceptions of their abilities to accomplish a variety of tasks and complete them correctly. There is a close relationship between e-learning systems and the users' self-efficiency in the classroom. The teachers' capability of efficiently and effectively using technology determines the actual teaching practices in classrooms. Therefore, if teachers have high efficiency, they will be able to perform the desired tasks accurately. This goal can be attained by involving students in different activities, and this will serve as an encouragement for teachers to use technologies more consistently and to slowly enhance their proficiency (Balkaya & Akkucuk, 2021; Raudenbush et al., 1992; Windschitl & Sahl, 2002; Zhao et al., 2002). It has been observed during COVID-19 that self-efficiency in the educational setting has been influenced by the pandemic situation. It was suggested by various researchers that COVID-19 has had an impact on self-efficiency. According to (Baloran & Hernan, 2020), during the pandemic crisis, work commitment among teachers has been influenced by self-efficiency. It was also stated by (Hernández-Padilla et al., 2020) that self-efficiency can have an impact on technology adoption during COVID-19. The authors asserted that the adoption can be curtailed or even avoided when there is awareness regarding the drawbacks of the pandemic. Therefore, there may be a protective role of self-efficiency during the pandemic because it could lead to a more adaptable atmosphere that encourages technology adoption. Although it appears that vaccination is a viable option for preventing pandemic spread, several people refuse to receive it for a variety of reasons. One of the most common reasons for vaccine rejection is the lack of trust in the healthcare system, which makes patients afraid to take the vaccination. (Hall et al., 2015; Plough et al., 2011; Schoch-Spana et al., 2020). Taking into account the fact that the fear of vaccination affects the mental and physical health of the users, the following were hypothesized:

H5: *SE has a positive and significant impact on POA.*

3.5 Flow Theory

Csikszentmihalyi presented the Flow Theory as a way of understanding the motivation of users. There is a close relationship between motivation and the psychological state in which the cognitive feeling of motivation and efficiency manages the users (Csikszentmihalyi & Csikzentmihaly, 1990; Csikszentmihalyi & MacAloon, 1975). The Flow Theory signifies the state in which the users are excessively involved in a specific activity. Users gain a highly enjoyable experience when using certain forms of technology; therefore, they will use it in any situation. There is a relationship between the Flow Theory and intrinsic motivation, and particularly to self-motivation. It is believed that self-motivation is one of the best ways in which users can be encouraged to do various activities while achieving inner satisfaction. Current research suggests that positive attitudes and high effectiveness are attained from the flow. Furthermore, it supports high education objectives achievements since students become motivated to attain specific objectives (Chan & Ahern, 1999; Hameed et al., 2021; Trevino & Webster, 1992). Since the beginning of the COVID-19 outbreak, various researchers presented similar results. The motivation of the students at the time of COVID-19 was affecting their satisfaction, success, and learning outcomes. According to the results, the student's motivation to learn within an online environment at the time of COVID-19 would indicate their satisfaction and success with the learning results (Bolliger et al., 2010; Chen et al., 2019). User performance is influenced by the fear of vaccination that is expected to reduce the pandemic's bad effects. Hence, the following was hypothesized:

H6: *EJ has a positive and significant impact on POA.*

3.6 Critical Mass Theory (PC)

According to the Critical Mass Theory, a significant contribution is made by a population group when specific actions are being adopted. Hence, the behavior is considered essential by the other individual and the same behavior is imitated. The critical mass influence for technology adoption is quite vital. If a group of friends has decided to make use of technology, it is expected that the next group would also adopt it (Chang et al., 2013; Hsieh et al., 2012; Lou et al., 2000). Hence, the following is the hypothesis:

H7: *PC has a positive and significant impact on POA.*

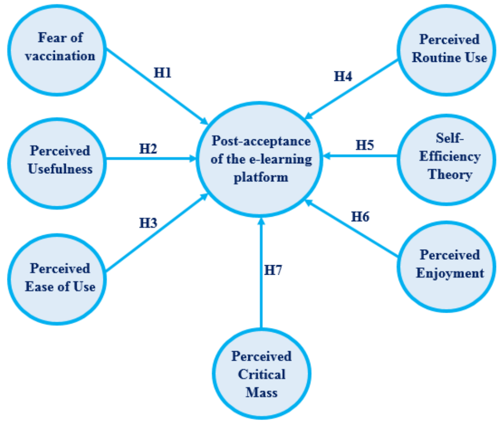

Fig. 1. Conceptual model

4. Research Method

4.1 Data Collection

The University of Sharjah students had been given online surveys to fill. During the winter semester 2020/2021, from 25-Jan-21 to 30-May-2021, data had been gathered. 700 questionnaires were randomly distributed by the research team, out of which 659 questionnaires were filled out by the respondents. Hence, the response rate stands at 94%. Since there were a few missing values, 44 of the filled questionnaires were rejected. Therefore, 659 questionnaires were considered useful and effective by the team. The sample size of 659 valid responses is quite appropriate as stated by (Krejcie & Morgan, 1970), where the projected sampling size for the 1500 population was considered as a part of 306 respondents. When compared to insignificant requests, the 659 sample size is quite high. Hence, as the sample size, the structural equation modeling would be accepted (Chuan & Penyelidikan, 2006), and this was needed for the confirmation of the hypotheses. Although current theories were employed to establish the hypotheses, they were also incorporated into the M-learning framework. The structural Equation Modeling (SEM) method was used to analyze the measurement model (SmartPLS Version 3.2.7). The final path model was used to perform advanced therapy.

4.2 Personal/Demographic Information

The respondents' personal/demographic data were presented in Fig. 1. 48% male and 52% female students responded, and their age group was within 18–29 years. Nearly 34% of the respondents were older than 29 years. Most respondents had a university degree and a sound educational background. 62% held a bachelor's degree, 23% a master's degree, 12% a doctoral degree, and the rest diplomas. The voluntary respondents of the research (Al-Emran & Salloum, 2017) recommended that a "purposive sampling approach" be used. The study sample has been developed using respondents of various ages, colleges, and different programs or levels. The IBM SPSS Statistics ver. 23 was used to measure the respondent demographic information.

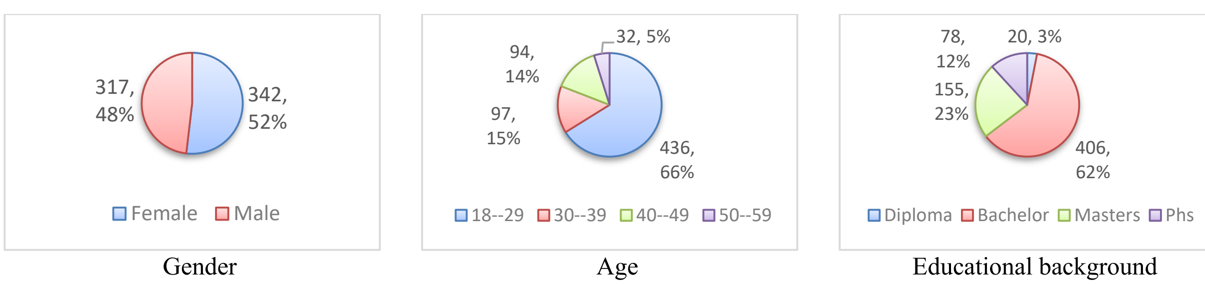

Fig. 1. Respondents' demographic information

4.3 Study Instrument

The survey is the instrument that has been developed to carry out the hypotheses testing of the research. 23 items are parts of the survey that assessed eight constructs present within the questionnaire. Table 1 indicates the sources of all eight constructs. Earlier studies' research questions, after being subjected to some modifications, have been included to make sure the research is applicable.

Table 1
Measurement Items

Constructs	Sources
POA	(Li et al., 2013)
PE	(Ngai et al., 2007; Persico et al., 2014)
PU	(Ngai et al., 2007; Persico et al., 2014)
PR	(Saga & Zmud, 1993)
EJ	(Nakamura & Csikszentmihalyi, 2009; Shernoff et
PC	(Hasan et al., 2016; Mahler & Rogers, 1999)
SE	(Bandura, 1982; Kwon, 2018)
FV	(Banerjee & Dash, 2013; Raza et al., 2020)

Table 2
Cronbach's Alpha values for the pilot study (Cronbach's Alpha ≥ 0.70)

Constructs	CA
POA	0.822
PE	0.860
PU	0.724
PR	0.867
EJ	0.802
PC	0.770
SE	0.866
FV	0.833

4.4 Pilot Study of the Questionnaire

A pilot study has been carried out to check the questionnaire items reliability. For the pilot study, 70 students were randomly selected from the mentioned population. Considering the total sample size to be 10% for the current analysis, the 700 student sample size was set and the research standards have been considered appropriately. To assess the pilot study findings, internal reliability has been tested using the Cronbach's alpha (CA) test along with the IBM SPSS Statistics ver. 23. Hence, for the measurement items, acceptable conclusions are presented. It is acceptable to have a 0.70 reliability coefficient if the social science research studies mentioned pattern is emphasized (Nunnally & Bernstein, 1978). Table 2 presents the seven measurement scales for the Cronbach alpha values.

5. Findings and Discussion

5.1 Data Analysis

The earlier empirical studies used the SEM to carry out a single-stage analysis. For the current research, the hybrid SEM-ANN approach using deep learning for validation of the hypothesized associations between the research model factors has been applied. There are two phases within this research. At first, the recommended research model would use the Partial Least Squares-Structural Equation Modeling (PLS-SEM) by applying SmartPLS (Ringle et al., 2015). The objective of using PLS-SEM within the research is the theoretical model's exploratory nature and the non-availability of earlier literature. General guidelines have been followed by the study for implementing the PLS-SEM within information systems research (Al-Emran et al., 2018). It has already been mentioned (Simpson, 1990) that the research model can be analyzed using a two-step approach, i.e., measurement and structural models. The Importance Performance Map Analysis (IPMA) was applied within this research as it is an advanced PLS-SEM technique. It would help extract each construct's performance and importance within the research model. Secondly, the PLS-SEM analysis investigation, complement, and authentication would be done through ANN. It would also help state the effectiveness of the independent variable upon the dependent variable. The ANN is an instrument for function approximation which is relevant in areas where the input(s) and output(s) collaboration is non-linear as well as complex. ANN states that there are three vital mechanisms which are network architecture, learning rule, and transfer function (Simpson, 1990). It would then be subdivided into radian basis, feed-forward Multilayer Perceptron (MLP) network, and recurrent network subcategories (Sim et al., 2014). One commonly used approach is the MLP neural network in which several layers are present like input and output. Hidden nodes are used to connect these input and output layers. Neurons or independent variables are present within the input layer, and they are responsible for taking the raw data ahead to the hidden layers as synaptic weights. The activation function choice determines the hidden layer output. A widely used activation function is the sigmoidal function (Asadi et al., 2019; Sharma & Sharma, 2019). The MLP neural network was utilized for the recommended research model training and testing.

5.2 Convergent Validity

The measurement model is assessed keeping in mind the construct reliability (which integrates Composite Reliability (CR), Dijkstra-Henseler's criterion (PA), and Cronbach's Alpha (CA)) along with validity (which integrates convergent and discriminant validity). (J. Hair et al., 2017) Has brought forward this recommendation. The construct reliability is determined using Table 3 which presents the Cronbach's Alpha (CA) values of 0.769 till 0.906. As compared to the threshold value of 0.7 (Nunnally & Bernstein, 1994), these figures are higher. Table 4 shows that the Composite Dependability (CR) values range from 0.786 to 0.927, which is higher than the suggested threshold value of 0.7 (Kline, 2015). The Dijkstra-Henseler's rho (pA) reliability coefficient could be utilized by the research for construct reliability evaluation and reporting.

The reliability coefficient ρA should be similar to the CA and CR with values of 0.70 or higher as part of the exploratory research. For advanced research stages, values should be over 0.80 or 0.90 (J. F. Hair et al., 2011; Henseler et al., 2009; Nunnally & Bernstein, 1994). Table 3 shows that the reliability coefficient Alpha for each measurement construct should be more than 0.70. As suggested by the results, the construct reliability should be confirmed, and the constructs must be assumed to be quite free of error toward the end. The convergent validity measurement testing should be done for the Average Variance Extracted (AVE) and factor loading (J. Hair et al., 2017). The 0.7 proposed value has remained lower than the factor loading values, according to Table 3. Furthermore, as shown in the table, the AVE generated values ranged from 0.686 to 0.842, which is significantly higher than the 0.5 threshold value. For all constructs, it is possible to appropriately attain the convergent validity keeping the future results in mind.

5.3 Discriminant Validity

For discriminant validity measurement, it is recommended that the Fornell-Larker criterion and the Heterotrait-Monotrait ratio (HTMT) be gauged (J. Hair et al., 2017). Table 4 results indicate that the Fornell-Larker condition confirms the requirements as the AVEs and their square roots are much higher than the correlation with the rest of the constructs (Fornell & Larcker, 1981). Table 5 illustrates the HTMT ratio results which indicate the fact that 0.85 is the threshold value, ahead of each constructs' value (Henseler et al., 2015). As a result, the HTMT ratio is established. The discriminant validity is stated based on these findings. With the results of the study in mind, there were no issues with the measurement model assessment in terms of reliability and validity. Therefore, it is possible to evaluate the structural model by making further use of the collected data.

Table 3
Measurement model

Factor	Items	Factor Loading	CA	CR	PA	AVE
POA	POA1	0.815	0.786	0.793	0.864	0.760
	POA2	0.876				
PR	PR1	0.691	0.788	0.790	0.877	0.706
	PR2	0.876				
	PR3	0.881				
PE	PE1	0.742	0.867	0.877	0.919	0.790
	PE2	0.873				
	PE3	0.863				
PU	PU1	0.841	0.892	0.927	0.931	0.819
	PU2	0.825				
	PU3	0.843				
EJ	EJ1	0.904	0.906	0.911	0.941	0.842
	EJ2	0.914				
	EJ3	0.934				
PC	PC1	0.889	0.880	0.890	0.926	0.807
	PC2	0.854				
	PC3	0.728				
SE	SE1	0.924	0.769	0.786	0.867	0.686
	SE2	0.867				
	SE3	0.902				
FV	FV1	0.867	0.844	0.847	0.906	0.763
	FV2	0.896				
	FV3	0.856				

Table 4
Fornell-Larcker Scale

	POA	PE	PU	PR	EJ	PC	SE	FV
PO	**0.873**							
PE	0.611	**0.89**						
PU	0.731	0.55	**0.88**					
PR	0.714	0.48	0.69	**0.91**				
EJ	0.694	0.68	0.68	0.70	**0.84**			
PC	0.721	0.70	0.72	0.59	0.64	**0.90**		
SE	0.678	0.45	0.75	0.58	0.60	0.64	**0.87**	
FV	0.446	0.69	0.73	0.67	0.71	0.73	0.61	**0.82**

Table 5
Heterotrait-Monotrait Ratio (HTMT)

	POA	PE	PU	PR	EJ	PC	SE	F
PO								
PE	0.70							
PU	0.65	0.62						
PR	0.61	0.53	0.68					
EJ	0.65	0.62	0.63	0.53				
PC	0.51	0.50	0.69	0.63	0.40			
SE	0.68	0.57	0.66	0.64	0.61	0.70		
FV	0.44	0.67	0.69	0.39	0.53	0.58	0.64	

5.4 Hypotheses Testing Using PLS-SEM

The Smart PLS, with maximum likelihood estimation, was integrated with the structural equation model to obtain the several structural model theoretical constructs interdependence (Al-Emran et al., 2020; Salloum et al., 2019). Hence, it was possible to assess the proposed model. It is observed in Table 6 and Fig. 3 that a moderate predictive power is present for the model since it attains a 45% variance percentage for post-acceptance of e-learning technology.

Table 7 shows the beta (β) values, t-values, and p-values for each hypothesis based on the PLS-SEM approach generated findings. All hypotheses have been supported by the researchers, it may be said. The empirical data supports the H1, H2, H3, H4, H5, H6, and H7 hypotheses, according to the data analysis. The results revealed that Post-Acceptance of e-learning technology (POA) significantly influenced Fear of Vaccination (FV) ($\beta = 0.293$, $t = 13.694$), Perceived Usefulness (PU) ($\beta = 0.487$, $t = 3.494$), Perceived Ease of Use (PE) ($\beta = 0.597$, $t = 17.001$), Perceived Routine Use (PR) ($\beta = 0.389$, $t = 7.009$), Self-

Efficiency (SE) (β = 0.548, t = 5.416), Perceived Enjoyment (EJ) (β = 0.363, t = 6.907), and Perceived Critical Mass (PC) (β = 0.287, t = 5.312) supporting hypothesis H1, H2, H3, H4, H5, H6, and H7, respectively.

Table 6
R-squared values

Constructs	R^2	Results
POA	0.450	Moderate

Table 7
Results of path tests

H	Relationship	Path	*t*-Value	*p*-Value	Comment
H1	FV→ POA	0.293	13.694	0.000	Significant**
H2	PU→ POA	0.487	3.494	0.036	Significant*
H3	PE→ POA	0.597	17.001	0.000	Significant**
H4	PR→ POA	0.389	7.009	0.003	Significant**
H5	SE→ POA	0.548	5.416	0.008	Significant**
H6	EJ→ POA	0.363	6.907	0.007	Significant**
H7	PC→ POA	0.287	5.312	0.000	Significant**

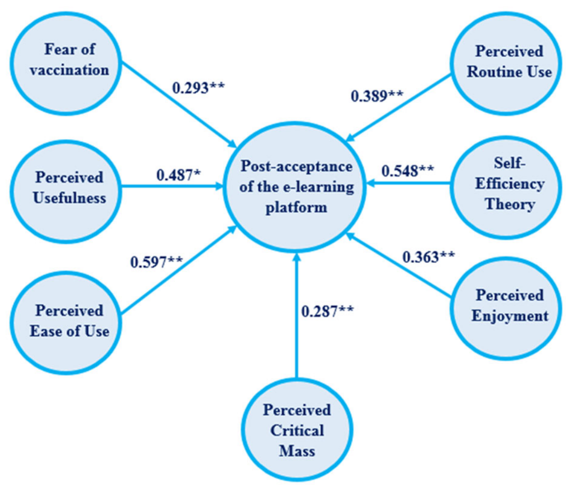

Fig. 3. PLS Results

5.5 ANN Results

The IBM SPSS Statistics ver. 23 was used to do the ANN review. Only the notable predictors were produced from the PLS-SEM findings which were then used in the ANN evaluation. For the ANN analysis, only the FV, PR, EN, SF, PC, PE, and PU variables are considered. The ANN model, as per Fig. 4, has a single output neuron, e.g., post-acceptance of E-learning Technology, and many input neurons, i.e., FV, PR, EN, SF, PC, PE, and PU. A two-hidden layer deep ANN model was utilized to enable deeper learning and to take effect for each of the output neuron nodes. In this experiment, the sigmoid function is employed to activate both hidden and output neurons. The spectrum for both input and output neurons were between [0, 1] to improve the efficiency of the provided study model. To avoid overfitting in ANN models, researchers adopted a tenfold cross-validation strategy with an 80:20 ratio for both training and testing data. The Root Mean Square of Error (RMSE) is offered as a metric for the correctness of a neural network model. Table 4 shows that the ANN model's RMSE parameters for both training and testing data are 0.1394 and 0.1405, respectively. Since the RMSE estimates and standard deviation for both training and testing data are of minuscule variances (0.0046 and 0.0098, respectively), it can be deduced that the presented research model achieves high accuracy with the use of ANN.

5.6 Sensitivity Analysis

The average of every predictor is compared to the maximum mean value expressed as a percentage to determine the normalized importance. Every predictor involved in ANN modeling is included in Table 8 with their mean importance and normalized importance. The sensitivity analysis results show that PE is by far the most important predictor of post-acceptance of E-learning Technology, preceded by FV, PR, EN, SF, PC, and PU, as shown in Table 8. It was proposed that the goodness of fit, which is identical to R^2 in PLS-SEM analysis (Leong et al., 2019), be determined to additionally authenticate and validate the ANN application's accuracy and performance. As an outcome, the predictive power of ANN evaluation ($R^2 = 53\%$) is far greater than that of PLS-SEM ($R^2 = 45\%$), according to the findings. These results show that the ANN model elucidates endogenous constructs more thoroughly than the PLS-SEM approach. Furthermore, the disparity invariances can be due to the deep learning ANN approach's dominance in deciding non-linear relationships between the constructs.

Table 8
Independent variable importance

	Importance	Normalized Importance
PE	.270	100.0%
FV	.181	67.1%
PR	.163	60.4%
EN	.135	49.9%
SF	.086	31.7%
PC	.085	31.5%
PU	.082	30.2%

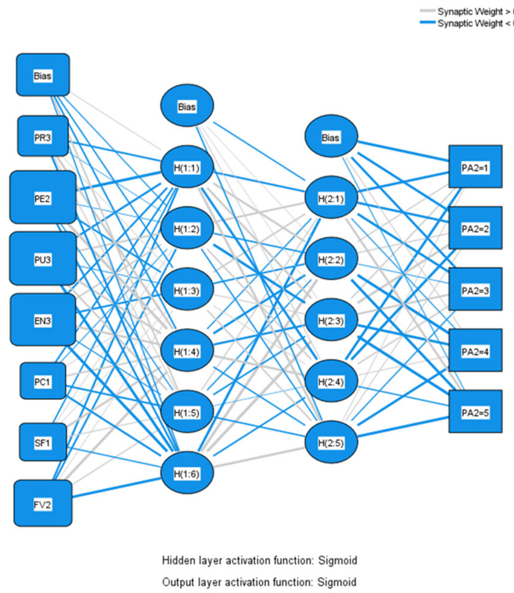

Fig. 4. ANN model

5.7 Importance–Performance Map Analysis

We used the IPMA as an efficient approach in PLS-SEM with post-acceptance of e-learning technology as the target variable in this study. IPMA, according to Ringle and Sarstedt (Ringle & Sarstedt, 2016), aids in the comprehension of PLS-SEM research evidence. IPMA includes the average value of the latent constructs and their indicators (such as performance measure) as an option to calculate the path coefficients (such as importance measure) (Ringle & Sarstedt, 2016). According to the IPMA, overall impact represents the importance of precedent factors in defining the target factor (post-acceptance of e-learning technology), while the average of latent constructs' values reflects their performance. The IPMA findings are shown in Fig. 5. In this study, the importance and performance of seven variables (fear of vaccination, perceived ease of use, perceived usefulness, perceived routine usage, perceived enjoyment, perceived critical mass, and self-efficacy) were assessed. According to the findings, PE has the maximum values for both importance and performance measures. It is also noteworthy that FV has the second-largest value in terms of importance and performance measures. Although PU has the third-largest value on the importance measure, on the performance measure, it has the lowest value. Moreover, even though SE has the lowest importance metric, it is crucial to note that it has the highest relative value to the PE on the performance measure.

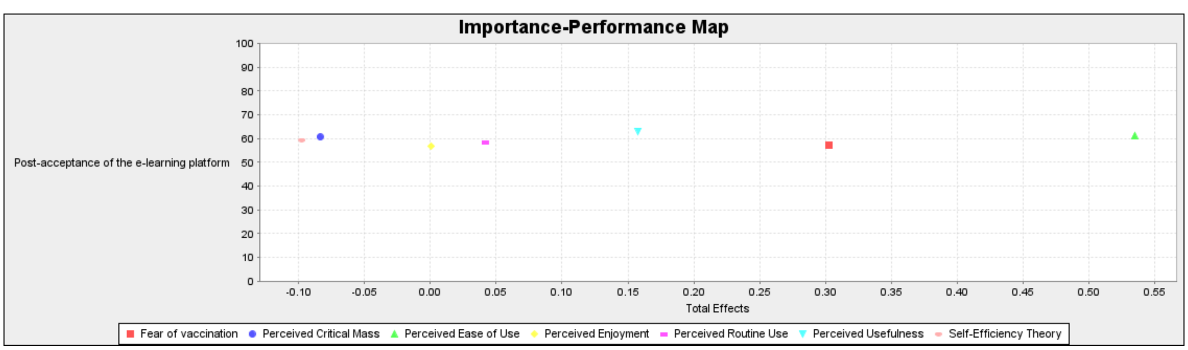

Fig. 5. IPMA results

6. Discussion

The current analysis investigated the key factors that influence the acceptance of an e-learning platform using the TAM model in conjunction with external factors such as fear of vaccination, perceived ease of use, perceived usefulness, perceived routine use, perceived enjoyment, perceived critical mass, and self-efficiency. The following are some of the most important findings. To begin, it was discovered that the variables have an impact and are linked to the dependent variable. This finding backs up the TAM in the study, which shows that the two constructs of perceived ease of use and perceived usefulness have a favorable impact on technology acceptance (Al-Maroof et al., 2021; Al-Maroof R.S., 2021; Jimenez et al., 2021; Rashid et al., 2021). According to a study by (Alfadda & Mahdi, n.d.), perceived ease of use and perceived usefulness have a significant impact on Zoom's acceptance as an e-learning platform, and they have a successful relationship with self-efficacy. The outcomes of this study show that both PEOU and PU have an important and optimistic effect on the e-learning platform's post-acceptance stage. Second, the assumptions concerning perceived routine use, perceived enjoyment have been ensured. These results are consistent with those observed in earlier research. According to (Saga & Zmud, 1993), the perceived routine use has a beneficial effect on technology acceptance and has a direct association with motivation similarly, prior research yielded that perceived enjoyment has an important impact on technology acceptance (Al-Maroof et al., 2021; Jimenez et al., 2021; Li et al., 2021; Wang et al., 2021). According to an analysis by (Maheshwari, 2021), perceived enjoyment enhances technology acceptance, and this factor is closely linked to fast internet and efficient systems. After that, the statistical analysis has backed up critical mass and self-efficiency. The outcome demonstrates that in moments of distress, people try to be compassionate. They assist one another in avoiding technical difficulties. As a result, these two parameters can act as a buffer throughout a crisis (Baloran & Hernan, 2020; Chang et al., 2013; Hernández-Padilla et al., 2020; Hsieh et al., 2012). According to an analysis by (Jimenez et al., 2021), self-efficacy, alongside TAM (PEOU and PU), are the most important factors that influence acceptance of technology. Eventually, fear of vaccination is a major variable that influences the acceptance of an e-learning platform. The results show that fear of vaccination has a beneficial effect on the key model constructs. Vaccine hesitancy has been identified as a critical problem, as it can build numerous obstacles in a post-crisis environment (Ogbuabor & Chime, 2021; Peretti-Watel et al., 2015; Piedrahita-Valdés et al., 2021). As a result, students ought to have vaccination confidence, as opposed to vaccination hesitancy; as a result, they would be able to build trust in the healthcare sector, allowing them to tolerate vaccinations and overcome their fears.

6.1 Practical Implication

Students' embrace of technology is hampered by their fear of vaccination. As a result, practical implications can help guide learning strategies and procedures in the right direction. Experts believe that fear of vaccination may sway consumers' opinions. As a result, when implementing e-learning models, educators and teachers should pay particular attention to students' perspectives and preferences. As a result, this research has many applications. To begin, teachers and healthcare workers should explore various methods for boosting vaccination confidence to be accepted by technology consumers. Second, to further explore this problem, investigators may obtain practical confirmation of the impact that vaccination fear can have on the learning process. Furthermore, the current research provides a scientific viewpoint. Fear of vaccination should be considered by academics in both educational institutions in the online learning environment, particularly in the teaching and learning surroundings. As a result, teachers should rethink the importance of evaluating their teaching strategies to address the current obstacles (Cardullo et al., 2021).

6.2 Managerial Implication

This study looks at the impact of vaccination hesitancy in the educational environment, to encourage healthcare executives and governments to emphasize vaccination fear and take appropriate measures to alleviate this fear. It provides an in-depth look at existing strategies for reducing fear and boosting vaccination morale among educators, teachers, and students, which will have an impact on society overall. For example, healthcare managers should accept these results to minimize the risk of a crisis that might end in student vaccination rejection (Simonetti et al., 2021). This research has the potential to improve educational institution teaching and learning efficiency, as well as increase vaccination acceptance, allowing educational institutions to execute their objectives and perspective more efficiently.

6.3 Theoretical Implications

In terms of technique, this study uses a hybrid SEM-ANN model focused on deep learning to refer to previous research in general and the e-learning domain in particular, unlike prior empirical investigations that mostly relied on SEM analysis. The ANN model outperforms the PLS-SEM model in terms of predictive capability. We infer that the deeper ANN architecture's ability to assess non-linear correlations between the elements in the theoretical model is responsible for the higher predictive power recovered from ANN analysis.

6.4 Limitations of the Study

There are certain drawbacks to the research. The key drawback is that only four universities in the UAE were engaged, which prevents a thorough examination of the factors influencing e-learning platforms following the propagation of COVID-19. With the involvement of a larger number of universities, the research may have been more useful. By thoroughly analyzing the factors that influence e-learning systems, additional analysis would enable an accurate understanding of e-learning systems. One downside is the small number of respondents who participated in the study (659 students). According to (Al-Emran & Salloum, 2017), the survey questionnaire was developed for data collection. The study could have been improved if a superior instrument and sampling method had been used. Furthermore, the participation of various universities from the Arab Gulf region, including those from the KSA, Kuwait, and Bahrain, would have enhanced study results. In the future, it will be imperative to engage more students about participating in research. Furthermore, interviews and focus groups will provide more reliable results. Finally, we hope that participating Arab universities will adopt an e-learning system.

References

Aguilera-Hermida, A. P. (2020). College students' use and acceptance of emergency online learning due to Covid-19. *International Journal of Educational Research Open*, *1*, 100011.

Al-Emran, M., Abbasi, G. A., & Mezhuyev, V. (2021). Evaluating the Impact of Knowledge Management Factors on M-Learning Adoption: A Deep Learning-Based Hybrid SEM-ANN Approach. *Recent Advances in Technology Acceptance Models and Theories*, 159–172.

Al-Emran, M., Arpaci, I., & Salloum, S. A. (2020). An empirical examination of continuous intention to use m-learning: An integrated model. *Education and Information Technologies*, 1–20.

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). PLS-SEM in Information Systems Research: A Comprehensive Methodological Reference. *4th International Conference on Advanced Intelligent Systems and Informatics (AISI 2018)*, 644–653.

Al-Emran, M., & Salloum, S. A. (2017). Students' Attitudes Towards the Use of Mobile Technologies in e-Evaluation. *International Journal of Interactive Mobile Technologies (IJIM)*, *11*(5), 195–202.

Al-Maroof, R. S., Alhumaid, K., Akour, I., & Salloum, S. (2021). Factors that affect e-learning platforms after the spread of COVID-19: post acceptance study. *Data*, *6*(5), 49.

Al-Maroof R.S., S. S. A. (2021). An Integrated Model of Continuous Intention to Use of Google Classroom. *In: Al-Emran M., Shaalan K., Hassanien A. (Eds) Recent Advances in Intelligent Systems and Smart Applications. Studies in Systems, Decision and Control, Vol 295. Springer, Cham*.

Alfadda, H. A., & Mahdi, H. S. (n.d.). Measuring Students' Use of Zoom Application in Language Course Based on the Technology Acceptance Model (TAM). *Journal of Psycholinguistic Research*, 1–18.

Alhassan, A., Ali, N. A., & Ali, H. I. H. (2021). EFL students' challenges in English-medium business programmes: Perspectives from students and content teachers. *Cogent Education*, *8*(1), 1888671.

Asadi, S., Abdullah, R., Safaei, M., & Nazir, S. (2019). An integrated SEM-Neural Network approach for predicting determinants of adoption of wearable healthcare devices. *Mobile Information Systems*, *2019*.

Balkaya, S., & Akkucuk, U. (2021). *Adoption and Use of Learning Management Systems in Education: The Role of Playfulness and Self-Management. Sustainability 2021, 13, 1127*. s Note: MDPI stays neutral with regard to jurisdictional claims in published ….

Baloran, E., & Hernan, J. (2020). *Crisis Self-Efficacy and Work Commitment of Education Workers among Public Schools during COVID-19 Pandemic*.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122.

Banerjee, S., & Dash, S. K. (2013). Effectiveness of disease awareness advertising in emerging economy: Views of health care professionals of India. *Journal of Medical Marketing: Device, Diagnostic and Pharmaceutical Marketing*, *13*(4), 231–241. https://doi.org/10.1177/1745790413516479

Barki, H., & Hartwick, J. (1994). Measuring user participation, user involvement, and user attitude. *MIS Quarterly*, 59–82.

Bhatt, V., Chakraborty, S., & Chakravorty, T. (2020). Impact of Information Sharing on Adoption and User Satisfaction among the Wearable Device Users. *International Journal of Control and Automation*, *13*(4), 277–289.

Bolliger, D. U., Supanakorn, S., & Boggs, C. (2010). Impact of podcasting on student motivation in the online learning environment. *Computers & Education*, *55*(2), 714–722.

Cardullo, V., Wang, C., Burton, M., & Dong, J. (2021). K-12 teachers' remote teaching self-efficacy during the pandemic. *Journal of Research in Innovative Teaching & Learning*.

Chan, T. S., & Ahern, T. C. (1999). Targeting motivation—adapting flow theory to instructional design. *Journal of Educational Computing Research*, *21*(2), 151–163.

Chang, C.-C., Tseng, K.-H., Liang, C., & Yan, C.-F. (2013). The influence of perceived convenience and curiosity on continuance intention in mobile English learning for high school students using PDAs. *Technology, Pedagogy and Education*, *22*(3), 373–386.

Chen, C.-H., Huang, C.-Y., & Chou, Y.-Y. (2019). Effects of augmented reality-based multidimensional concept maps on students' learning achievement, motivation and acceptance. *Universal Access in the Information Society*, *18*(2), 257–268.

Chuan, C. L., & Penyelidikan, J. (2006). Sample size estimation using Krejcie and Morgan and Cohen statistical power analysis: A comparison. *Jurnal Penyelidikan IPBL*, *7*, 78–86.

Crawford, J., Percy, A., & Kelder, J.-A. (2020). JUTLP Editorial 17.3: Connection, digital education, and student-centric teaching practice before COVID-19. *Journal of University Teaching & Learning Practice*, *17*(3), 1.

Csikszentmihalyi, M., & Csikzentmihaly, M. (1990). *Flow: The psychology of optimal experience* (Vol. 1990). Harper & Row New York.

Csikszentmihalyi, M., & MacAloon, D. (1975). *In Csikszentmihalyi, M. Beyond boredom and anxiety*. San Francisco, California: Jossey-Bass.

Davis, F. D. (1985a). A technology acceptance model for empirically testing new end-user information systems: Theory and results. In *Massachusetts Institute of Technology: Vol. Ph.D.* https://doi.org/oclc/56932490

Davis, F. D. (1985b). *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. Massachusetts Institute of Technology.

Dijkstra, T. K., & Henseler, J. (2015). Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational Statistics & Data Analysis*, *81*, 10–23.

Douglas, M., & Wildavsky, A. (1982). *How can we know the risks we face? Why risk selection is a social process 1*. Wiley Online Library.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models With Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Hair, J., Hult, G. T. M., Ringle, C., Sarstedt, M., Hair, J. F. F., Hult, G. T. M., … Sarstedt, M. (2016). A primer on partial least squares structural equation modeling (PLS-SEM). *Sage Publications.*

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, *19*(2), 139–152.

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*, *117*(3), 442–458. https://doi.org/10.1108/IMDS-04-2016-0130

Hall, W. J., Chapman, M. V, Lee, K. M., Merino, Y. M., Thomas, T. W., Payne, B. K., Eng, E., Day, S. H., & Coyne-Beasley, T. (2015). Implicit racial/ethnic bias among health care professionals and its influence on health care outcomes: a systematic review. *American Journal of Public Health*, *105*(12), e60–e76.

Hameed, I., Zaman, U., Waris, I., & Shafique, O. (2021). A Serial-Mediation Model to Link Entrepreneurship Education and Green Entrepreneurial Behavior: Application of Resource-Based View and Flow Theory. *International Journal of Environmental Research and Public Health*, *18*(2), 550.

Hasan, H., Linger, H., Chen, A., Lu, Y., & Wang, B. (2016). Enhancing perceived enjoyment in social games through social and gaming factors. *Information Technology & People*.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., Ketchen Jr, D. J., Hair, J. F., Hult, G. T. M., & Calantone, R. J. (2014). Common beliefs and reality about PLS: Comments on Rönkkö and Evermann (2013). *Organizational Research Methods*, *17*(2), 182–209.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In *New challenges to international marketing* (pp. 277–319). Emerald Group Publishing Limited.

Hernández-Padilla, J. M., Granero-Molina, J., Ruiz-Fernández, M. D., Dobarrio-Sanz, I., López-Rodríguez, M. M., Fernández-Medina, I. M., Correa-Casado, M., & Fernández-Sola, C. (2020). Design and psychometric analysis of the COVID-19 prevention, recognition and home-management self-efficacy scale. *International Journal of Environmental Research and Public Health*, *17*(13), 4653.

Ho, N. T. T., Sivapalan, S., Pham, H. H., Nguyen, L. T. M., Van Pham, A. T., & Dinh, H. V. (2020). Students' adoption of e-learning in emergency situation: the case of a Vietnamese university during COVID-19. *Interactive Technology and Smart Education*.

Hsieh, J.-K., Hsieh, Y.-C., Chiu, H.-C., & Feng, Y.-C. (2012). Post-adoption switching behavior for online service substitutes: A perspective of the push–pull–mooring framework. *Computers in Human Behavior*, *28*(5), 1912–1920.

Huang, W., & Stokes, J. W. (2016). MtNet: a multi-task neural network for dynamic malware classification. *International Conference on Detection of Intrusions and Malware, and Vulnerability Assessment*, 399–418.

Jimenez, I. A. C., García, L. C. C., Violante, M. G., Marcolin, F., & Vezzetti, E. (2021). Commonly Used External TAM Variables in e-Learning, Agriculture and Virtual Reality Applications. *Future Internet*, *13*(1), 7.

Kakinami, L., Newman, P. A., Lee, S.-J., & Duan, N. (2008). Differences in HIV vaccine acceptability between genders. *AIDS Care*, *20*(5), 542–546.

Karkar, A. J. M., Fatlawi, H. K., & Al-Jobouri, A. A. (2020). Highlighting E-learning Adoption Challenges using data Analysis Techniques: University of Kufa as a Case Study. *Electronic Journal of E-Learning*, *18*(2), pp136-149.

Khan, A. N., & Ali, A. (2018). Factors affecting retailer's adopti on of mobile payment systems: A SEM-neural network modeling approach. *Wireless Personal Communications*, *103*(3), 2529–2551.

Kline, R. B. (2015). *Principles and practice of structural equation modeling*. Guilford publications.

Krejcie, R. V, & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement*, *30*(3), 607–610.

Kwon, Y. (2018). Effects of Organizational Climates on the Self-Efficacy of Practitioners in Continuing Higher Education in Korea. *Performance Improvement Quarterly*, *31*(2), 141–163.

Lazim, C. S. L. M., Ismail, N. D. B., & Tazilah, M. D. A. K. (n.d.). *APPLICATION OF TECHNOLOGY ACCEPTANCE MODEL (TAM) TOWARDS ONLINE LEARNING DURING COVID-19 PANDEMIC: ACCOUNTING STUDENTS PERSPECTIVE*.

Leong, L.-Y., Hew, T.-S., Ooi, K.-B., Lee, V.-H., & Hew, J.-J. (2019). A hybrid SEM-neural network analysis of social media addiction. *Expert Systems with Applications*, *133*, 296–316.

Leong, L.-Y., Hew, T.-S., Tan, G. W.-H., & Ooi, K.-B. (2013). Predicting the determinants of the NFC-enabled mobile credit card acceptance: A neural networks approach. *Expert Systems with Applications*, *40*(14), 5604–5620.

Li, C., He, L., & Wong, I. A. (2021). Determinants predicting undergraduates' intention to adopt e-learning for studying english in chinese higher education context: A structural equation modelling approach. *Education and Information Technologies*, 1–19.

Li, X., Hsieh, J. J. P.-A., & Rai, A. (2013). Motivational differences across post-acceptance information system usage behaviors: An investigation in the business intelligence systems context. *Information Systems Research*, *24*(3), 659–682.

Lohmöller, J. B. (1989). *Latent variable path modeling with partial least squares. Heidelberg, Germany: Physica-Verlag*.

Lou, H., Luo, W., & Strong, D. (2000). Perceived critical mass effect on groupware acceptance. *European Journal of Information Systems*, *9*(2), 91–103.

MacQuarrie, M., Blinn, N., MacLellan, S., Flynn, M., Meisner, J., Owen, P., & Spencer, B. (2021). Starting from the Same Spot: Exploring Mindfulness Meditation and Student Transitions in the Introductory Health Promotion Classroom. *Canadian Journal of Education/Revue Canadienne de l'éducation*, *44*(1), 256–276.

Mad, S., Omar, N. A., Sarudin, E. S., & Aziz, N. H. (2020). Perception And Intention To Use E-learning From Students' Point of View-An Evidence From Malaysia Local University. *Journal of Computing Research and Innovation*, *5*(2), 11–20.

Maheshwari, G. (2021). Factors affecting students' intentions to undertake online learning: an empirical study in Vietnam. *Education and Information Technologies*, 1–21.

Mahler, A., & Rogers, E. M. (1999). The diffusion of interactive communication innovations and the critical mass: the adoption of telecommunications services by German banks. *Telecommunications Policy*, *23*(10–11), 719–740.

Maier, V., Alexa, L., & Craciunescu, R. (2020). Online Education During the COVID19 Pandemic: Perceptions and Expectations of Romanian Students. *European Conference on E-Learning*, 317–XVII.

Muqtadiroh, F. A., Herdiyanti, A., & Puspitasari, N. (2020). The e-Learning Quality Model to Examine Students' Behavioral Intention to Use Online Learning Platform in a Higher Education Institution. *Khazanah Informatika: Jurnal Ilmu Komputer Dan Informatika*, *6*(2).

Nai, X. (2020). *An investigation of the influencing factors of user learning motivation for using the online learning platform of the foreign language school at Baise Universityn*.

Nakamura, J., & Csikszentmihalyi, M. (2009). Flow theory and research. *Handbook of Positive Psychology*, 195–206.

Ngai, E. W. T., Poon, J. K. L., & Chan, Y. H. C. (2007). Empirical examination of the adoption of WebCT using TAM. *Computers & Education*, *48*(2), 250–267.

Nuere, S., & de Miguel, L. (2020). The digital/technological connection with Covid-19: An unprecedented challenge in university teaching. *Technology, Knowledge and Learning*, 1–13.

Nunnally, J. C., & Bernstein, I. H. (1978). *Psychometric theory*.

Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory. In *McGraw-Hill, New York*. https://doi.org/10.1037/018882

Ogbuabor, D. C., & Chime, A. C. (2021). Prevalence and predictors of vaccine hesitancy among expectant mothers in Enugu metropolis, South-east Nigeria. *Journal of Public Health Policy*, 1–14.

Paakkari, L., & Okan, O. (2020). COVID-19: health literacy is an underestimated problem. *The Lancet Public Health*, *5*(5), e249–e250.

Pal, D., & Vanijja, V. (2020). Perceived usability evaluation of Microsoft Teams as an online learning platform during COVID-19 using system usability scale and technology acceptance model in India. *Children and Youth Services Review*, 105535.

Peretti-Watel, P., Larson, H. J., Ward, J. K., Schulz, W. S., & Verger, P. (2015). Vaccine hesitancy: clarifying a theoretical framework for an ambiguous notion. *PLoS Currents*, *7*.

Persico, D., Manca, S., & Pozzi, F. (2014). Adapting the technology acceptance model to evaluate the innovative potential of e-learning systems. *Computers in Human Behavior*, *30*, 614–622.

Piedrahita-Valdés, H., Piedrahita-Castillo, D., Bermejo-Higuera, J., Guillem-Saiz, P., Bermejo-Higuera, J. R., Guillem-Saiz, J., Sicilia-Montalvo, J. A., & Machío-Regidor, F. (2021). Vaccine Hesitancy on Social Media: Sentiment Analysis from June 2011 to April 2019. *Vaccines*, *9*(1), 28.

Plough, A., Bristow, B., Fielding, J., Caldwell, S., & Khan, S. (2011). Pandemics and health equity: lessons learned from the H1N1 response in Los Angeles County. *Journal of Public Health Management and Practice*, *17*(1), 20–27.

Posner, R. A. (1993). *Private choices and public health: The AIDS epidemic in an economic perspective*. Harvard University Press.

Rashid, A. H. A., Shukor, N. A., Tasir, Z., & Na, K. S. (2021). Teachers' Perceptions and Readiness toward the Implementation of Virtual Learning Environment. *International Journal of Evaluation and Research in Education*, *10*(1), 209–214.

Raudenbush, S. W., Rowan, B., & Cheong, Y. F. (1992). Contextual effects on the self-perceived efficacy of high school teachers. *Sociology of Education*, 150–167.

Raza, S. A., Qazi, W., Khan, K. A., & Salam, J. (2020). Social Isolation and Acceptance of the Learning Management System (LMS) in the time of COVID-19 Pandemic: An Expansion of the UTAUT Model. *Journal of Educational Computing Research*, 0735633120960421.

Ringle, C. M., & Sarstedt, M. (2016). Gain more insight from your PLS-SEM results. *Industrial Management & Data Systems*.

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). *SmartPLS 3. Bönningstedt: SmartPLS*.

Saga, V. L., & Zmud, R. W. (1993). The nature and determinants of IT acceptance, routinization, and infusion. *Proceedings of the IFIP TC8 Working Conference on Diffusion, Transfer and Implementation of Information Technology*, 67–86.

Salali, G. D., & Uysal, M. S. (2020). COVID-19 vaccine hesitancy is associated with beliefs on the origin of the novel coronavirus in the UK and Turkey. *Psychological Medicine*, 1–3.

Salloum, S. A., Alhamad, A. Q. M., Al-Emran, M., Monem, A. A., & Shaalan, K. (2019). Exploring Students' Acceptance of E-Learning Through the Development of a Comprehensive Technology Acceptance Model. *IEEE Access*, *7*, 128445–128462.

Saxena, C., Baber, H., & Kumar, P. (2020). Examining the moderating effect of perceived benefits of maintaining social distance on e-learning quality during COVID-19 pandemic. *Journal of Educational Technology Systems*, 0047239520977798.

Schoch-Spana, M., Brunson, E. K., Long, R., Ruth, A., Ravi, S. J., Trotochaud, M., Borio, L., Brewer, J., Buccina, J., & Connell, N. (2020). The public's role in COVID-19 vaccination: Human-centered recommendations to enhance pandemic vaccine awareness, access, and acceptance in the United States. *Vaccine*.

Schwarz, A. H. (2003). *Defining information technology acceptance: A human-centered, management-oriented perspective*. UMI Diss. Services.

Sentell, T., Vamos, S., & Okan, O. (2020). *Interdisciplinary perspectives on health literacy research around the world: more important than ever in a time of COVID-19*. Multidisciplinary Digital Publishing Institute.

Sharma, S. K., & Sharma, M. (2019). Examining the role of trust and quality dimensions in the actual usage of mobile banking services: An empirical investigation. *International Journal of Information Management*, *44*, 65–75.

Shaukat, R., Asghar, A., & Naveed, M. A. (n.d.). *Impact of Health Literacy on Fear of Covid-19, Protective Behavior, and Conspiracy Beliefs: University Students' Perspective*.

Shen, X.-L., Cheung, C. M. K., & Lee, M. K. O. (2013). Perceived critical mass and collective intention in social media-supported small group communication. *International Journal of Information Management*, *33*(5), 707–715.

Shernoff, D. J., Csikszentmihalyi, M., Schneider, B., & Shernoff, E. S. (2014). Student engagement in high school classrooms from the perspective of flow theory. In *Applications of flow in human development and education* (pp. 475–494). Springer.

Sim, J.-J., Tan, G. W.-H., Wong, J. C. J., Ooi, K.-B., & Hew, T.-S. (2014). Understanding and predicting the motivators of mobile music acceptance–a multi-stage MRA-artificial neural network approach. *Telematics and Informatics*, *31*(4), 569–584.

Simonetti, V., Durante, A., Ambrosca, R., Arcadi, P., Graziano, G., Pucciarelli, G., Simeone, S., Vellone, E., Alvaro, R., & Cicolini, G. (2021). Anxiety, sleep disorders and self-efficacy among nurses during COVID-19 pandemic: A cross-sectional study. *Journal of Clinical Nursing*.

Simpson, P. K. (1990). *Artificial neural systems*. Pergamon press.

Starr, C. (1969). Social benefit versus technological risk. *Science*, 1232–1238.

Sukendro, S., Habibi, A., Khaeruddin, K., Indrayana, B., Syahruddin, S., Makadada, F. A., & Hakim, H. (2020). Using an extended Technology Acceptance Model to understand students' use of e-learning during Covid-19: Indonesian sport science education context. *Heliyon*, *6*(11), e05410.

Sundaram, S., Schwarz, A., Jones, E., & Chin, W. W. (2007). Technology use on the front line: how information technology enhances individual performance. *Journal of the Academy of Marketing Science*, *35*(1), 101–112.

Tiwari, P. (2020). Measuring the Impact of Students‟ Attitude towards Adoption of Online Classes during COVID 19: Integrating UTAUT Model with Perceived Cost. *Education*, *1673968*(6), 1759790.

Trevino, L. K., & Webster, J. (1992). Flow in computer-mediated communication: Electronic mail and voice mail evaluation and impacts. *Communication Research*, *19*(5), 539–573.

Viscusi, W. K. (1983). *Risk by choice: Regulating health and safety in the workplace*. Harvard University Press.

Waithanji, E., Kairu-Wanyoike, S. W., & Liani, M. (2019). The Role of Gender and Other Socioeconomic Factors in the Adoption of the Contagious Bovine Pleuropneumonia Vaccine: A Literature Review. *East African Agricultural and Forestry Journal*, *83*(3), 221–238.

Wang, J.-G., Cao, Z.-D., Yang, B.-H., Ma, S.-W., Fei, M.-R., Wang, H., Yao, Y., Chen, T., & Wang, X.-F. (2017). A mothed of improving identification accuracy via deep learning algorithm under condition of deficient labeled data. *2017 36th Chinese Control Conference (CCC)*, 2281–2286.

Wang, Y.-T., Lin, K.-Y., & Huang, T. (2021). An analysis of learners' intentions toward virtual reality online learning systems: a case study in Taiwan. *Proceedings of the 54th Hawaii International Conference on System Sciences*, 1519.

Watermeyer, R., Crick, T., Knight, C., & Goodall, J. (2020). COVID-19 and digital disruption in UK universities: Afflictions and affordances of emergency online migration. *Higher Education*, 1–19.

Windschitl, M., & Sahl, K. (2002). Tracing teachers' use of technology in a laptop computer school: The interplay of teacher beliefs, social dynamics, and institutional culture. *American Educational Research Journal*, *39*(1), 165–205.

Zhao, Y., Pugh, K., Sheldon, S., & Byers, J. L. (2002). Conditions for classroom technology innovations. *Teachers College Record*, *104*(3), 482–515.