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ORIGINAL ARTICLE

Factors Affecting the Acceptance of E-learning by Learners in the Context of the Covid-19 Pandemic: A Hybrid Artificial Neural Network - SEM Method

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ABSTRACT
This research aims to determine the factors affecting the student's intention of E-learning adoption in the context of the Covid-19 pandemic in Vietnam. An online survey was used to assess the proposed psychological determinants of E-learning adoption. Confirmatory factor analysis and structural equation modeling were conducted on the collected data (n=310) using the SPSS 20 and the AMOS 24 statistical software. The reliability and validity of the measurement were examined via Cronbach's alpha, EFA, CFA while the strength and direction of the hypothesized causal paths among the constructs were analyzed via SEM. Finally, the results from SEM were used as the inputs for an Artificial Neural Network (ANN) model to predict acceptance factors. The results of the study indicated that there was a significant positive relationship between the attitude toward risk (Covid-19), PU, PE and the intention of E-learning adoption. Furthermore, combining SEM and neural networks enabled the capture of linear and complex nonlinear relationships between predictors and the dependent variables.

1. INTRODUCTION

E-learning is a fairly popular form of training in the world. With the strong growth and power of technology, especially the Internet, a new training method - E-learning, was introduced and contributed to satisfying students' needs to improve their knowledge. However, E-learning in Vietnam still holds a very small market share in the education field, especially at the undergraduate and postgraduate levels (Pham & Bui, 2020). During the time of Covid-19 pandemic prevention and control in Vietnam and around the world, the benefits of this learning model have become increasingly evident when helping universities continue to maintain training activities and connect customers every day with million classes for students and faculty nationwide (Phan et al., 2020). In addition, experts and higher education administrators share the same view that it is necessary to promote education through the form of E-learning. But to perform effectively through E-learning, universities need to understand learners as they play a central role in training outcomes.

In fact, there have been many research directions on the factors affecting the choice and acceptance of E-learning by learners. One of them is the research direction which applies the TAM technology acceptance model in studying the factors affecting the intention to E-learning adoption (Pituch & Lee, 2006; Park, 2009; Kanwal & Rehman, 2017; Ji et al., 2019).

However, the above studies have not taken into account the impact of risk aversion context (Covid-19) nor explore non-linear relationship between the items measuring factors affecting choice behavior in the TAM model. Therefore, the combined application of the ANN-SEM method is expected to solve this research gap.

2. LITERATURE REVIEW

E-learning is not only a normal teaching and learning activity but also a blended learning format, which combines online and face-to-face instructions (Roberts, 2004). E-learning is a form of teaching in which learning activities as well as teaching and learning content are all through an online platform (Concanon et al., 2005).

E-learning is an important component of teaching in universities today as it has become an effective way to deliver educational materials all over the world. It is believed that E-learning helps improve performance, develop skills, provide easy access, reduce costs and increase motivation levels (Ali & Magalhaes, 2008). E-learning is defined as a wide set of applications and processes such as Web-based learning, computer-based learning, virtual classrooms, and digital collaboration. It includes the delivery of content via Internet, intranet/extranet (LAN/WAN), audio and videotape, satellite broadcast, interactive TV, and CD-ROM (Kaplan-Leiserson, 2018).

According to Ajzen (2002), the intention is the mediator leading to the behavior. The purchase intention is human thinking guided by three factors including beliefs in behavior, subjective standard (social impact) and control. The stronger these beliefs are, the greater the human intention to exercise behavior is. Besides, according to Elbeck and Tirtiroglu (2008), purchase intention is the buyer's willingness to buy the product. Predicting purchase intention is the first step in predicting the actual purchase behavior of customers (Howard & Sheth, 1969). There are many theories explaining consumer behavior.

Fishbein and Ajzen (1975) propose Reasonable Behavioral Theory (TRA), which states that people often weigh the results of different actions before doing them and they choose to take actions that will lead to the results they want. The best tool to judge behavior is intention. According to TRA theory, the intention is influenced by attitudes toward subjective behavior and standards. Attitude is an individual's positive or negative feelings about performing a certain behavior. Attitude describes how well an individual rates the outcome of action as positive or negative. The subjective standard is the human perception of how to behave in association with the requirements of society.

Ajzen (1991) with Planning Behavior Theory (TPB), argues that intention is the motivating factor for the behavior or in other words the decision to perform the act is the result of the individual intention to choose a behavior. Based on the theory of behavioral selection and application in the field of technology, Davis (1989, 1993) proposes a new model called the technology acceptance model (TAM). The TAM model assumes that the perceived usefulness (PU) and the perceived ease of Use (PE) for technology will influence attitudes and intentions to use or buy certain technology products/services. From the perspective of applying the TAM model and the actual situation of implementing E-learning in training and in the context of E-learning being simultaneously applied by many universities in Vietnam during the Covid-19 pandemic, we propose to study the factors affecting the intention to adopt E-learning by learners which include the perceived usefulness, the perceived ease of use, the attitude, and the intention to adopt.

Taylor (1974) states that the central problem of consumer behavior is choice. Since the outcome of a choice can only be known in the future, the consumer is forced to deal with uncertainty or risk. Perception of risk is one pivotal aspect of consumer behavior because risk is often perceived to be painful in that it may produce anxiety, in which it must be dealt with in some manner by the consumer. Both the amount of perceived risk in a particular choice situation and the selection of methods for dealing with the risk will be affected by the individual consumer's level of self-esteem.

According to Fishbein and Ajzen (1975), attitude will influence intention and lead to behavior that consumers consider reasonable. Therefore, if consumers are weighing behavioral intentions in terms of risk, their attitudes are already pre-reactive to that risk. And thus, we believe that the attitude of students (consumers) as well as the intention to study by E-learning in the context of Covid-19 will be more or less affected by the fear of getting infected with coronavirus if learning directly by the traditional way.

Therefore, the hypotheses were proposed as follows: + H1: The perceived ease of use (PE) will positively impact on the perceived usefulness of E-learning; + H2a: The perceived usefulness (PU) will positively impact on the attitude to use E-learning in the context of users' fear of Covid-19; + H2b: The PU will positively impact on the intention to use E-learning in the context of users' fear of Covid-19; + H3a: The PE will positively impact on the attitude to use E-learning in the context of users' fear of Covid-19; + H3b: The PE will positively impact on the intention to use E-learning in the context of users' fear of Covid-19; + H4: The attitude will positively impact on the intention to use E-learning in the context of users' fear of Covid-19.

Social influence (SI) or subjective norm refers to the perception that the people who are important think that one should either use the system or not (Ajzen, 1991). Considering the E-learning environment, many learners choose to use E-learning because their friends are doing so, and they recommend it to them. Some studies have found that the subjective norm is directly related to attitude in the TAM (Park, 2009) whereas other studies have found that the SI indirectly influences attitude and adoption intention via PU (Park, 2009; Kanwal & Rehman, 2017). Moreover, it has been found that SI significantly affects PU, which leads to an individual's attitude and adoption behavior (Park, 2009). In this study, it is hypothesized that: H5: SI will positively affect the PU of the E-learning system.

According to Venkatesh (2003), system characteristics (SC) are the salient features of a system that can help individuals develop favorable (or unfavorable) perceptions regarding the usefulness or ease of use of a system. Pituch and Lee (2006) points out that system characteristics strongly affect PU and PE, then motivate learners to use the E-learning system. The results of the empirical study of Park (2009) confirm that the system characteristics affect the PE of E-learning in Korea. Ji et al. (2019) also confirm that the SC have a positive relationship with PU of online learning. Therefore, hypothesis H6 is as follows: + H6a: SC will positively affect the PU of the E-learning; + H6b: SC will positively affect the PE of the E-learning.

Self-efficacy (SE), the first user's characteristics, reflects one's beliefs about the ability to perform certain tasks successfully (Bandura, 1986). Furthermore, computer self-efficacy has been defined to reflect one's beliefs about the ability to use computers effectively (Compeau & Higgins, 1995a). Similarly, in this study, self-efficacy is defined as the confidence in one's ability to perform certain learning tasks using an e-learning system. Prior research has indicated that self-efficacy influences performance or behavior (Compeau & Higgins, 1995b) including behavioral intention (Tan & Teo, 2000; Venkatesh, 1999), and other studies have found that computer self-efficacy and perceived ease of use are related (Davis, 1989; Pituch & Lee, 2006; Park, 2009; Kanwal & Rehman, 2017). Therefore, hypothesis H7 is as follows: H7: Self-efficacy will positively affect the PE of the e-learning system.

The research model is presented below:

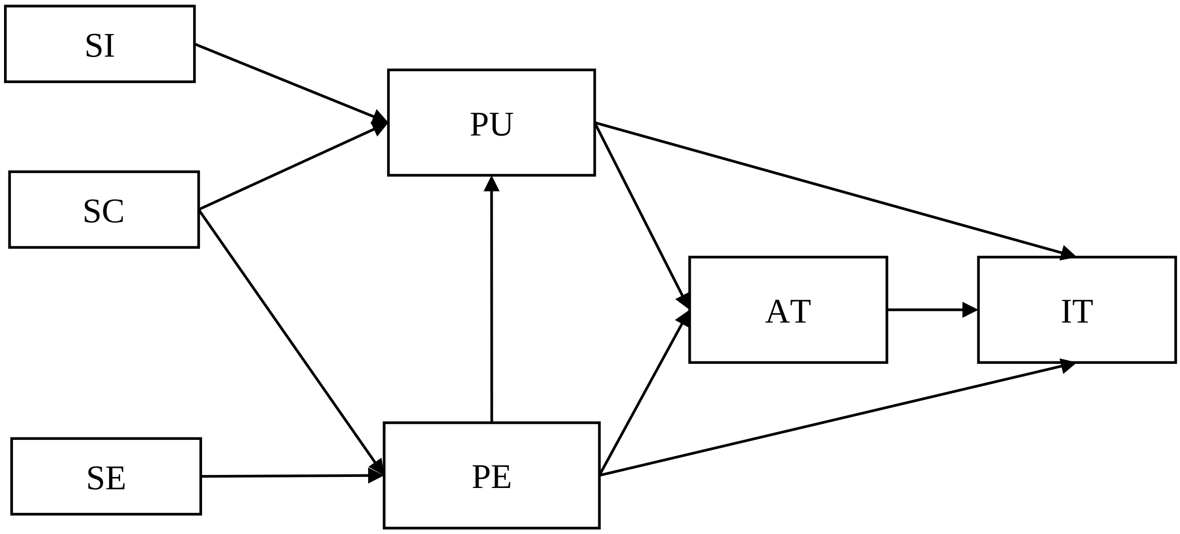


Figure 1. The research model

3. MATERIALS AND METHODS

3.1. Research Procedures

The research process included 02 main steps: preliminary and official quantitative research. The research team used preliminary quantitative research in order to adjust the research scale to suit the context of Vietnam. The population in this study consists of university students at Thu Dau Mot University which is one of the multidisciplinary state - owned universities in the Southeast of Vietnam.

In the preliminary quantitative research stage: We conducted a quantitative preliminary survey through the Microsoft Form tool, collected 174 survey responses, filtered 150 valid ones for the analysis (data collection time:

March 1st to March 7th , 2020). In this step, we evaluated the scale reliability and validity through Cronbach's alpha analysis and Exploratory factor analysis (EFA).

In the official quantitative research stage: We used the Microsoft Form tool to collect 352 survey responses, filtered out 310 valid ones (data collection time: March 18th to March 30th, 2020). Then, we assessed the scale reliability and validity with EFA, confirmatory factor analysis (CFA), and hypothesis testing as well as evaluated the theoretical model through Structural equation modeling (SEM). Finally, the artificial neural networks (ANN) analysis was employed to identify significant predictors.

3.2. Measurement method

The scales were designed based on previous studies. Both the original Perceived usefulness scale and the Perceived ease of use scale include 03 items according to Davis's TAM model (Davis, 1989, 1993) and the scale of Park (2009). The scale of Social Influence includes 03 items which was extracted from Venkatesh et al. (2003) and accorded to the scale of Park (2009). The scale of System characteristics includes 03 items which were extracted from Venkatesh and Bala (2008) and accorded to the scale of Ji et al. (2019). The scale of the Self-efficacy includes 03 items which were extracted from Pituch and Lee (2006). The scale of the Attitude includes 04 items which were extracted from Venkatesh et al. (2003) and adjusted to suit in the context of Viet Nam. The scale of the Intention includes 03 items which were extracted from Davis's TAM model (Davis, 1989, 1993) and accorded to Venkatesh et al. (2003).

4. RESULTS AND DISCUSSION

4.1. Results

4.1.1. The preliminary quantitative results

The preliminary quantitative analysis was conducted with a sample of 123 observations. There were two independent items excluded from the research model because their item - total correlations coefficient in Cronbach's alpha analysis was < 0.3. After assessing the scale reliability twice, the standardized Cronbach's Alpha coefficient reached up to 0.937 and the scale validity with the KMO's coefficient reached 0.891 (satisfactory), the remaining set of 22 items were finalized into the official quantitative analysis.

4.1.2. The official quantitative results

Demographic analysis of the sample: The official survey sample consisted of 310 valid responses, of which female respondents accounted for 72.26%, and males 27.74%. By the academic year, first-year students accounted for 24.84%, second-year students 34.52%, third-year students 30.32%, and fourth-year students 10.32%. By discipline, students majoring in pedagogy accounted for 53.23%; Students majoring in food technology 14.2%, students majoring in Economics 12.26%, students majoring in engineering and technology 12.9%, students majoring in administration 7.42%. Table 1 presents the demographic information of the sample:

Table 1. Demographic results of the data sample

Major	Gender				Student							
	Man		Woman		Freshman		Sophomore		3rd year		Senior	
	Amount	Proportion (%)	Amount	Proportion (%)	Amount	Proportion (%)	Amount	Proportion (%)	Amount	Proportion (%)	Amount	Proportion (%)
Pedagogy	0	0.00	165	53.23	46	14.84	62	20.00	52	16.77	5	1.61
Food Technology	42	13.55	2	0.65	15	4.84	11	3.55	5	1.61	13	4.19
Economics	17	5.48	21	6.77	7	2.26	20	6.45	8	2.58	3	0.97

Construction	18	5.81	22	7.10	4	1.29	12	3.87	15	4.84	9	2.90
Management Science	9	2.90	14	4.52	5	1.61	2	0.65	14	4.52	2	0.65
Total	86	27.74	224	72.26	77	24.84	107	34.52	94	30.32	32	10.32

4.1.3. Evaluating the scale reliability and validity

By assessing the scale reliability, the Cronbach's Alpha coefficient of the set of 22 items was 0.865 and all of the item - total correlations coefficients met the requirements (> 0.3). Then, regarding the scale validity with EFA, the set of 22 items reached the required statistical significance and established 07 groups of factors with the KMO coefficient of 0.855 and at eigenvalue with total variance extracted at 65.01%.

Table 2. Item - Total Correlation Statistics

	Corrected Item-Total Correlation	**Squared Multiple Correlation**	**Cronbach's Alpha if Item Deleted**
PU1	.516	.538	.856
PU2	.412	.464	.860
PU3	.485	.545	.857
PE1	.367	.329	.861
PE2	.377	.366	.861
PE3	.399	.377	.860
SE1	.445	.310	.859
SE2	.424	.356	.859
SE3	.403	.329	.860
SC1	.466	.319	.858
SC2	.457	.366	.858
SC3	.394	.326	.860
SI1	.529	.421	.856
SI2	.459	.400	.858
SI3	.483	.393	.857
AT1	.443	.319	.859
AT2	.449	.375	.858
AT3	.463	.367	.858
AT4	.442	.339	.859
IT1	.498	.387	.857
IT2	.379	.291	.861
IT3	.397	.268	.860

Table 3. Rotated Component Matrix

	Factor Loadings						
	1	2	3	4	5	6	7
PU1		.803					
PU2		.825					
PU3		.831					
PE1				.751			
PE2				.786			
PE3				.801			
SE1							.695
SE2							.732
SE3							.773
SC1						.683	
SC2						.783	
SC3						.742	
SI1			.683				
SI2			.804				
SI3			.758				
AT1	.697						
AT2	.737						
AT3	.727						
AT4	.703						
IT1					.745		
IT2					.761		
IT3					.697		

4.1.4. Analyzing the scale validation results with CFA

With standardized CFA results as shown in Figure 2, CMIN/df value was 1.019, CFI index was 0.998, GFI was 0.947, TLI was 0.998, RMSEA reached 0.008, all met the requirements. Besides, all component scales had estimated weights higher than 0.5; the lowest was the variable SE1 of the SE scale with a weight of 0.62. Furthermore, the critical value was much higher than 1.96 and the P-value was in the sign estimation tables (***), so it can be concluded that the estimated result was statistically significant.

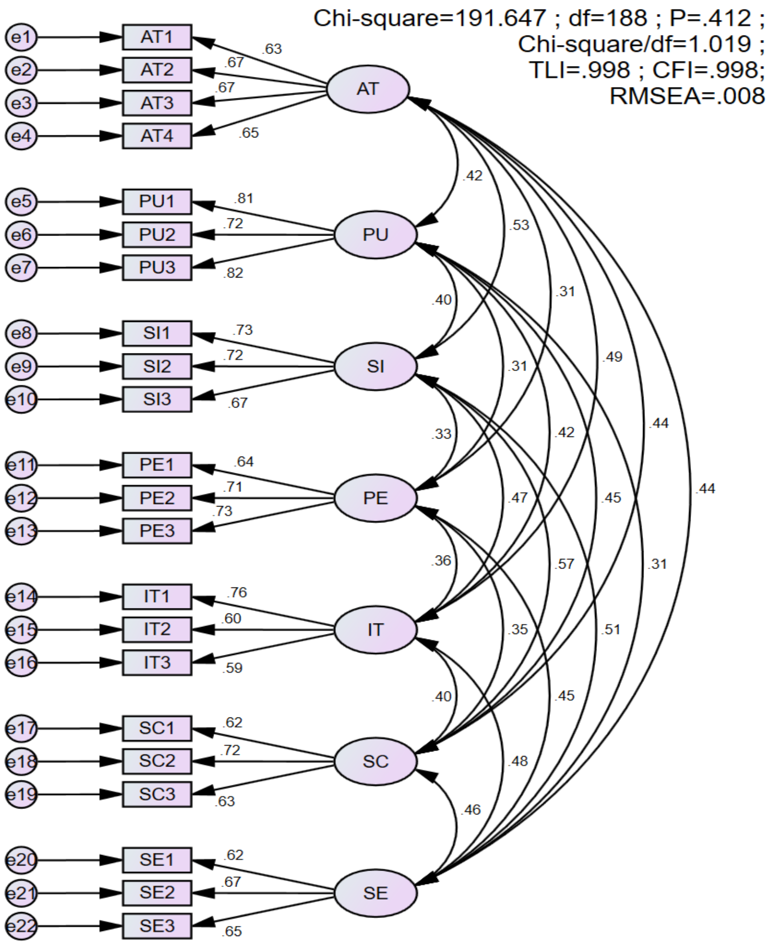


Figure 2. Critical measurement model by CFA (Standardized estimates)

Next, the results of extracted variance of all scales were higher than 40%, PU scale had the largest AVE value with 61.5%; on the other hand, all scales had aggregated confidence index (C.R) > 60% and greater than AVEs (Table 4). According to Fornell and Larcker (1981), all scales achieved convergent validity.

Table 4. Internal Consistency and Correlation Across Constructs

	C.R	AVE	MSV	MaxR(H)	AT	PU	SI	PE	IT	SC	SE
AT	0.751	0.431	0.279	0.752	0.656						
PU	0.827	0.615	0.204	0.833	0.425***	0.784					
SI	0.748	0.498	0.326	0.750	0.528***	0.396***	0.706				
PE	0.734	0.480	0.201	0.738	0.309***	0.312***	0.333***	0.692			
IT	0.690	0.429	0.243	0.713	0.493***	0.420***	0.469***	0.361***	0.655		
SC	0.697	0.435	0.326	0.704	0.439***	0.452***	0.571***	0.354***	0.401***	0.659	
SE	0.681	0.416	0.261	0.683	0.437***	0.310***	0.511***	0.448***	0.481***	0.465***	0.645

To analyze discriminant validity, the Heterotrait-monotrait ratio (HTMT) was believed to be more effective than the Fornell-Larcker and cross loading criteria since these only work well with high sample sizes and very heterogeneous loading patterns (Henseler et al., 2015). To evaluate discriminant validity, more conservative studies suggest values below 0.85 (Kline, 2016). Table 5 indicates that the different latent variables were lower, with a maximum value of 0.584, so there were no discriminant validity problems in this model.

Table 5. HTMT Analysis

	AT	PU	SI	PE	IT	SC	SE
AT							
PU	0.417						
SI	0.527	0.387					
PE	0.301	0.320	0.349				
IT	0.485	0.415	0.465	0.370			
SC	0.456	0.466	0.584	0.353	0.395		
SE	0.446	0.312	0.510	0.450	0.503	0.463	

4.1.5. Testing of hypotheses

Testing of hypotheses was conducted using the structural equation modeling (SEM). Because the distribution results of the items had deviations and sharpness in the range [-1, +1], ML estimation was used (Muthén & Kaplan, 1985). According to the SEM results with the ML estimation below, the model had 199 degrees of freedom, χ^2/df = 1.78, CFI = 0.915, TLI = 0.901, GFI = 0.903, RMSEA = 0.05, indicating that the structural equation modeling was suitable and qualified for analysis.

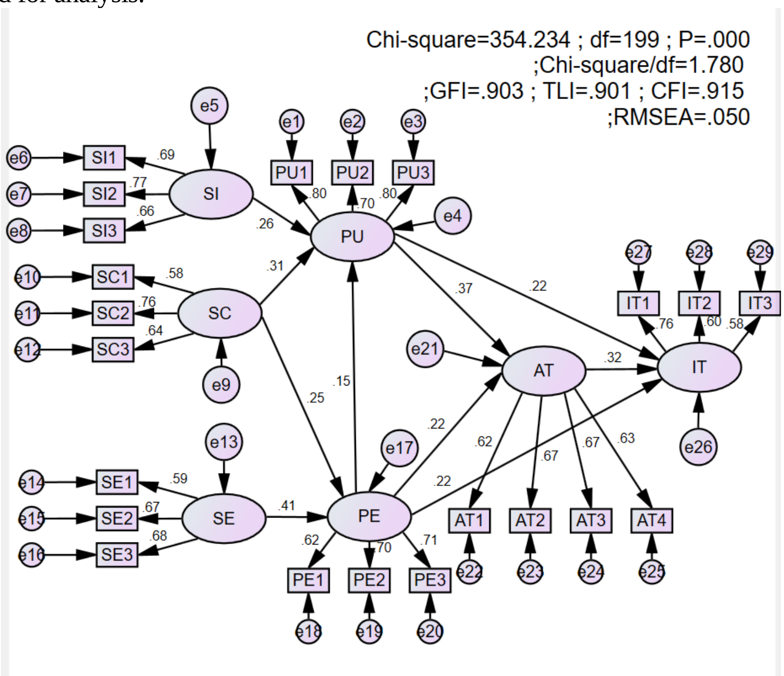


Figure 3. Structural model of E-learning adoption (Standardized estimates)

Based on the standardized estimation results in Table 6, with 95% statistical significance, all of the hypotheses were supported, by probability ($p<0.05$). Through the estimated coefficients, there was a very strong relationship between SE and PE, which showed that the individual's ability to use technology would have great significance with the perceived ease of use of E-learning. SC seemed to have a significant impact on the learner's perception, especially on PU. Furthermore, PU had a significant impact on the attitude and the intention to use E-learning. In addition, PE had no significant impact on the PU. It is also worth noting that the attitude (in the pandemic Covid -19) had a significant influence on the intention to E-learning adoption. On the other hand, concerning the level of attitude towards learning through E-learning, it is indicated that learners were not highly aware of the attitude to learning through this form. Therefore, it showed that E-learning was only a situational choice.

Table 6. The Results of Hypothesis Test (Results of estimating the relationship between the hypotheses in the standardized model)

Hypothesis	Path			Coefficients (Standardized estimate value)	Standard Error (S.E)	Critical Value (C.R)	(P-value)	Support/ Not Support
H7	PE	←	SE	.412	.095	4.692	***	Support
H6b	PE	←	SC	.248	.088	3.157	.002	Support
H5	PU	←	SI	.259	.086	3.657	***	Support
H6a	PU	←	SC	.314	.094	3.993	***	Support
H1	PU	←	PE	.151	.078	2.066	.039	Support
H3a	AT	←	PE	.222	.068	2.855	.004	Support
H2a	AT	←	PU	.372	.064	4.794	***	Support
H2b	IT	←	PU	.224	.076	2.803	.005	Support
H4	IT	←	AT	.317	.104	3.522	***	Support
H3b	IT	←	PE	.216	.080	2.715	.007	Support

Table 7. The Results of Hypothesis Test using Bootstrap (Results of estimating the relationships between hypotheses in the standardized model using Bootstrap)

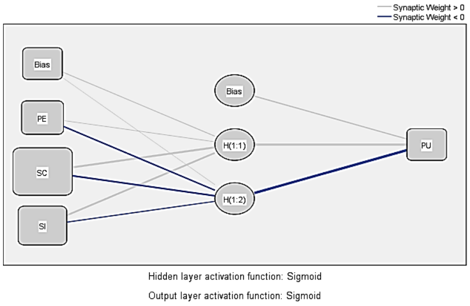
Path			SE	SE-SE	Estimation (Bootstrap)	Bias	SE-Bias
DSD	←	CN	.085	.003	.403	-.009	.004
DSD	←	HT	.080	.003	.250	.003	.004
HD	←	XH	.084	.003	.261	.002	.004
HD	←	HT	.081	.003	.315	.001	.004
HD	←	DSD	.083	.003	.145	-.006	.004
TD	←	DSD	.084	.003	.212	-.010	.004
TD	←	HD	.074	.002	.375	.003	.003

YD	←	HD	.084	.003	.224	.001	.004
YD	←	TD	.086	.003	.318	.001	.004
YD	←	DSD	.076	.002	.211	-.005	.003

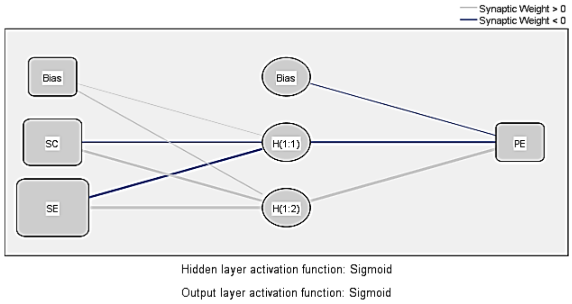
To confirm the validity and suitability of the theoretical model, the Bootstrap method was adopted, with the repeat sample of 500. According to the results in Table 7, the estimation results by Bootstrap with the official estimate results (in ML) had a very small deviation over the Bias and SE-Bias coefficients. On the other hand, the absolute value of the C.R coefficients of all estimates was less than 1.96. Thereby, it indicates that the estimation model of Bootstrap was appropriate and the reliability achieved 95%.

4.1.6. Artificial Neural network analysis

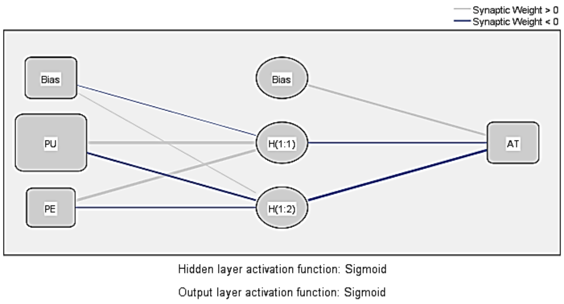
Common linear statistical techniques, such as multiple regression analysis and SEM, often are not sufficient to model the complex nature of human decision making process (Chan & Chong, 2012; Sim et al., 2014), because they usually oversimplify the complexity of adoption decision, as they are capable to examine only linear models (Leong et al., 2013; Tan et al., 2014). To overcome this problem, the application of the artificial neural networks (ANN), one of the most important artificial intelligence techniques, is suggested. The ANN approach not only identifies linear but also sophisticated non-linear and noncompensatory relationships (Leong et al., 2013), and it does not require any distribution assumption, such as normality, linearity or homoscedasticity to be fulfilled (Chong, 2013a; Leong et al., 2015; Tan et al., 2014). Also, ANN models are highly robust and adaptable (Sim et al., 2014; Tan et al., 2014), with higher prediction accuracy than linear models (Tan et al., 2014), which usually outperform traditional statistical techniques, such as MRA, in technology adoption prediction (Chong, 2013a; Chong et al., 2015; Sim et al., 2014). However, due to its “black-box” nature, the ANN approach is not suitable for hypothesis testing and examining causal relationships (Chong, 2013b; Leong et al., 2013). Therefore, in this study, a linear and compensatory SEM model is complemented with nonlinear and noncompensatory ANN model (Leong et al., 2013; Tan et al., 2014) i.e. a hybrid, two-stage approach was adopted (Chan & Chong, 2012; Chong, 2013b; Leong et al., 2013; Tan et al., 2014). In the first stage, SEM was used to determine the statistically significant determinants of dependent variables, whereas in the second stage the identified significant predictors were used as inputs to the neural network models in order to quantify the importance of each of them and to predict smart-watch adoption. ANN is a parallel distributed processor made up of simple processing units, called neurons or nodes, used for storing knowledge and making it available for use (Haykin, 2001). ANN architecture is based on human brain structure i.e. neurons are analogous to the biological neurons in the brain. The knowledge, acquired through the learning process, is stored in interneuron connection strengths called synaptic weights. To quantify the relationships between predictors and dependent variables in this study, the most common and popular neural network model - feedforward back-propagation multilayer perceptron (MLP) was used (Chan & Chong, 2012; Chong, 2013a; Chong, 2013b; Leong et al., 2013; Sim et al., 2014; Tan et al., 2014). A typical neural network is made up of several hierarchical layers, i.e. one input, one output, and one or more hidden layers between the input and the output. The first question in ANN design, after selecting the type of ANN, is to determine the number of hidden layers, which depends on the complexity of the problem to be solved. In the most cases, like in technology acceptance neural network models (Chong, 2013a; Chong, 2013b; Chong et al., 2015; Leong et al., 2013; Sim et al., 2014; Tan et al., 2014) one hidden layer is sufficient, as it is able to represent any continuous function, while with two hidden layers, even discontinuous functions can be modeled (Negnevitsky, 2011). Each layer consists of neurons, connected with the neurons of the following layer through an adaptable synaptic weight. In the feed-forward networks the signals are fed forward from the input layer, through the entire network, to the output layer. The inputs to each neuron are multiplied by its synaptic weights and summed, and this signal is transformed to the output value using a nonlinear activation function such as sigmoid, hyperbolic tangent or arctangent (Leong et al., 2013). The knowledge is stored in the network by iteratively exposing it to patterns of known inputs and outputs (supervised learning), and during this process the error, i.e. the difference between known output and the output predicted by the network, is calculated, propagated back in the opposite direction through the network, and used to adjust all synaptic weights so to minimize the estimation error. Another question in ANN design is to determine the number of neurons in each layer. It is easy to set the number of neurons in the input and the output layers, as they correspond to the number of inputs, i.e. predictors, and the number of outputs, i.e. dependent variables. The selection of the number of neurons in the hidden layer is more complex, as it can depend on the number of hidden layers, the sample size, the neural network architecture, the complexity of the activation function, the training algorithm, etc. (Gnana Sheela & Deepa, 2013). It affects both prediction accuracy and speed of network training. Generally, higher number of hidden neurons gives higher estimation accuracy (Negnevitsky, 2011), but only to some point, after which a further increase can dramatically increase the computational load without estimation accuracy improvement. Also, a large number of hidden neurons may lead to the overfitting problem when the network simply memorizes all training examples, without the ability to generalize. Unfortunately, there is no general rule to determine the number of hidden neurons, so usually trial-and-error (Chan & Chong, 2012; Chong, 2013a; Chong, 2013b; Chong et al., 2015) and the rules-of-thumb are used. One of the most common rules-of-thumb is that the optimal number of the neurons in the hidden layer is usually between the number of input and output neurons (Blum, 1992). In this study, the neural networks were modeled in the SPSS 20 software. Taking into account that only statistically significant predictors obtained by SEM can be used in ANN models, the research model presented in Figure 3 can be decomposed in four ANN models, as presented in Figure 4.



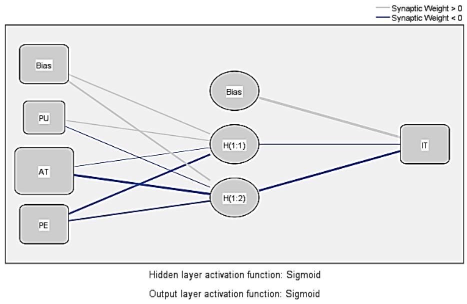
Model A



Model B



Model C



Model D

Figure 4. ANN Models

Model A had three inputs (PE, SC, SI) and one output (PU). Model B also had two inputs (SC and SI) and one output (PE). Model C had two inputs (PU and PE) and one output (AT). And the last was Model D with three inputs (PU, AT, PE) and one output (IT).

All four models had one hidden layer, with the number of hidden neurons generated automatically by SPSS (Leong et al., 2013; Leong et al., 2015; Ooi & Tan, 2016; Tan et al., 2014), which was 2 for all four models. In both hidden and output layers, sigmoid was used as an activation function (Chan & Chong, 2012; Leong et al., 2013; Leong et al., 2015; Ooi & Tan, 2016; Sim et al., 2014). In addition, all inputs and outputs were normalized to the range [0, 1], in order to obtain better model performances (Negnevitsky, 2011). A ten-fold cross validation procedure was performed in order to avoid overfitting problems, with 90% of the data used for network training and the remaining 10% used for testing (Chan & Chong, 2012; Chong, 2013a; Chong, 2013b; Leong et al., 2013; Ooi & Tan, 2016; Sim et al., 2014; Tan et al., 2014). The predictive accuracy of the model was assessed based on the values of Root Mean Square of Error (RMSE) (Chong, 2013a; Chong, 2013b; Leong et al., 2013; Ooi & Tan, 2016; Sim et al., 2014; Tan et al., 2014), and RMSEs of both training and testing data sets for all four models and all ten neural networks, as well as the averages and standard deviations for both data sets are computed and presented in Table 8.

Table 8. RMSE values of artificial neural networks

	Model A		Model B		Model C		Model D	
Network	RMSE Training	RMSE Testing	RMSE Training	RMSE Testing	RMSE Training	RMSE Testing	RMSE Training	RMSE Testing
1	0.1669	0.1557	0.1773	0.1792	0.1423	0.1607	0.1721	0.1410
2	0.1717	0.1422	0.1647	0.1632	0.1459	0.1525	0.1512	0.1671
3	0.1595	0.1609	0.1651	0.1575	0.1478	0.1516	0.1611	0.1393
4	0.1654	0.1567	0.1680	0.1502	0.1474	0.1522	0.1720	0.1568
5	0.1700	0.1531	0.1818	0.1691	0.1497	0.1499	0.1539	0.1543
6	0.1613	0.1610	0.1645	0.1600	0.1519	0.1432	0.1515	0.1568
7	0.1694	0.1506	0.1648	0.1589	0.1484	0.1574	0.1566	0.1457
8	0.1646	0.1638	0.1590	0.1708	0.1530	0.1405	0.1553	0.1635
9	0.1607	0.1668	0.1632	0.1633	0.1538	0.1312	0.1495	0.1589
10	0.1578	0.1774	0.1768	0.1803	0.1514	0.1446	0.1589	0.1470
Mean	0.1647	0.1588	0.1685	0.1653	0.1492	0.1484	0.1582	0.1530
Standard deviation	0.0048	0.0096	0.0074	0.0096	0.0035	0.0087	0.0081	0.0094

All four ANN models provided a quite accurate prediction, as the average RMSEs of all neural network models, for both training and testing data sets, were very small (Leong et al., 2013; Leong et al., 2015; Ooi & Tan, 2016; Sim et al., 2014; Tan et al., 2014).

The relative importance of every determinant is a measure of how much the predicted output value varies with different values of the determinant (Chong, 2013a). The relative importance of the determinants is then used in sensitivity analysis to compute normalized importance as the ratio of the relative importance of each variable with its highest relative importance, expressed in percentages (Leong et al., 2013; Ooi & Tan, 2016; Sim et al., 2014; Tan et al., 2014). The results of the sensitivity analysis for all the ANN models are presented in Table 9.

Table 9. Neural network sensitivity analysis

	Model A inputs: PE, SC, SI; output: PU			Model B inputs: SC, SE; output: PE		Model C inputs: PU, PE; output: AT		Model D inputs: PU, PE, AT; output: IT		
Network	PE	SC	SI	SC	SE	PU	PE	PU	AT	PE
1	0.244	0.438	0.318	0.416	0.584	0.643	0.357	0.068	0.624	0.308
2	0.212	0.436	0.352	0.419	0.581	0.702	0.298	0.291	0.378	0.331
3	0.223	0.474	0.304	0.411	0.589	0.645	0.355	0.254	0.438	0.309
4	0.272	0.410	0.318	0.416	0.584	0.621	0.379	0.287	0.484	0.229
5	0.255	0.428	0.317	0.377	0.623	0.597	0.403	0.373	0.323	0.304
6	0.217	0.401	0.382	0.313	0.687	0.742	0.258	0.333	0.418	0.248
7	0.239	0.471	0.290	0.258	0.742	0.530	0.470	0.306	0.440	0.255

8	0.226	0.433	0.341	0.434	0.566	0.704	0.296	0.093	0.546	0.362
9	0.233	0.343	0.424	0.445	0.555	0.642	0.358	0.392	0.347	0.261
10	0.347	0.423	0.230	0.359	0.641	0.564	0.436	0.416	0.365	0.219
Average importance	0.247	0.426	0.328	0.385	0.615	0.639	0.361	0.281	0.436	0.283
Normalized importance (%)	58	100	77	62.55	100	100	56.49	64.47	100	64.77

Interestingly, the sensitivity analysis results from ANN were similar to those from SEM. Thereby, these results confirmed the reliability in assessing the factors affecting the acceptance of E-learning by learners.

4.2. Discussion

Although the Covid-19 pandemic has been gradually controlled, the world is still heavily affected by the global Covid-19 pandemic. This pandemic affects all aspects of life, lifestyle and behavior of all individuals and organizations in the world. Many countries did choose blockade, social distance and recommend schools to apply online teaching, including Vietnam. The purpose of this study is to explore the factors affecting the intention to learn in the form of E-learning on the basis of application and expansion of the TAM model in the context of Covid-19. The results confirmed the hypothesis, TAM model for learning intention by E-learning. There are some theoretical and practical implications as follows:

Firstly, the Vietnamese student's intention to learn with E-learning was primarily influenced by the perceived usefulness and the perceived ease of use. This result confirmed the proposal of the TAM model again (Davis, 1989, 1993).

Secondly, social influence had a significant impact on the perceived usefulness of learning by E-learning, similar to the research results of (Park, 2009; Kanwal & Rehman, 2017).

Thirdly, self-efficacy (individual differences) towards technology had a great impact on the perceived ease of use and thereby, affecting the attitude and intention to learn by E-learning, once again confirming the previous research results of (Pituch & Lee, 2006; Park, 2009; Kanwal & Rehman, 2017).

Fourth, the characteristics of the E-learning system by the school affected both the perceived usefulness and the perceived ease of use. This result once again confirmed the previous research results of (Pituch & Lee, 2006; Venkatesh, 2008; Park, 2009; Ji et al., 2019).

Fifth, the results of the study revealed that the risk aversion by the infection if learning directly had the greatest influence on the acceptance of learning by means of E-Learning. This is a completely new discovery compared to previous studies.

Sixth, the combined approach of ANN-SEM is suitable for studies on behavioral intention.

5. CONCLUSION

This study has identified important factors affecting students' adoption of E-learning in the context of the ongoing covid-19 pandemic in Vietnam: the attitude toward risks, the perceived usefulness, the perceived ease of use. The research results would support educational policy makers in implementing E-learning in Vietnam. However, this study has some limitations. First, the authors conducted an online survey with a convenient sampling method. In addition, the survey subjects mainly involved students, which might neglect other subjects who would also adopt E-learning. Regarding recommendations for future research direction, the research should survey in countries where risk avoidance is low (Vietnam is a country with a high risk avoidance mentality) to identify the similarities and differences.

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