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Factors Affecting Students' Intention to Use Mobile Learning at Universities: An Empirical Study

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Abstract. Mobile Learning (M-Learning) is a new learning form that is more and more interesting and applied wisely. Although this form shows a significant improvement in the teaching and learning process, various studies show that the application of technology in education also brings a lot of anxiety and concerns to teachers and learners. The purpose of this study is to build and estimate the model to determine the factors affecting students' intention to use M-learning at universities in Ho Chi Minh City, Vietnam. From that, draw policy implications for Vietnamese universities in operating and managing students' online learning activities. To achieve these purposes, we used an integrated method SEM-ANN with primary data from the survey of 452 students. The results show that factors affecting students' intention of M-Learning are Perceived Ease of Use, Performance Expectancy, Social Influence, Facilitating Condition, and Price Value. Our research results have provided empirical evidence for the appropriateness of the UTAUT2 theoretical model in a developing country like Vietnam. Besides, we also propose some implications to increase students' intention to use M-Learning at universities in Ho Chi Minh City.

Keywords: M-Learning, Structural Equation Modeling (SEM), Artificial Neural Network (ANN)

1. Introduction

Nowadays, organizations are operating in the vibrant environment with the rapid development of technology, requiring organizations to bring the creativity and innovation to the products and services they provide. For the education sector, the trend of digital transformation, along with the rapid development of technology and telecommunications, has greatly impacted education and learning methods at universities (Ahmed et al., 2022; Khan & Jacob, 2015; O'Connor & Andrews, 2018). Besides traditional learning forms, modern technologies in education are becoming more popular (Lai et al., 2019). As a result, the use of technology such as artificial intelligence, digital (Pacheco et al., 2017), and virtual reality (Chassignol et al., 2018) are integrated with mobile devices and become user-friendly, useful learning tools (Crompton et al., 2018; Hamidi & Chavoshi, 2018; Jeng et al., 2010). This has made the trend of digital in education increasingly growing in recent years (Paul et al., 2018).

Because of the high popularity and flexibility combined with intelligent applications with simple and user-friendly interfaces, learning systems in M-learning and mobile applications have been more and more interesting and applied wisely, showing the significant improvement in teaching and learning processes as well as training, education, and research (Almaiah et al., 2016; Khan & Jacob, 2015).

However, along with the benefits of M-learning, various studies have shown that the application of technology in education also brings a lot of anxiety and concerns to both teachers and users (Engel et al., 2022). This directly affects learners' adaptation and acceptance of technology and indirectly affects teaching success through M-learning and other modern methods in general. Therefore, the concern and acceptance of technology were checked in many previous studies to find the factors affecting the learner's behavioral intention to use technology. A study conducted by Mac Callum et al. (2014) with data from 446 students showed that understanding abilities about technology and media and its anxiety affect Perceived Ease of Use and Perceived Usefulness, since then affecting learners' behavioral intention to use M-learning. The study by Arpaci (2016) aimed to determine factors affecting students' attitudes and intention to use cloud storage services on mobile phones. Arpaci (2016) used Structural Equation Modeling to identify influencing factors with data collected from 262 students in a university. The result of this study showed that Perceived Usefulness, Subjective Criteria, and Trust have a significant positive influence on attitude, which in turn affects students' use intention. The study by Alhumaid et al. (2021) aimed to determine the factors affecting the intention to use M-learning during the Covid-19 pandemic. Alhumaid et al. (2021) also used the SEM model to determine the influencing factors based on data collected from 280 students at Zayed University. Like Arpaci (2016), Alhumaid et al. (2021) also found that the factors affecting the intention to use M-learning are Perceived Ease of Use, Perceived Usefulness, Satisfaction, Subjective Standards, and Cognitive Behavioral Abilities. In addition, Alhumaid et al. (2021) found that Perceived Fear of technology and expectations are also factors affecting students' intention to use M-learning. Similar to the case studies above, the other studies by Hew et al. (2015), and Kang (2014) also found quite similar results about factors affecting the intention to use mobile applications in general and M-learning in particular.

However, this study topic still has many research gaps. The first research gap is from theory. Specially, theoretically, most studies related to this field are based on the theory of reasoned action (TRA) (Arpaci, 2016; Kang, 2014), technology acceptance model (TAM) (Alhumaid et al., 2021; Arpaci, 2016; Kang, 2014; Mac Callum et al., 2014), motivation model (MM) (Mac Callum et al., 2014), theory of planned behavior (TPB), connection model between TAM and TRA, combination model between TAM and TPB (Alhumaid et al., 2021; Arpaci, 2016; Kang, 2014; Mac Callum et al., 2014). However, these models still have many limitations in determining the influencing factors. In order to solve this gap, this study aims to identify the factors affecting the intention to use M-Learning based on the inheriting of the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (Venkatesh et al., 2003). Due to high generalizability, the UTAUT model is used by many studies to assess the adoption and use of technology (AbuShanab et al., 2010; Dajani & Yaseen, 2016). However, according to Venkatesh et al. (Venkatesh et al., 2012), UTAUT is not yet a generalized model that comprehensively identifies the factors influencing the intention to use technology. Therefore, Venkatesh et al. (Venkatesh et al., 2012) developed an adoption model and used the extended technology (UTAUT2) by adding new factors to UTAUT. In this study, we evaluate the factors affecting students' intention to use M-Learning through the UTAUT2 model to overcome the limitations of previous models.

The second research gap is from the method of model estimation in previous studies. Most studies use structural equation modeling (SEM) to determine the influencing factors and draw conclusions. However, SEM is only able to evaluate linear relationships. In case, the relationship between the variables is non-linear, the results drawn from SEM will not guarantee reliability. Therefore, this study overcomes the disadvantages of the SEM by integrating an Artificial Neural Network (ANN) to evaluate the non-linear relationship between factors in the model (Binsawad, 2020). In particular, ANN does not need a structural equation for the linear or non-linear relationships of the variables. Therefore, the problem of non-linear relationship will be solved.

Following this section, section 2 will review the literature and the development of hypotheses, the methodology will be shown in section 3, section 4 will present the study results, and the conclusions and management implications will be presented in section 5.

2. Development of Hypotheses and Research model

2.1. Development of Hypotheses

Perceived Ease of Use

In the UTAUT2 model, we adjusted the Expectancy Effort factor to Perceived Ease of Use to better suit the context of technology research in Viet Nam. This adjustment didn't lose the basic properties of the UTAUT2 model, but only made the model more suitable. According to Venkatesh et al. (2012), Perceived Ease of Use is the degree which people believe that using a particular system won't require physical and mental effort. Tung and Chang (2007) demonstrated a positive relationship between Perceived Ease of Use and intention to learn online. Perceived Ease of Use has a huge and direct influence on the intention to join online courses. A recent study by Joo et al. (2016) have shown that perceived ease of use has a positive influence on the intention to use M-Learning of students at Korean universities. Besides, this finding is also supported by the results of Alshurideh et al. (2020), who conducted a similar study with students from universities in the United Arab Emirates (UAE). Also, with the research scope of the United Arab Emirates (UAE), Al-Emran et al. (2020) also found evidence of a positive impact of perceived ease of use on the intention to use M-Learning of postgraduate students. Therefore, we propose the following hypothesis:

Hypothesis 1 (H1). Perceived Ease of Use has a positive impact on students' intention to M-Learning

Performance Expectancy

According to Davis (1993), Performance Expectancy is the degree to which an individual believes that using the system will help them achieve their work goals. Performance Expectancy from a new technology stems from its usefulness (Davis, 1993). The usefulness is the extent to which a particular technology will be beneficial when performing certain activities (Venkatesh et al., 2012). Performance Expectancy relates to an individual's belief about the usefulness of technology in performing different activities (Venkatesh et al., 2003; Waheed & Kaur, 2016). The experimental studies by Al-Emran et al. (2020), Alshurideh et al. (2020), and Sewandono et al. (2022) showed that Performance Expectancy positively impacts students' intention to use M-Learning. Therefore, we propose the following hypothesis:

Hypothesis 2 (H2). Performance Expectancy has a positive impact on students' intention to use M-Learning.

Social Influence

Social influence is defined as the degree to which significant others influence an individual to believe in using a particular technology application (Venkatesh et al., 2003). Collectivist learners often see themselves as members of a community, emphasize the opinions of others or group standards, be submissive, maintain relationships, and be more concerned with the needs and desires of others (Ajzen, 1991; Davis, 1989). These influencers here can be families, relatives, friends, and teachers. Social influence has been shown to positively impact users' intention to use technology (Alshurideh et al., 2020; Jairak et al., 2009; Thomas et al., 2013; Razzak and Jassem 2021). Therefore, we propose the following hypothesis:

Hypothesis 3 (H3). Social influence has a positive impact on students' intention to use M-Learning.

Facilitating Conditions

Facilitating Conditions are understood that students have all favorable conditions for using the online learning system. Facilitating Conditions include resources (computer, internet, 3G/4G networks), necessary knowledge to use the system (how to control and interact with the system), and support from experts when facing technical issues. This factor positively impacts the intention to use a technology or an information system in many previous studies (Camilleri & Camilleri, 2022; Nahla Aljojo, 2020; Thomas et al., 2013; Razzak and Jassem 2021). As a result, we suggest the following:

Hypothesis 4 (H4). Facilitating Conditions has a positive impact on students' intention to use M-Learning.

Hedonic Motivation

Hedonic Motivation is defined as a pleasure in using technology, and it has been shown to play an important role in determining technology adoption and use (Brown & Venkatesh, 2005). In a recent study by Al-Azawei & Alowayr (2020), and Ameen & Willis (2019), authors found a positive impact of Hedonic Motivation on students' intention to use M-Learning. Therefore, we propose the following hypothesis:

Hypothesis 5 (H5). Hedonic Motivation has a positive impact on students' intention to use M-Learning

Price value

In the marketing study, value and cost are often conceptualized with the product and service quality to determine the perceived value of the product or service (Zeithaml, 1988). In this study, Price Value is defined as the perception of the user about the difference between the benefits received from M-learning and the monetary costs of using it (Boyinbode, et al., 2015). According to the aforementioned perspective, using a mobile phone while learning may result in higher costs for students. They can therefore recognize both its financial cost and possible rewards. On a mobile device, this element was discovered to have an impact on learning applications (Al-Azawei & Alowayr, 2020; Ameen & Willis, 2019). As a result, we suggest the following:

Hypothesis 6 (H6). Price Value has a positive impact on students' intention to use M-Learning

Trust

Based on the previous studies, in this study, we adjusted the habit factor in the UTAUT2 model to the Trust factor. Specifically, Trust in technology mentions to user's trust that the use of such technology is reliable and trustworthy (Nikou & Economides, 2017). This can include stability, reliability, security, and reputation, all of which have a positive impact on behavioral intention to technology (Nikou & Economides, 2017; Tarhini et al., 2016). In this study, trust is defined as the level of trust that learners receive when learning through a mobile device. In the recent studies by Alalwan et al. (2017, 2018), Nikou & Economides (2017), and Tarhini et al. (2016), trust has been found to have a positive impact on students' intention to use M-Learning. Therefore, we propose the following hypothesis:

Hypothesis 7 (H7). Trust has a positive impact on students's intention to use M-Learning.

2.2. Research Model

Based on the developed research hypotheses, we propose the following research model:

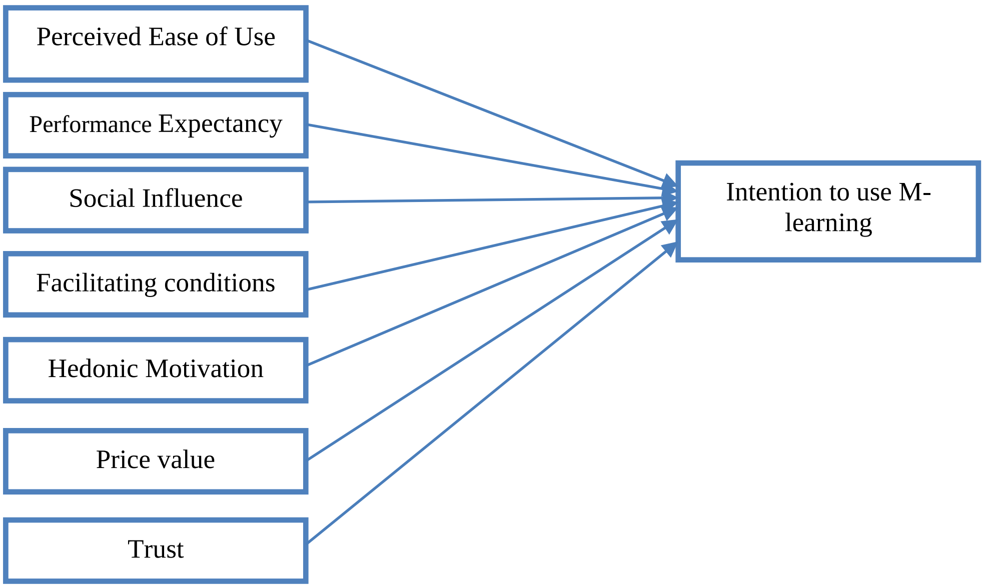

Fig. 1: Proposed Research Model

3. Research Methodology

This study uses a combination of qualitative and quantitative methods. As follow:

3.1. Qualitative Method

In this study, we selected two subjects to conduct qualitative research, including: first, experts in university education, and educational technology; second, middle managers (manager, dean) at Vietnamese universities. Specifically, we selected an expert with whom we had a pre-existing relationship. Then we asked this expert to recommend to other experts. The process of performing the qualitative method is shown in 3 steps as follows:

Step 1: In this step, we build scales for factors in the research model, including Perceived Ease of Use scale, Performance Expectancy, Social Influence, Facilitating conditions, Hedonic Motivation, Price value, Trust, and Intention to use M-learning. The scales are inherited from previous studies, as presented in Table 1.

Step 2: After synthesizing the scales from previous studies, the purpose of this step is to clarify more about the theory and build, adjust, and develop scales. Therefore, we use the focus group including 7 experts and 7 middle managers (manager, dean) at Vietnamese universities. The appropriateness of the research model's scales and the clarity of the questionnaire's statements were both topics that were discussed with the focus group.

Step 3: After obtaining the preliminary scales from the focus group, we continue conducting one-on-one interviews to adjust and develop the scale to ensure the value of content for quantitative research. The scales in the research model are in Table 1.

The 5-point Likert scale is used to measure the observed variables in each factor. The 5-point Likert scale is used at ascending level. Specially, point 1 represents "strong disagreement", point 2 represents "disagreement", point 3 represents "neutral", point 4 represents "agreement", and point 5 represents "strong agreement".

Table 1: The scale factors in the research model

Scale's Description	Scale Name	Sources
Perceived Ease of Use	PEOU	Joo et al. (2016), Alshurideh et al. (2020), and Al-Azawei & Alowayr (2020)
I feel that learning to use M-Learning is very easy	PEOU1	
I find that operations performed on M-Learning are clear and easy to understand	PEOU2	
If guided, I can immediately use M-learning to learn fluently	PEOU3	
I think that I will not have any difficulty to use M-Learning	PEOU4	
Performance Expectancy	PE	Al-Emran et al. (2020), Alshurideh et al. (2020), and Al-
I find that using M-Learning helps increase to my learning efficiency	PE1	
I find that using M-Learning helps increase ability to solve problems	PE2	

I find that using M-Learning helps save time	PE3	Azawei & Alowayr (2020)
I find that using M-Learning helps me learn faster	PE4	
Social Influence	SI	Thomas et al. (2013), Al-Azawei & Alowayr (2020)
My relatives think that I should use M-Learning	SI1	
Most of my friends around me think that I should learn M-learning	SI2	
My teachers think that I should use M-Learning	SI3	
Facilitating conditions	FC	Thomas et al. (2013), Al-Azawei & Alowayr (2020)
I have enough resources to use form M-Learning	FC1	
I have enough knowledge (how to access, how to use, how to check information) to use form M-Learning	FC2	
I can use form M-Learning with my other learning systems	FC3	
There is always someone or a team willing to support when I have difficulty or system issues	FC4	
Hedonic Motivation	HM	Al-Azawei & Alowayr (2020), Ameen & Willis (2019)
I find that using M-Learning is very interesting	HM1	
Using M-Learning brings me many experiences	HM2	
I find that learning through M-Learning as a form of entertainment	HM3	
Price value	PV	Al-Azawei & Alowayr (2020)
I find that cost of using M-Learning is lower than the other learning forms	PV1	
I find that using M-Learning offers many free lessons	PV2	
I find that using M-Learning helps me save money	PV3	
Trust	TR	Al-Azawei & Alowayr (2020)
I believe that learning technology on mobile is reliable	TR1	
I believe in learning technology on mobile	TR2	
I feel that learning on mobile device is recognized by law	TR3	
Intention to use mobile learning	IU	Alshurideh et al. (2020), Al-Azawei & Alowayr (2020)
I will recommend M-Learning to others in the near future	IU1	
I intend to use M-Learning more often in the near future	IU2	
I plan to use M-Learning in my daily learning	IU3	

3.2. Quantitative Research

3.2.1. Sample and Data Collection

Our data was collected by distributing survey forms directly to students at universities in Ho Chi Minh City area. According to Hair et al. (2006), the sample size needs to be considered in the correlation to the number of estimated parameters, and if the method of the maximum likelihood estimation (ML - Maximum Likelihood) is used, the sample size should be at least 100 to 150. In addition, according to Bollen (1989), there must be at least five observations per estimator (ratio 5:1). Experience shows that the sample size of 300 is good, 500 is very good, and 1000 is excellent (Tabachnick & Fidell, 2007). In this study, we identified 27 observed variables, so the minimum sample size is 135 students, as suggested by Bollen (1989). In fact, we distributed 510 survey forms and collected 480 survey forms. After eliminating questionnaires that lacked information, the number of survey questionnaires used for analysis was 452. Descriptive statistics of the sample are presented in Table 2.

Table 2. Descriptive statistics

			Year of study				Total
			First	Second	Third	Fourth	
Gender	Female	Count	59	52	73	69	253
		% of Total	13.1%	11.5%	16.2%	15.3%	56.0%
	Male	Count	42	47	55	55	199
		% of Total	9.3%	10.4%	12.2%	12.2%	44.0%
Total		Count	101	99	128	124	452
		% of Total	22.3%	21.9%	28.3%	27.4%	100.0%

3.2.2. Data Analysis

In this study, we conduct analysis as the following steps:

Step 1: Preliminary assessments of the reliability and values of scale by Cronbach’s alpha reliability coefficient and exploratory factor analysis (EFA) to further screen and remove observed variables that do not meet the criteria.

Step 2: Analyze the Structural Equation Modeling (SEM) to test the model fit and the research hypotheses.

Step 3: Analyze the Artificial Neural Network model (ANN). An artificial Neural Network (ANN) is a computational tool that simulates neural networks in the human brain and is capable of non-linear mapping relationships between input and output variables. Artificial Neural Networks (ANNs) are increasingly used in statistical scientific research because of the impressive outcomes they have produced in a variety of sectors (Movagharnejad et al., 2011). The general structure of an ANN is a feedforward neural network, consisting of an input layer, an output layer, and a hidden layer(s). In this study, an ANN is developed with an input layer including factors affecting students’ intention to use M-Learning at universities in Ho Chi Minh City. These factors are obtained from the SEM model results. One problem with the ANN model is the number of hidden layers. In theory, there can be one or several hidden layer(s), but universal approximation theory suggests that an ANN has a single hidden layer with a large enough number of neurons that can interpret any input-output structure (Tambe et al., 1996). Therefore, the proposed

ANN for this study has only a single hidden layer.

We use the Python language to conduct data analysis through the Jupyter Notebook compiler. The detailed analysis process with the codes is stored on GitHub (see https://github.com/anhle32/Factors-affecting-intention-to-use-M-learning.git).

4. Research Result

4.1. The Reliability Assessment of the Scale using Cronbach's Alpha Coefficient

The result of the reliability assessment of the scales corresponding to the factors in the model are presented in Table 3. Specially, Cronbach's Alpha coefficient of Perceived Ease of Use, Performance Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price value, Trust, and Intention to use M-learning are all greater than 0.6 with values of 0.797, 0.827, 0.790, 0.830, 0.810, 0.752, 0.820, and 0.842, respectively. In addition, the corrected item-total correlation of the observed variables in each scale is greater than 0.3. Thus, the scales are reliable for conducting the analysis.

Table 3. Reliability Analysis

Factors	Items before reliability analysis	Cronbach's Alpha	Items after reliability analysis
Perceived Ease of Use	PEOU1, PEOU2, PEOU3, PEOU4	0.797	PEOU1, PEOU2, PEOU3, PEOU4
Performance Expectancy	PE1, PE2, PE3, PE4	0.827	PE1, PE2, PE3, PE4
Social Influence	SI1, SI2, SI3	0.790	SI1, SI2, SI3
Facilitating conditions	FC1, FC2, FC3, FC4	0.830	FC1, FC2, FC3, FC4
Hedonic Motivation	HM1, HM2, HM3	0.810	HM1, HM2, HM3
Price value	PV1, PV2, PV3	0.752	PV1, PV2, PV3
Trust	TR1, TR2, TR3	0.820	TR1, TR2, TR3
Intention to use mobile learning	IU1, IU2, IU3	0.842	IU1, IU2, IU3

4.2. Exploratory Factor Analysis Result

Before performing exploratory factor analysis (EFA), we performed a correlation analysis between the observed variables in the model. Table 4 shows that the observed variables in each scale are highly correlated with each other. This implies that the observed variables measure the same for the factors in the research model and the exploratory factor analysis method is appropriate

Table 4: Correlation Matrix

	PEOU1	PEOU2	PEOU3	PEOU4	PE1	PE2	PE3	PE4	SI1	SI2	SI3	FC1	FC2	FC3	FC4	HM1	HM2	HM3	PV1	PV2	PV3	IU1	IU2	IU3	TR1	TR2	TR3
PEOU1	1.00	0.47	0.44	0.57	0.19	0.15	0.16	0.22	0.15	0.21	0.16	0.19	0.14	0.19	0.19	0.29	0.23	0.29	0.09	0.10	0.16	0.33	0.38	0.37	0.02	0.00	0.03
PEOU2	0.47	1.00	0.48	0.53	0.13	0.04	0.09	0.14	0.20	0.16	0.22	0.13	0.18	0.14	0.22	0.22	0.23	0.28	-0.01	0.04	0.11	0.29	0.27	0.31	-0.05	-0.08	-0.08
PEOU3	0.44	0.48	1.00	0.48	0.08	-0.01	-0.03	0.06	0.18	0.18	0.19	0.17	0.11	0.05	0.18	0.20	0.27	0.16	-0.03	0.00	0.10	0.14	0.17	0.25	0.03	-0.03	-0.04
PEOU4	0.57	0.53	0.48	1.00	0.14	0.18	0.11	0.20	0.15	0.21	0.21	0.14	0.13	0.17	0.21	0.25	0.25	0.26	0.08	0.07	0.09	0.28	0.26	0.32	0.02	0.01	-0.01
PE1	0.19	0.13	0.08	0.14	1.00	0.54	0.60	0.48	0.09	0.19	0.14	0.16	0.16	0.20	0.18	0.24	0.22	0.28	0.19	0.07	0.14	0.35	0.34	0.32	0.01	0.06	0.07
PE2	0.15	0.04	-0.01	0.18	0.54	1.00	0.58	0.51	0.16	0.16	0.10	0.28	0.11	0.19	0.16	0.26	0.23	0.36	0.20	0.11	0.04	0.33	0.29	0.34	-0.04	-0.02	0.07
PE3	0.16	0.09	-0.03	0.11	0.60	0.58	1.00	0.57	0.22	0.27	0.23	0.21	0.19	0.23	0.18	0.22	0.29	0.30	0.19	0.06	0.07	0.40	0.36	0.37	0.00	0.01	0.08
PE4	0.22	0.14	0.06	0.20	0.48	0.51	0.57	1.00	0.18	0.18	0.21	0.13	0.14	0.23	0.11	0.24	0.34	0.33	0.23	0.13	0.21	0.32	0.38	0.34	0.09	0.08	0.13
SI1	0.15	0.20	0.18	0.15	0.09	0.16	0.22	0.18	1.00	0.51	0.59	0.23	0.23	0.16	0.26	0.27	0.27	0.34	0.17	0.14	0.10	0.33	0.25	0.34	0.08	0.04	0.04
SI2	0.21	0.16	0.18	0.21	0.19	0.16	0.27	0.18	0.51	1.00	0.57	0.26	0.23	0.19	0.28	0.28	0.27	0.34	0.13	0.14	0.08	0.39	0.34	0.40	0.04	0.08	0.01
SI3	0.16	0.22	0.19	0.21	0.14	0.10	0.23	0.21	0.59	0.57	1.00	0.15	0.28	0.14	0.19	0.22	0.31	0.38	0.15	0.15	0.08	0.34	0.22	0.34	0.07	0.08	0.02
FC1	0.19	0.13	0.17	0.14	0.16	0.28	0.21	0.13	0.23	0.26	0.15	1.00	0.50	0.54	0.58	0.35	0.31	0.30	0.22	0.15	0.13	0.30	0.31	0.34	-0.08	-0.07	0.01
FC2	0.14	0.18	0.11	0.13	0.16	0.11	0.19	0.14	0.23	0.23	0.28	0.50	1.00	0.58	0.57	0.31	0.28	0.30	0.15	0.08	0.19	0.36	0.26	0.34	0.04	0.02	0.06
FC3	0.19	0.14	0.05	0.17	0.20	0.19	0.23	0.23	0.16	0.19	0.14	0.54	0.58	1.00	0.54	0.35	0.32	0.39	0.19	0.12	0.19	0.29	0.34	0.33	-0.08	-0.03	0.04
FC4	0.19	0.22	0.18	0.21	0.18	0.16	0.18	0.11	0.26	0.28	0.19	0.58	0.57	0.54	1.00	0.26	0.28	0.25	0.15	0.04	0.16	0.37	0.37	0.36	-0.04	-0.05	0.00
HM1	0.29	0.22	0.20	0.25	0.24	0.26	0.22	0.24	0.27	0.28	0.22	0.35	0.31	0.35	0.26	1.00	0.53	0.61	0.24	0.23	0.28	0.43	0.42	0.45	0.05	0.04	0.06
HM2	0.23	0.23	0.27	0.25	0.22	0.23	0.29	0.34	0.27	0.27	0.31	0.31	0.28	0.32	0.28	0.53	1.00	0.62	0.21	0.19	0.21	0.43	0.36	0.42	-0.02	-0.04	0.00
HM3	0.29	0.28	0.16	0.26	0.28	0.36	0.30	0.33	0.34	0.34	0.38	0.30	0.30	0.39	0.25	0.61	0.62	1.00	0.20	0.19	0.19	0.49	0.43	0.51	0.02	0.02	0.03
PV1	0.09	-0.01	-0.03	0.08	0.19	0.20	0.19	0.23	0.17	0.13	0.15	0.22	0.15	0.19	0.15	0.24	0.21	0.20	1.00	0.58	0.44	0.34	0.27	0.27	-0.01	0.00	0.05
PV2	0.10	0.04	0.00	0.07	0.07	0.11	0.06	0.13	0.14	0.14	0.15	0.15	0.08	0.12	0.04	0.23	0.19	0.19	0.58	1.00	0.49	0.23	0.22	0.22	-0.02	0.00	0.03
PV3	0.16	0.11	0.10	0.09	0.14	0.04	0.07	0.21	0.10	0.08	0.08	0.13	0.19	0.19	0.16	0.28	0.21	0.19	0.44	0.49	1.00	0.16	0.21	0.21	0.05	0.04	0.07
IU1	0.33	0.29	0.14	0.28	0.35	0.33	0.40	0.32	0.33	0.39	0.34	0.30	0.36	0.29	0.37	0.43	0.43	0.49	0.34	0.23	0.16	1.00	0.61	0.68	0.01	0.04	0.06
IU2	0.38	0.27	0.17	0.26	0.34	0.29	0.36	0.38	0.25	0.34	0.22	0.31	0.26	0.34	0.37	0.42	0.36	0.43	0.27	0.22	0.21	0.61	1.00	0.63	0.03	0.05	0.06
IU3	0.37	0.31	0.25	0.32	0.32	0.34	0.37	0.34	0.34	0.40	0.34	0.34	0.34	0.33	0.36	0.45	0.42	0.51	0.27	0.22	0.21	0.68	0.63	1.00	-0.03	0.01	0.04
TR1	0.02	-0.05	0.03	0.02	0.01	-0.04	0.00	0.09	0.08	0.04	0.07	-0.08	0.04	-0.08	-0.04	0.05	-0.02	0.02	-0.01	-0.02	0.05	0.01	0.03	-0.03	1.00	0.69	0.54
TR2	0.00	-0.08	-0.03	0.01	0.06	-0.02	0.01	0.08	0.04	0.08	0.08	-0.07	0.02	-0.03	-0.05	0.04	-0.04	0.02	0.00	0.00	0.04	0.04	0.05	0.01	0.69	1.00	0.60
TR3	0.03	-0.08	-0.04	-0.01	0.07	0.07	0.08	0.13	0.04	0.01	0.02	0.01	0.06	0.04	0.00	0.06	0.00	0.03	0.05	0.03	0.07	0.06	0.06	0.04	0.54	0.60	1.00

The number of factors extracted from EFA is determined by us based on the eigenvalue. Specially, the extracted factors will stop at the eigenvalue greater than 1. Figure 2 showed that EFA extracted 7 factors at the eigenvalue greater than 1.

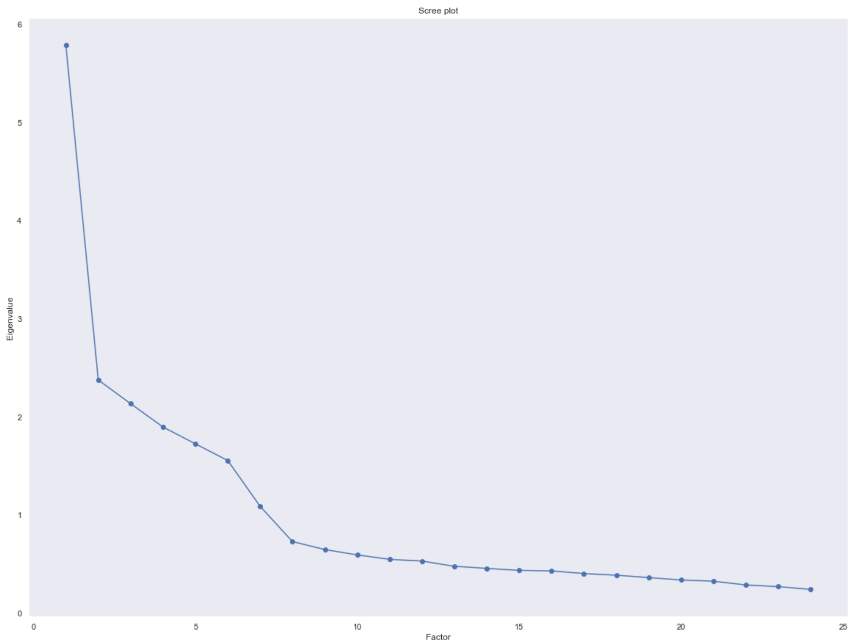

Fig. 2: Number of factors extracted by the eigenvalue

Next, we use the rotated component matrix to determine the observed variables of each extracted factor. The result of the rotated component matrix is presented in Table 5.

The result of the rotated component matrix shows that all observed variables have factor loading coefficients greater than 0.5. The factors are extracted, and the specific component of observed variables are as follows: (i) the first factor includes the observed variables PE1, PE2, PE3, PE4, representing Performance Expectancy, named PE; (ii) the second factor includes the observed variables FC1, FC2, FC3, FC4, representing Facilitating conditions, named FC; (iii) the third factor includes the observed variables PEOU1, PEOU2, PEOU3, PEOU4, representing Perceived Ease of Use, named PEOU; (iv) the fourth factor includes the observed variables TR1, TR2, TR3, representing Trust, named TR; (v) the fifth factor includes the observed variables HM1, HM2, HM3, representing Hedonic Motivation, named HM; (vi) the sixth factor includes the observed variables SI1, SI2, SI3, representing Social Influence, named SI; (vii) the seventh factor including the observed variables PV1, PV2, PV3, representing Price value, named PV.

Table 5. The rotated component matrix

	1	2	3	4	5	6	7
PEOU1			0.6859				
PEOU2			0.6843				
PEOU3			0.6757				
PEOU4			0.7689				
PE1	0.7240						
PE2	0.7363						
PE3	0.8447						
PE4	0.6512						
SI1						0.6881	
SI2						0.6401	
SI3						0.8504	
FC1		0.6893					
FC2		0.7393					
FC3		0.7138					
FC4		0.8306					
HM1					0.6834		
HM2					0.6821		
HM3					0.8838		
PV1							0.7170
PV2							0.8417
PV3							0.6091
TR1				0.7974			
TR2				0.8647			
TR3				0.6900			

4.3. The Estimation Result of Structural Equation Modeling (SEM)

To test the research hypotheses, we estimate the SEM. The result of the estimations is presented in Figure 3 and Table 6.

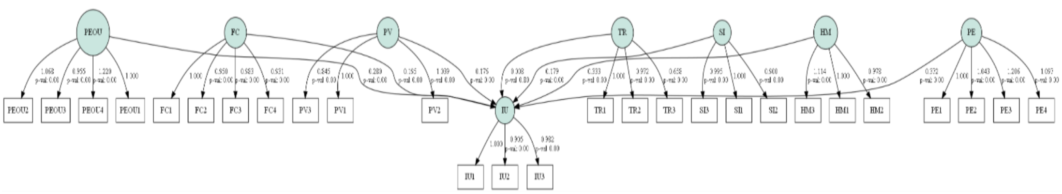

Fig. 3: The Estimation Result of SEM Model

Table 6: The Model's Goodness of Fit Criteria

Criteria	Value
Chi-square/df	1.912
AGFI	0.876
GFI	0.896
NFI	0.896
CFI	0.947
TLI	0.937
RMSEA	0.045

To access the model fit of the proposed mode, we continue to consider the value of the model's goodness of fit indicators. They include AGFI – adjusted goodness-of-fit index; GFI – goodness-of-fit index; NFI – normed fit index; CFI – comparative goodness of fit; TLI – Tucker-Lewis Index; RMSEA – root mean square error of approximation. The values of these indicators are shown in Table 6. Value of Chi-square/df is 1.912 less than the threshold of 3, recommended by Carmines & McIver (1983). The respective AGFI, GFI, and NFI values are 0.876, 0.896, and 0.896. The results for the CFI and TLI are all more than 0.90. Additionally, the RMSEA is between the desired range of 0.05 and 0.08 (Hair & Hampson, 2006). The proposed model, therefore, fits with the findings of the study.

Table 7: Hypothesis testing result

Explained Variable	Explanatory variable	Regression coefficient	Standard error	z-value	p-value	Hypothesis
IU	PEOU	0.2804	0.0656	4.2758	0.0000	H1: Supported
IU	PE	0.3716	0.0697	5.3324	0.0000	H2: Supported
IU	SI	0.1786	0.0628	2.8443	0.0045	H3: Supported
IU	FC	0.1946	0.0589	3.3036	0.0010	H4: Supported
IU	HM	0.3329	0.0771	4.3169	0.0000	H5: Supported
IU	PV	0.1765	0.0569	3.0988	0.0019	H6: Supported
IU	TR	0.0081	0.0324	0.2490	0.8034	H7: Non-supported

Table 7 shows that the regression coefficient of Perceived Ease of Use factor is 0.2804 and significant at the level of 5%. Thus, Perceived Ease of Use factor has a positive impact on students' intention to use M-Learning, and hypothesis H1 is supported. This result is also consistent with studies by Joo et al. (2016), Alshurideh et al. (2020), and Al-Azawei & Alowayr (2020). Then, the regression coefficient of Performance Expectancy factor has a value of 0.3716 and is significant at the level of 5%. Thus, Performance Expectancy factor has a positive impact on students' intention to use M-Learning and hypothesis H2 is supported. This result is also consistent with studies by Al-Emran et al. (2020), Alshurideh et al. (2020), and Al-Azawei & Alowayr (2020).

The regression coefficient of Social Influence has a value of 0.1786 and is significant at the level of 5%. Thus, Social Influence has a positive impact on students' intention to use M-learning and hypothesis H3 is supported. This result is also consistent with studies by Thomas et al. (2013), Al-Azawei & Alowayr (2020). Facilitating Conditions factor has the regression coefficient of 0.1946 and is significant at the level of 5%. Thus, Facilitating Conditions has a positive impact on students' intention to use M-learning and hypothesis H4 is supported. This result is also consistent with studies by Thomas et al. (2013), Al-Azawei & Alowayr (2020).

In addition, Hedonic Motivation has the regression coefficient of 0.3329 and is significant at the level of 5%. Thus, Hedonic Motivation has a positive impact on students' intention to use M-learning and hypothesis H5 is supported. This result is also consistent with studies by Al-Azawei & Alowayr (2020), Ameen & Willis (2019). Price Value also has the regression coefficient of 0.1765 and is significant at the level of 5%. Thus, Price value has a positive impact on students' intention to use M-learning and hypothesis H6 is supported. This result is also consistent with studies by Al-Azawei & Alowayr (2020). Finally, Trust has no impact on students' intention to use M-Learning and hypothesis H7 is non-supported. This result is contrary to the study by Al-Azawei & Alowayr (2020).

4.4. The Estimation Result of Artificial Neural Network

The estimation result of the SEM model shows that the factors affecting students' intention to use M-Learning are Perceived Ease of Use, Performance Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, and Price Value. Thus, these six factors will be brought to the input layer of the ANN model. The output layer is the student's intention to use M-Learning. When there are six input variables for the hidden layer, the number of neurons in the hidden layer is calculated, and built ANN model as proposed by Fang & Ma (2009), and Yao et al. (1999). Specially, according to Fang & Ma (2009), the number of neurons in the hidden layer will be calculated as $log_2(6) = 2.58$. Thus, according to Fang & Ma (2009), the number of neurons in the hidden layer is 3. According to Yao et al. (1999), the number of neurons in the hidden layer will be calculated as $ln(6) = 1.79$. Thus, according to Yao et al. (1999), the number of neurons in the hidden layer is 2.

In the hidden and output layers, the neurons are activated using the Sigmoid function. In this study, the model is trained using 80% of the sample data, and its accuracy is tested using the remaining 20%.

The ANN models are built as proposed by Fang & Ma (2009), Yao et al. (1999) are shown in the figures below.

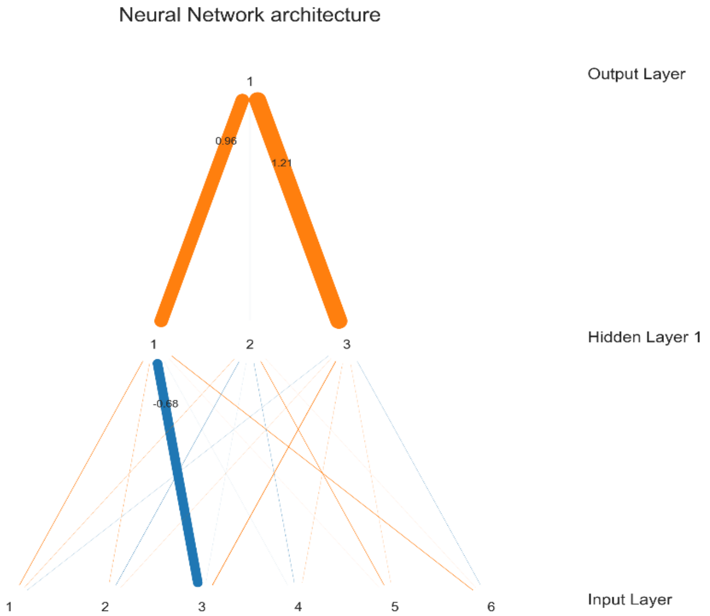

Fig. 4: ANN model as proposed by Fang & Ma (2009)

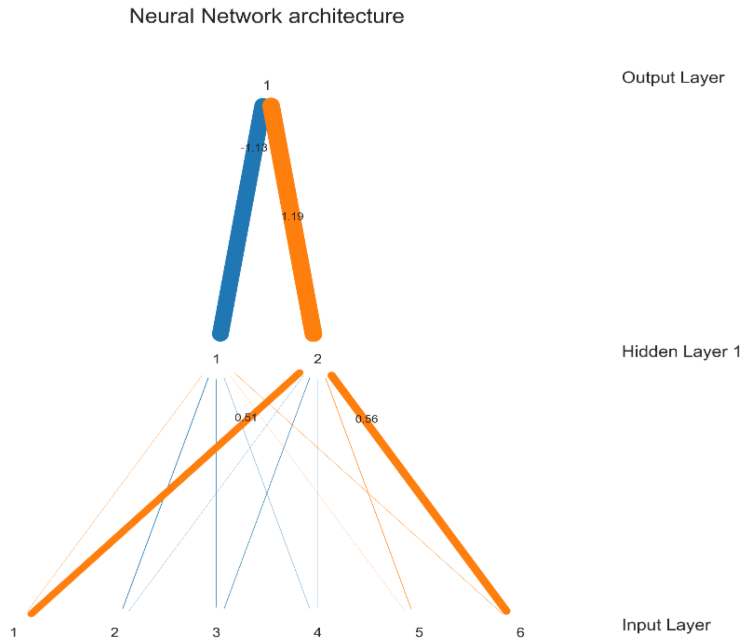

Fig. 5: ANN Model Proposed by Yao et al. (1999)

To select the model with the highest accuracy between the two above models, we use the accuracy evaluation criteria, including MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error). The results of the accuracy evaluation are presented in Table 7.

Table 8: Model performance

Criteria	ANN proposed by Fang và Ma [43]	ANN proposed by Yao et al. [44]
MAE (Mean Absolute Error)	0.422	1.167
MSE (Mean Squared Error)	0.267	1.957
RMSE (Root Mean Squared Error)	0.516	1.399

Table 8 shows that the ANN model proposed by Fang and Ma (2009) has the most accurate prediction according to all 3 criteria MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error).

Thus, we will use the ANN model proposed by Fang and Ma (2009) to calculate the importance of factors affecting the student's intention to use M-Learning.

The importance of each influencing factor shows that students' intention to use M-Learning will change when the influencing factor changes. We calculate the important level of each factor by the algorithm proposed by Garson (1991). The result of the important level of each factor is represented in Table 9.

Table 9: The results of the importance of each factor in the models

	ANN model proposed by Fang and Ma (2009)	**ANN model proposed by Yao et al. (1999)**
PEOU	0.160	0.179
PE	0.133	0.185
SI	0.316	0.208
FC	0.091	0.086
HM	0.165	0.128
PV	0.136	0.213

Table 9 shows that the selected ANN model proposed by Fang và Ma (2009), the impact of Social Influence on students' intention to M-Learning has the highest importance (0.316). Then, the remaining factors in descending order of importance are as follows: Hedonic Motivation (0.165), Perceived Ease of Use (0.160), Price value (0.136), Performance Expectancy (0.133), Facilitating conditions (0.091).

5. Conclusions and Implication

5.1. Conclusions

The result of the study shows that factors affecting students' intention to use M-Learning are Perceived Ease of Use, Performance Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, and Price Value. In which, the impact of Social Influence on students' intention to use M-Learning has the highest importance (0.316). Then, the remaining factors in descending order of importance are as follows: Hedonic Motivation (0.165), Perceived Ease of Use (0.160), Price value (0.136), Performance Expectancy (0.133), Facilitating conditions (0.091). The results of this study are consistent with the theory of the UTAUT2 model. Specifically, the results confirmed this theoretical model when finding evidence that the factors, including Perceived Ease of Use, Performance Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, and Price Value, all had positive effects, promoting students' intention to use M-Learning at universities in Ho Chi Minh City, Vietnam.

Based on the research result, we propose some management implications to increase students' intention to use M-Learning at the university in Ho Chi Minh City.

5.2. Management Implications

First, due to the impact of Social Influence on students' intention to use M-Learning has the highest importance, universities need to strengthen communication and introduce to parents, relatives, and families of students about the usefulness of the M-learning system. In particular, the obtained value and the output of the M-learning system should be emphasized because many people still worry that the output of M-learning is not as good as the official learning in the classrooms.

Then, in order to increase Perceived Ease of Use and Hedonic Motivation of students, it is necessary to provide the sufficient instructions on how to use M-learning system to all of learners, help leaners understand clearly about how to use the system and ease of use and encourage their intention to participate in the system. In addition, it is necessary to build a support team for technical issues and be available all the time. In order to increase Facilitating Conditions, it is necessary to improve convenience in accessing the system. This measure is related to technical factors such as improving the system's accessibility (allowing many people to access it at the same time), allowing learners to actively register and use the system, and creating more system versions on different learners' devices.

5.3. Limitations and Future Research Expansion

Although the research objectives have been achieved, this study can't avoid some objective limitations. First of all, due to the limitation of time and financial resources, we only conducted the study with a sample of 452 students at universities in Ho Chi Minh City area. Therefore, the future studies may add new factors to the research model to find the other evidence on factors affecting students’ intention to use M-Learning.

Author Contributions: Dr. Anh Hoang Le conceived the idea, wrote Introduction, Development of Hypotheses and Research model. Dr. Chau Bao Do Huynh wrote Research Methodology, Research result. Dr. An Hoang Nguyen and Msc. Thuong Hoai Thi Nguyen wrote Conclusions and Implication and revised the manuscript.

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Data Availability Statement: The data for this study can be found on our GitHub page: https://github.com/anhle32/Factors-affecting-intention-to-use-M-learning.git (accessed on 12 October 2022).

Conflicts of Interest: The authors declare no conflict of interest.

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