Print ISSN: 1738-3110 / Online ISSN 2093-7717
JDS website: http://www.jds.or.kr/
http://dx.doi.org/10.15722/jds.20.06.202206.75

Impact of Digital Literacy on Intention to Use Technology for Online Distribution of Higher Education in Vietnam: A Study of Covid19 Context

Thi Lan Huong LE[1], Vu Hiep HOANG[2*], Mai Duc Minh HOANG[3], Hong Phuc NGUYEN[4], Xuan Bach BUI[5]

Received: April 16, 2022. Revised: May 14, 2022. Accepted: June 05, 2022.

Abstract

Purpose: This research aims to provide empirical evidence on the impact of digital literacy on behavioural intention regarding using technology for distribution of higher education. **Design, Methodology, and Approach**: Quantitative analysis was carried out using Covariance-Based Structural Equation Model with data collected from 901 students who fully experienced 2-year study online at different universities in Vietnam. The structural model was built with digital literacy as the primary indicator and other variables were included based on modified version of Unified Theory of Acceptance and Use of Technology (UTAUT2) by adopting performance expectancy, effort expectancy, social influence, habit, and hedonic motivation variables specifically for education sector. Self-efficacy was added to eliminate possible bias in technology acceptance. **Results**: From the results of model estimation, digital literacy presented positive impact on the online distribution of higher education in Vietnam. The mediating effects of various indicators such as performance expectancy, effort expectancy, social influence, habit, hedonic motivation, and self-efficacy are significantly determined by research model. **Conclusion**: The higher level of digital literacy of the students, the more likely that they will use technology in higher education study, especially online learning. Additionally, the mediating effects of indicators from the UTAUT2 theoretical model were also evident to be positively significant.

Keywords: Digital Literacy, Distribution of Education, Technology Acceptance, Structural Equation Modelling

JEL Classification Code: C91, D91, I23, O33

1. Introduction

According to Aburub and Alnawas (2019), using mobile technology devices is considered a new and important breakthrough in universities. Applying technology in learning will be more effective than traditional learning methods (Ghavifekr & Rosdy, 2015). Although the use of technology in learning will increase critical thinking and learning motivation, many students are still not able to master the use of digital technology. Digital transformation in education was said to face significant challenges such as the lack of holistic vision, digital transformation

1 First Author. Dean, Business School, National Economics University, Vietnam. Email: lelanhuong@neu.edu.vn
2 Corresponding Author, Head, Division of Post-Graduate Studies, Business School, National Economics University, Vietnam, Email: hiephoang@neu.edu.vn
3 Student, Advanced Education Program, National Economics University, Vietnam. Email: hmdminh310502@gmail.com
4 Student, Advanced Education Program, National Economics University, Vietnam. Email: nhp24022002@gmail.com
5 Student, Advanced Education Program, National Economics University, Vietnam. Email: buixuanbach1205@gmail.com

competency, and data structure and processing (Marks, Atassi, Abualkishik, & Rezgui, 2020) that were still halting schools to efficiently implement online distribution of higher education. However, Covid-19 pandemic changed the whole education sector and forced the whole world to digitally transform. According to Cooper (2006), technology acts as an assistant to help people absorb knowledge more effectively which might enhance the degree of education distribution and there is a close relationship between the educational environment and digital technology. According to Laakso, Kaila, and Rajala (2018), technology is no longer a tool for entertainment but contributes to change the traditional way of teaching and distributing education with paper and textbooks.

Therefore, research on intention to use technology for learning is one of the most interesting topics at the present time in education since more and more modern and innovative teaching methods appear and change the whole world of education especially online classes in the context of the Covid-19 epidemic (Jang, Aavakare, Nikou, & Kim, 2021). Previous studies on behavioural intention to use digital technology indicated different opinions regarding determinants on intention to use digital technology in education (Huffman, Whetten, & Huffman, 2013; Huang, 2015; Jaradat, 2011; Jang et al., 2021). This study attempts to empirically develop and test the conceptual framework on digital technology acceptance for Vietnam in the Covid-19 context.

It can be seen that the current digital level in Vietnam is not too high compared to the world, but we have begun to make changes on the way to improve digital literacy and develop the digital economy. In order to carry out digital transformation in education, the Government of Vietnam has also put into operation the Project of the Digital Vietnamese Knowledge System. The issue of applying digital technology in learning in Vietnam is improving dramatically and is on the way to further development especially in the context that the digital economy of Vietnam is also taking the first steps of transformation in the era of industrial revolution 4.0.

From these points, this paper is significantly essential for measuring and estimating the effect of digital literacy on students' behavioural intention to use technology in learning. The conceptual model focuses on both direct effect and mediating effects with the involvement of multiple mediator variables such as performance expectancy, effort expectancy, social influence, hedonic motivation, and habit which are inherited from the traditional UTAUT2 framework on behavioural intention; self-efficacy is also added to the structural model based on empirical recommendation.

2. Theoretical Framework and Literature Review

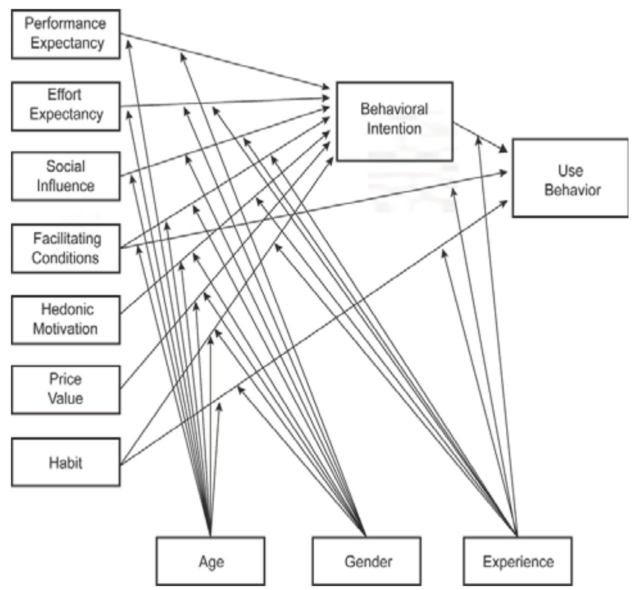
The concept of digital literacy was firstly introduced in the 1990s during the revolution of internet by Gilster (1997) as all fields of knowledge are digitised and could be used anytime and anywhere. Gilster (1997, p.1) further defined it as *"the ability to understand and use information in multiple formats from a wide range of sources when it is presented via computers"*. Digital literacy has since emerged as a priority in everyday life, demonstrating the ability to absorb and apply technology from a variety of available information sources (Gilster, 1997) as well as effective use of information and communication technology (Bawden, 2001). According to Hasan and Ahmed (2010), digital literacy is a prerequisite factor affecting the intention to use different types of technology. Especially in terms of learning purpose, it was indicated by Knutsson, Blåsjö, Hållsten, and Karlström (2012) that digital literacy is a crucial learning influence in the era of the 4th industrial revolution by strictly associating with learner autonomy (Ting, 2015).

Martin and Grudziecki (2006) defines digital literacy as a type of competency that is formed from other types of competencies including information competence, communication capacity, internet capacity, and information technology capacity. Similarly, according to Ng (2012), digital literacy is *"the cultural diversity associated with the use of digital technology"* (p. 1006) which can be identified as a survival skill in the digital age (Eshet-Alkalai, 2004). However, although these perspectives successfully provided a specific view of the importance of digital literacy, they have not yet sufficiently explained the insight and dimension of digital literacy. Indeed, Eshet-Alkalai (2004) proposed a conceptual framework to include the skills mentioned when using the term "digital literacy" which includes five types of literacy knowledge: visual literacy, reproducibility, information literacy, contextualised literacy, and socio-emotional level. In addition, Ng (2012) also offers a view on the multidimensionality of digital literacy in which it is determined by three dimensions: technical, cognitive, and socio-emotional level. In specific, the technical dimension focuses on the technical and operational capabilities related to information-communication technology used in daily operations. For the cognitive dimension, connotative issues include abilities related to thinking and judgment when managing information. Finally, there is the social-emotional dimension, which is used to refer to the possibilities associated with using digital responsibly while performing communicative, social, and academic tasks (Ng, 2012).

In the matter of digital literacy and behavioural psychology, a variety of theoretical frameworks have been developed and tested for understanding technology knowledge in different contexts. Some of the most notable theories include Theory of Rational Action (TRA), Theory of Planned Behaviour (TPB), Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), and the Unified Theory of Acceptance and Use of Technology (UTAUT). In which, from the bases of multiple original theories such as TRA, TPB, TAM, Venkatesh, Morris, Davis, and Davis (2003) further developed and created a unified theoretical framework for technology acceptance and use (UTAUT). UTAUT also inherited the implications of other theories such as Motivational Model (MM) of Davis, Bagozzi, and Warshaw (1992), Model of PC utilisation (MPCU) of Thompson, Higgins and Howell (1991), combined TAM and TPB model (C-TAM-TPB) by Taylor and Todd (1995) and the Social Cognitive Theory (SCT) by Compeau and Higgins (1995). Therefore, it can be indicated that the UTAUT model was developed in an attempt to comprehensively assess the relationship between different concepts related to each individual's acceptance of digital technology (Huang, Baptista, & Galliers, 2013). In specific, Venkatesh et al. (2003) identified seven concepts as *"important factors that directly determine intention or use in one or more individual models"* (p. 446). Stemming from these seven factors, four core factors have been proposed to be the direct determinants of users' acceptance as well as their digital technology usage behaviour. These concepts are performance expectancy, effort expectancy, social influence, and facilitating conditions which are moderated based on gender, age, experience, and voluntariness of use. As such concepts are theorised to affect behavioural intentions, thereby affecting actual use behaviour.

Venkatesh, Thong, and Xu (2012) extended the previous UTAUT framework to came up with a new version of UTAUT2. The UTAUT2 is the product of previous research on technology adoption and use, modification of existing relationships in the original UTAUT model, and the introduction of new relationships (Venkatesh et al., 2012). The new extended version identified three additional key concepts, called hedonic motivation, price value, and habit (Venkatesh et al., 2012). The three new concepts, accompanying the four core concepts already in the original UTAUT model, are also moderated by age, gender, and experience (Venkatesh et al., 2012).

Kang, Liew, Lim, Jang, and Lee (2015) provided a theoretical framework including concepts such as digital literacy, information literacy, performance expectancy, effort expectancy, hedonic motivation and habit. This was a model that had been adapted based on the UTAUT2 model, designed to specifically study the impact of digital literacy and information literacy on the intention to apply digital technology in education practice. The results of this study show that digital literacy has a positive relationship with intention to use digital technology in learning. In addition, digital literacy has a positive impact on all four mediating concepts which are performance expectancy, effort expectancy, hedonic motivation, and habit, respectively. This is a logical finding and coincides with previous research by Mohammadyari and Singh (2014), who found a clear influence of digital literacy on performance expectancy and effort expectancy. However, the article also shows that information literacy does not have a clear relationship with intention to use digital technology in learning. These findings contrast with the findings of Nikou, Brännback, and Widén (2018).



Source: Venkatesh et al. (2012)

Figure 1: UTAUT2 framework on behaviour

According to Venkatesh et al. (2003, 2012), performance expectancy, effort expectancy, hedonic motivation, and habit are considered to be the factors that clearly influence behavioural intention. Therefore, these factors are expected to have relationships in the proposed model of this study. However, this is the case only for expected performance and operating habits, as no significant relationship can be confirmed between expected effort and intention to use or enjoyment motivation with intention to use. In another study of Ghavifekr and Rosdy (2015), with the support of information and communication technology right from the first steps, students will enhance their effectiveness and gain great success in their studies. As the results, other studies have emerged to investigate and analyse the relationship between multi-knowledge and technology proficiency (Eshet-Aakalai, 2004; Glister, 1997; Nikou et al., 2018). The level of understanding of many different areas of knowledge is directly proportional to the intention to use technology in learning (Nikou & Aavakare, 2021).

3. Hypotheses Development

3.1. Data Collection

The formula for determining sample size of Yamane (1973) is described as follows:

$$n = \frac{N}{1 + N(e)^2}$$

In which:
n: sample size required
N: number of people in the population
e: allowable error (%)

To ensure statistical reliability, this study determined a minimum sample size of 385 observations to satisfy the requirement of further quantitative tests and estimations. The data was collected with a total of 901 valid responses. The total number of participants strongly satisfied the minimum sample size of 385 and thereby ensuring statistical reliability.

Table 1: Sample information

Gender	Number	%
Male	475	52.7%
Female	411	45.6%
Prefer not to say	15	1.7%
Total	**901**	**100.0%**
Year of study		
Year 1	518	57.5%
Year 2	245	27.2%
Year 3	99	11.0%
Year 4	31	3.4%
>= Year 5	8	0.9%
Total	**901**	**100.0%**
University		
North West University	94	10.4%
National Economics University	74	8.2%
Hanoi University of Business and Tec hnology	138	15.3%
Banking Academy	93	10.3%
Foreign Trade University	84	9.3%
Vinh University	45	5.0%
The University of Danang - University of Economics	57	6.3%
Nha Trang University	95	10.5%
Quy Nhon University	84	9.3%
University of Economics Ho Chi Minh City	102	11.3%
University of Finance - Marketing	35	3.9%
Total	**901**	**100.0%**

3.2. Proposed Research Model and Hypotheses

Based on the in-depth review of literature and explanation of related variables, the research model is proposed as Figure 2. In specific, since UTAUT2 framework is confirmed to significantly explain the social behavioural intention of consumers especially in terms of technological products, a list of independent and explanatory variables is adopted including “performance expectancy”, “effort expectancy”, “social influence”, “habit”, and “hedonic motivation”. These are indicated to have direct impact on consumers’ behavioural intention to use technological products (Venkatesh et al., 2012). Additionally in this paper, digital literacy is the latent variable that is also known as an underlying factor which can be measured through “performance expectancy”, “effort expectancy”, “habit”, and “hedonic motivation” (Nikou & Aavakare, 2021). Moreover, it can also directly impact the intention to use technology in learning (Nikou & Aavakare, 2021). Therefore, the following hypotheses are proposed for estimation:

Performance expectancy is inherited from the comprehensive framework UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012). Many previous studies have demonstrated and confirmed that performance expectancy is a significant predictor of behavioural intention (Ghalandari, 2012; Goncalves, Oliveira, & Jesus, 2018; Kang et al., 2015; Venkatesh et al., 2003).

Effort expectancy is adapted from the framework UTAUT (Venkatesh et al., 2003) and UTAUT2 (Venkatesh et al., 2012). According to Ghalandari (2012), Lowenthal (2010), Sung, Jeong, Jeong, and Shin (2015), and Venkatesh et al. (2003), effort expectancy is one of the best predictors of behavioural intention.

Habit is conceptually differentiated in two ways. The first definition is made by Limayem, Hirt, and Cheung (2007), who proposed habit as *“the degree to which people tend to perform behaviours automatically as a result of learning”*. The other definition is given by Kim and Malhotra (2005), who argued that habit is simply *“previous behaviour”* (Venkatesh et al., 2012, p. 9). The inclusion of the habit element was promoted by Venkatesh et al. (2012) when introducing habit as an element to describe some of the basic processes involved in the use of technology.

Hedonic motivation was defined by Venkatesh et al. (2012, p.8) as *“the pleasure or satisfaction derived from using a technology”*. Previous research has shown that the hedonic motivation dimension is not only important in the adoption and use of technology but also in the use of consumer products. However, it has been shown that as individuals gain more experience in using technology, the sense of novelty gained from technology will diminish over time as usage shifts to more utilitarian purposes (Venkatesh et al., 2012).

Hence, based on the theoretical model UTAUT2 and empirical evidence, the following hypotheses are proposed.

H1: Digital literacy (DL) has a positive relationship with performance expectancy (PE)
H2: Digital literacy (DL) has a positive relationship with self-efficacy (SE)
H3: Digital literacy (DL) has a positive relationship with effort expectancy (EE)
H4: Digital literacy (DL) has a positive relationship with behavioural intention to use digital technology in learning (BI)
H5: Digital literacy (DL) has a positive relationship with habit (HB)
H6: Digital literacy (DL) has a positive relationship with hedonic motivation (MO)

Self-efficacy refers to an individual's belief in his or her ability to perform the behaviours necessary to produce specific performance achievements (Bandura, 1977, 1986, 1997). It is not concerned with the overall skills but focusing on an assessment of what people can do with whatever skills they have (Bandura, 1986). This description suggests that self-efficacy is not just of a general nature, rather, it is related to specific situations. Individuals may rate themselves as very good in a particular area and less competent in a particular area. Self-efficacy is added to this study based on the findings of Sung et al. (2015) since it has a positive influence on performance expectancy, effort expectancy, and social influence. Hence, adding self-efficacy to the research model will not only help the estimation be more accurate, but also provide a new direction for future studies using the UTAUT2 model. In detailed, self-efficacy is another latent variable which is measured by performance expectancy, effort expectancy, and social influence. Additionally, in the study of Prior, Mazanov, Meacheam, Heaslip, & Hanson (2016), digital literacy was indicated to affect self-efficacy directly and positively in terms of determining learners' behavioural intention with online-learning activities.

H7: Self-efficacy (SE) has a positive relationship with performance expectancy (PE)
H8: Self-efficacy (SE) has a positive relationship with effort expectancy (EE)
H9: Self-efficacy (SE) has a positive relationship with social influence (SI)

Social influence is defined by Venkatesh et al. (2003, p.451) as *"the degree to which an individual perceives importance when others believe that they should use the new system"*. Therefore, this concept focuses on the perceived external attitudes of other people in relation to the individual's choice to use a particular system. In the study of Sung et al. (2015), authors found evidence for the positive impact of social influence on performance expectancy and effort expectancy. This was a new finding since it had not been indicated by the traditional UTAUT2 framework. Hence, these hypotheses will be tested in this study.

H10: Social influence (SI) has a positive relationship with performance expectancy (PE)
H11: Social influence (SI) has a positive relationship with effort expectancy (EE)

Besides, social influence is also suggested by the theoretical framework UTAUT and UTAUT2 (Venkatesh et al., 2003; Venkatesh et al., 2012) to significantly affect individual's intention to use technology.

Finally, the five mediator concepts including performance expectancy, social influence, effort expectancy, habit, and hedonic motivation are all constructs that have been introduced in the UTAUT2 model and have been shown to be positively correlated with behavioural intention. However, in the specific context of the intention to use digital technology in learning as well as performing on a more specific target group, it is also necessary to verify these relationships with the following hypotheses.

H12: Performance expectancy (PE) has a positive relationship with behavioural intention to use digital technology in learning (BI)
H13: Social influence (SI) has a positive relationship with behavioural intention to use digital technology in learning (BI)
H14: Effort expectancy (EE) has a positive relationship with behavioural intention to use digital technology in learning (BI)
H15: Habit (HB) has a positive relationship with behavioural intention to use digital technology in learning (BI)
H16: Hedonic motivation (MO) has a positive relationship with the behavioural intention to use digital technology in learning (BI)

These variables are taken into a conceptual structural model below with 16 hypotheses to be estimated using Structural Equation Modelling technique with AMOS 24.

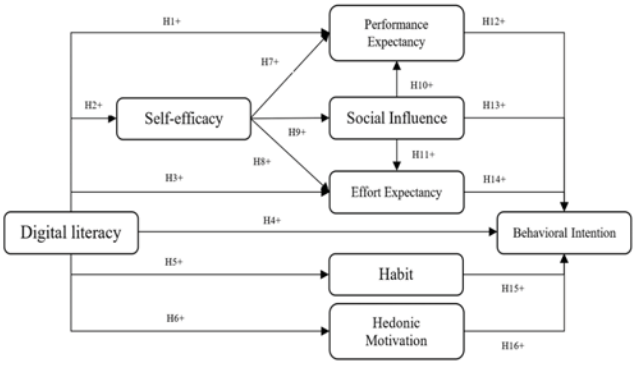


Figure 2: Conceptual model

4. Model Testing and Estimation

Firstly, exploratory factor analysis (EFA) was conducted. Even though the primary purpose of EFA is to discover the factor structure of measures and examine their internal reliability, this paper approaches this test to confirm whether the proposed factor structures of eight variables in the research model were valid. The test is carried out three times to ensure the eliminate all the observed instruments that has the factor loading less than 0.5. Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) is 0.925 with significance at 1% level. Thus, the variables are correlated with each other and satisfy the condition for EFA. As the results, from the initial 49 observed instruments, six of them was removed. The third EFA results on 43 observed instruments with the minimum Factor Loading of 0.5, resulting in 8 groups of factors, the total variance extracted is 56.388, which explains over 56% of the variation of the dependent variables.

Secondly, Cronbach's α is conducted to evaluate the reliability and internal consistency of each set of scale. The results indicated that all items load significantly on each variable and all Cronbach's α score exceeds the minimum threshold of 0.8, which suggests good reliability (Fornell & Larcker, 1981; Nunnally & Bernstein, 1994).

Table 2: Multicolinearity test results

	DL	EE	HB	IB	MO	PE	SE	SI
DL		1.061	1.000	1.173	1.000	1.061	1.000	
EE				1.400				
HB				1.456				
IB								
MO				1.232				
PE				1.167				
SE		1.129				1.129		1.000
SI		1.111		1.293		1.111		

Thirdly, the multicollinearity issue was considered with VIF inner values generated by AMOS as shown in Table 2. According to Hair, Risher, Sarstedt, & Ringle (2019), all the inner VIF values reported less than 3, which indicates that there is no multicollinearity in this structural model.

Fourthly, the reliability, discriminant and convergence of structural model were tested three times to fully validate the factor structure. As the results, three instruments were removed (DL8, IB5, and IB2), which means that the updated structure remained 40 observed instruments. The composite reliability (CR) and the total variance extracted (AVE) of the observed instruments were used to evaluate the reliability and validity of the observed variables. The reliability of the observed variables was good and acceptable with all the CR values were higher than 0.7 (Hair, Anderson, Tatham, & Black, 1998). According to Fornell & Bookstein (1982), the convergence value of the observed variables in this model were all good and acceptable since the AVE values were all higher than 0.5. Measuring discriminant validity helps to ensure that there is no difference between the factors used to measure the factors. The discriminant of the observed variables in this model were also guaranteed when the square root of the AVEs were all higher than their Inter-Construct Correlations.

Table 3: Test results for Reliability, Convergence and Discriminant

	CR	AVE	MSV	MaxR(H)	DL	SE	SI	PE	EE	IB	MO	HB
DL	0.876	0.504	0.171	0.878	0.710							
SE	0.892	0.582	0.278	0.904	0.237***	0.763						
SI	0.888	0.612	0.228	0.888	0.187***	0.335***	0.783					
PE	0.868	0.568	0.159	0.869	0.153***	0.265***	0.214***	0.754				
EE	0.875	0.583	0.253	0.877	0.413***	0.476***	0.400***	0.299***	0.764			
IB	0.740	0.507	0.439	0.933	0.362***	0.312***	0.477***	0.357***	0.503***	0.712		
MO	0.839	0.566	0.219	0.839	0.152***	0.276***	0.335***	0.258***	0.259***	0.468***	0.752	
HB	0.839	0.514	0.439	0.871	0.129***	0.528***	0.464***	0.399***	0.427***	0.663***	0.465***	0.717

Note: N = 901; † p < 0.100; * p < 0.050; ** p < 0.010; *** p < 0.001

Fifthly, confirmatory factor analysis (CFA) is carried out using AMOS to assess the overall suitability and fitness of the measurement approach (Byrne, 2010; Kline, 2011). The conceptual model has a chi-square (χ^2) of 1855.665 on 903 degrees of freedom (df), giving a χ^2 to df ratio of 2.055, which is within the acceptable range of between two and five (Byrne, 2010; Kline, 2011). The model also has a comparative fit index (CFI) of 0.958 and a goodness of fit index (GFI) of 0.922, which represent a very good fit between the hypothesised model and the observed covariance matrix as they are close to one (Byrne, 2010; Kline, 2011). The root mean standard error of approximation (RMSEA) score is 0.034, which also suggested a good fit since it is between the recommended range of 0.01 to 0.05 (Browne and Cudeck, 1993; Byrne, 2010; Kline, 2011). The PCLOSE of 1.000 indicated that the result of RMSEA lower than 0.05 is significant. In overall, the measurement model suggests a good fit.

Since the conceptual model is confirmed by CFA, the study adapts structural equation modelling technique using AMOS to estimate the correlation coefficients of the model and examine the hypotheses results. According to Hu and Bentler (1999), Browne and Cudeck (1993), Byrne (2010), and Kline (2011), the final model presents acceptable fit properties with χ^2 = 2454.354; df = 903; χ^2 to df ratio = 2.718; CFI = 0.931; GFI = 0.900; RMSEA = 0.044 with PCLOSE = 1.000.

According to the estimation results, the intention to use technology in learning is explained by 40.6%. At the same time, the change of effort expectancy variable is also well explained at 37.1%. Performance expectancy and social influence were explained as 9.6% and 12.2%, respectively. Meanwhile, self-efficacy, habit and hedonic motivation all have relatively low explanations at 5.8%, 2.3% and 2.8%.

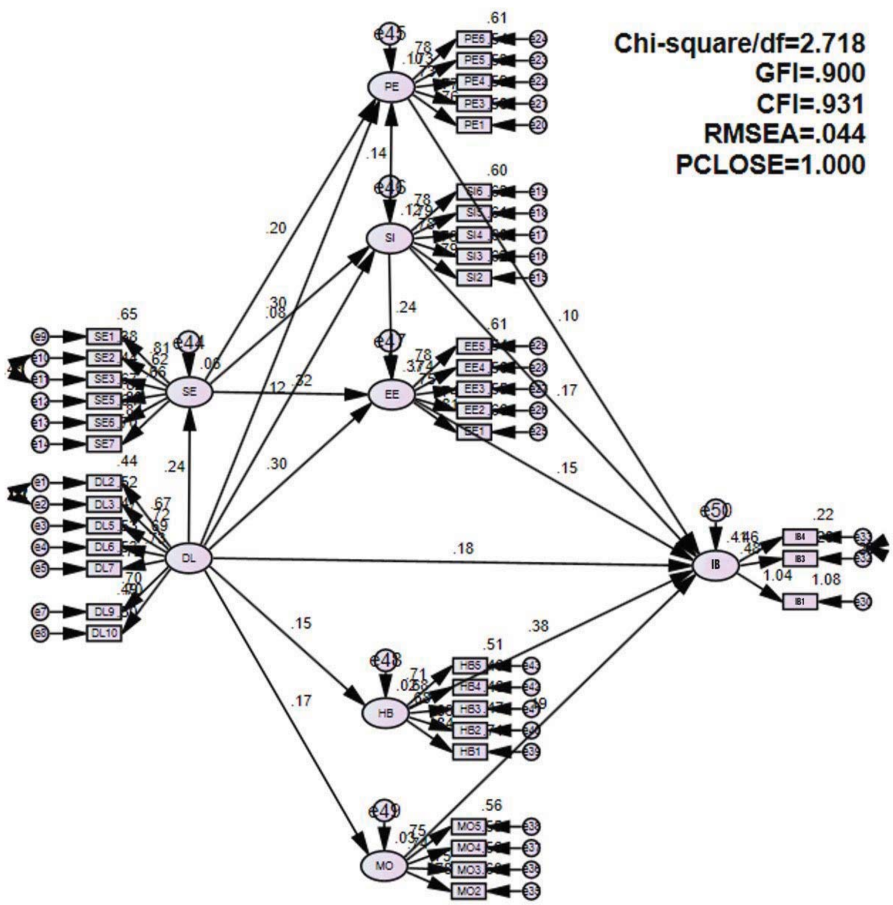


Figure 3: Structural Equation Modelling estimation

The positive relationship between digital literacy and intention to use digital technology was clearly shown with β=0.181, CR=5.667, $p<0.001$, so hypothesis H_4 is supported. Similarly, the estimation also indicated a clear positive relationship between digital literacy and its constructs including performance expectancy (β=0.078, CR=2.002, $p<0.05$), self-efficacy (β= 0.242, CR = 6.175, $p<0.001$), effort expectancy (β=0.296, CR=8.185, $p<0.001$), habit (β=0.150, CR=3.874, $p<0.001$), and hedonic motivation (β=0.167, CR=4.223, $p<0.001$). Hence, the hypotheses H_1, H_2, H_3, H_5, and H_6 are significantly supported. In addition, the SEM estimation gave a new finding on the positive correlation between digital literacy and social influence (β=0.119, CR=3.146, $p<0.05$).

Regarding the relationship between self-efficacy and performance expectancy (β=0.202, CR=5.004, $p<0.001$), social influence (β=0.301, CR=7.872, $p<0.001$), and effort expectancy (β=0.322, CR=8.913, $p<0.001$), all of which showed a clear positive correlation. The SEM estimation also presented a significant and positive relationship between social influence and its constructs such as performance expectancy (β=0.137, CR=3.447, $p<0.05$) and effort expectancy (β=0.238, CR=6.763, $p< 0.001$). Thus, it can be concluded that H_7, H_8, H_9, H_{10}, and H_{11} are also supported.

Finally, there was a clear positive relationship between intention to use technology in learning and other independent variables: performance expectancy (β=0.102, CR=3.658, $p<0.001$), social influence (β=0.172, CR=5.694, $p<0.001$), effort expectancy (β=0.152, CR=4.634, $p<0.001$), habit (β=0.379, C/R=13.270, $p<0.001$), and hedonic motivation (β=0.190, CR=6.743, $p<0.001$). This was to conclude that H_{12}, H_{13}, H_{14}, H_{15}, and H_{16} are supported.

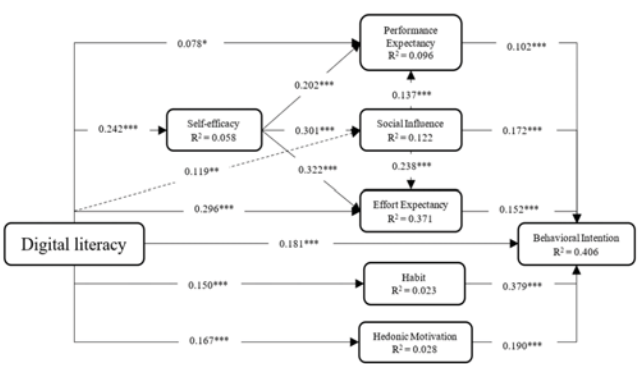


Figure 4: Coefficient results

5. Discussion

From the structural estimation, hypotheses are all supported and showed a relatively significant relationship. In addition, the estimation also helps to discover a new correlation between digital literacy and social influence.

Firstly, digital literacy directly and positively affects the intention to use digital technology in learning of students. The relationship between digital literacy and behavioural intention variable is clearly shown with β=0.181, C.R.=5.667, $p<0.001$. This result is also consistent with the previous research results of Nikou et al. (2018). Accordingly, digital literacy has a direct influence on intention to use digital technology. Indeed, the application of digital technology in learning requires users to have a certain digital level to be able to apply, this also means that students might have more intention to use digital technology in learning if their digital literacy is improved.

Secondly, habit construct has the strongest impact on the intention to use digital technology in learning with the significance at 1%, the correlation coefficient is 0.379. This finding is consistent with literature where habit was found to be the most important and decisive factor of behavioural intention (Venkatesh et al., 2012; Alalwan, Dwivedi, Rana, Lal, & Williams, 2015; Escobar-Rodríguez & Carvajal-Trujillo, 2013; Kang et al., 2015; Morosan & DeFranco, 2016; Sharif & Raza, 2017). It can be indicated that since using technology becomes a daily habit, users certainly feel confident in accessing the same technologies for different purposes including learning. Since habits are automatic repetitive actions through learning, the level of knowledge acquisition will be one of the decisive factors in forming habits. Therefore, besides the fact that habit has a strong impact on the intention to use digital technology in learning, it also acts as an intermediate construct that helps digital literacy to have a stronger influence on the intention to use digital technology in learning of students in Vietnam and that is also reflected clearly with the influence coefficient of 0.150 with 1% significance.

Table 4: Standardized Regression Weights

			Estimate	S.E.	C.R.	P	Hypotheses
SE	<---	DL	0.242	0.046	6.275	***	Supported
SI	<---	DL	0.119	0.042	3.146	0.002	Supported – New finding
SI	<---	SE	0.301	0.036	7.872	***	Supported
PE	<---	DL	0.078	0.042	2.002	0.045	Supported
EE	<---	DL	0.296	0.044	8.185	***	Supported
PE	<---	SE	0.202	0.037	5.004	***	Supported
EE	<---	SE	0.322	0.037	8.913	***	Supported
HB	<---	DL	0.150	0.052	3.874	***	Supported
MO	<---	DL	0.167	0.042	4.223	***	Supported
PE	<---	SI	0.137	0.039	3.447	***	Supported
EE	<---	SI	0.238	0.038	6.763	***	Supported
BI	<---	PE	0.102	0.037	3.658	***	Supported
BI	<---	SI	0.172	0.038	5.694	***	Supported
BI	<---	EE	0.152	0.039	4.634	***	Supported
BI	<---	HB	0.379	0.030	13.270	***	Supported
BI	<---	MO	0.190	0.037	6.743	***	Supported
BI	<---	DL	0.181	0.045	5.667	***	Supported

Note: N = 901; † $p < 0.100$; * $p < 0.050$; ** $p < 0.010$; *** $p < 0.001$

Thirdly, the construct social influence has a medium and positive impact on the intention to use digital technology in learning with the impact coefficient of 0.172 at 1% significance level. This finding is consistent with the results of Venkatesh et al. (2003). Additionally, the indicators also show that social influence has influences on the two constructs: effort expectancy and performance expectancy with coefficients of 0.238 and 0.137, respectively at 1% significance level. This suggests that students are optimistic about the results of using digital technology when they are advised by those around them.

Fourthly, hedonic motivation witnesses a medium positive influence on the intention to use digital technology in learning. This conclusion is coherent with other studies such as Kang et al (2015), San-Martin & Herrero (2012), Herrero, San-Martín, and Garcia-De los Salmones (2017) and Alalwan et al. (2017). As such, students will use technology more often if they find it effective for their own learning. Effectiveness can come from improvement of course grades, better teamwork spirit and performance, or more in-depth presentation. Hence, hedonic motivation is considered as one of the most important factors affecting behavioural intention of using technology in learning.

Fifthly, the authors find that the effort expectancy construct has a medium influence on the intention to use digital technology in learning with $\beta=0.152$, C.R.=4.634, $p<0.001$. This is consistent with the study of Nikou et al. (2018) by indicating that effort expectancy is one of the variables with the most obvious impact on intention to use technology (Ghalandari, 2012; Lowenthal, 2010; Sung et al., 2015; Venkatesh et al., 2003). Most of students agree that creating an application that is easy to use and does not require a deep dive to fully utilize its functionality can make it easier for newcomers to use digital technology in their learning. Thereby, stimulating the intention to use digital technology in learning of university students. In addition, digital literacy also plays an important role in reducing the effort expectancy of people accessing digital technology. Effort expectancy is strongly influenced by digital literacy with $\beta=0.296$, C.R.=8.185, $p<0.001$. When students have high digital literacy, the effort expectancy for digital technology applications in general and digital technology applications in learning in particular will be reduced easier. This also contributes to stimulating the intention to use digital technology in learning. Thus, in addition to directly affecting the intention to use digital technology in learning, the effort expectancy construct also acts as a mediator variable that helps the digital literacy to more clearly affect the intention to use digital technology in learning of students in Vietnam.

Sixthly, the performance expectancy construct also presents a positive but only mild impact on the intention to use digital technology in learning of students in Vietnam. In detail, the relationship is confirmed by the estimation with $\beta=0.102$, C.R.=3.658, $p<0.001$. This result is significantly consistent with Nikou et al. (2018), Ventakesh (2003), Ghalandari (2012), Goncalves et al. (2018), Kang et al. (2015), and Venkatesh et al. (2003). Quickly interviewing several students, some of them concluded that everyone realizes the effectiveness of digital technology; especially in the era of industrial revolution 4.0, digital technology has emerged as an immutable trend. The efficiency and productivity that digital technology makes is far superior to other technologies that human has ever invented. Therefore, the application of digital technology in learning is certainly effective. Therefore, more and more people are using digital technology in learning, the superiority of digital technology not only encourages but also forces students to approach the curriculum in a new way. However, the finding of this paper indicated that the performance expectancy construct does not have a great impact on the intention to use digital technology in learning compared to other variables. Explaining this, authors believes that digital efficiency has spread quickly, and no one is unaware of the effectiveness of digital technology, however, between the effectiveness of digital technology and the intention of others to use it is hindered by many other factors such as digital literacy or effort, equipment cost, application cost, etc. Especially in Vietnam, many university students today do not have many opportunities to access digital technology and directly using it in learning can cause many difficulties, which has created a barrier between the performance expectancy and the intention to use digital technology in learning.

6. Conclusions

This study was conducted to fulfil two objectives: (1) to examine the UTAUT2 framework on behavioural intention in the context of accepting technology in learning with the case of Vietnam, a typical developing country that is experiencing a fast-growing digital economy; (2) estimating the mediation effects of digital literacy through several constructs of behavioural intention. The results found that UTAUT2 framework works perfectly in the scenario of students' intention to use technology in learning. The finding greatly supported the positive relationship between the construct inherited from UTAUT2 (including performance expectancy, effort expectancy, social influence, habits, and hedonic motivation) and students' intention to use technology in learning. Additionally, the estimation also provides evidence for performance expectancy and effort expectancy to act as mediator variables for the impact of social influence on behavioural intention, which is consistent with the studies of Sung et al. (2015). Besides, digital literacy was recommended from the result to not only have a direct impact on behavioural intention to use technology in learning but also provide mediation effects by positively affecting self-efficacy, performance expectancy, effort expectancy, social influence, habits, and hedonic motivation to finally support the intention to use technology of students.

Regarding the implication for practice, it is said from this paper that increasing students' digital literacy is of paramount importance to students' desire to increase their intention to use technology in learning. According to this research results, it can be seen that digital literacy affects the intention to use digital technology clearly both directly and indirectly through mediator variables such as performance expectancy, effort expectancy, social influences, habits, and motivations. Thus, the foundation of the intention to use digital technology in learning is developed from the fact that students in Vietnam have sufficient digital skills.

One of the digital technology applications in learning that universities have introduced and appear to be effective is the use of digital learning materials and digital libraries. This forces students to know how to use digital devices and applications to be able to obtain study materials as well as efficiently take them as valuable sources of knowledge for understanding the lecture. Moreover, with the outbreak of the COVID-19 pandemic, students at universities around the world in general and in Vietnam in particular were required to use digital technology to be able to participate in online learning through applications such as Microsoft Teams, Zoom, Google Meet, etc.

In order to help students to get access digital technology applications, the Vietnamese universities can consider to include in the curriculum with additional subjects and lectures on training how to use digital technology in learning. This can help students build a basic digital literacy foundation, thereby easily developing a higher digital literacy and thereby forming an intention to use digital technology in learning.

References

Aburub, F., & Alnawas, I. (2019). A new integrated model to explore factors that influence adoption of mobile learning in higher education: An empirical investigation. *Education and Information Technologies*, *24*(3), 2145–2158. https://doi.org/10.1007/s10639-019-09862-x.

Alalwan, A. A., Dwivedi, Y. K., Rana, N. P., Lal, B., & Williams, M. D. (2015). Consumer adoption of Internet banking in Jordan: Examining the role of hedonic motivation, habit, self-efficacy and trust. *Journal of Financial Services Marketing*, *20*(2), 145-157. https://doi.org/10.1057/fsm.2015.5

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191–215. https://doi.org/10.1037/0033-295X.84.2.191

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice- Hall, Inc.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W H Freeman/Times Books/ Henry Holt & Co.

Bawden, D. (2001). Information and digital literacies: a review of concepts. *Journal of documentation, 57*(2), 218-259.

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen and J. S. Long (Eds.), *Testing structural equation models* (136-162). Newbury Park, CA: Sage.

Byrne, B. M. (2010). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (2nd ed.). Routledge/Taylor & Francis Group.

Cooper, J. (2006). The digital divide: the special case of gender. *Journal of Computer Assisted Learning*, *22*(5), 320–334. https://doi.org/10.1111/j.1365-2729.2006.00185.x

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology*, *22*(14), 1111–1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

Escobar-Rodríguez, T. and Carvajal-Trujillo, E. (2013). Online drivers of consumer purchase of website airline tickets. *Journal of Air Transport Management, 32*, 58-64. https://doi.org/10.1016/j.jairtraman.2013.06.018

Eshet-Alkalai, Y. (2004). Digital Literacy: A Conceptual Framework for Survival Skills in the Digital Era. *Journal of Educational Multimedia and Hypermedia*, *13*(1), 93-106.

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

Ghalandari, K. (2012). The Effect of Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions on Acceptance of E-Banking Services in Iran: The Moderating Role of Age and Gender. *Middle-East Journal of Scientific Research*, *12*(6), 801-807. https://doi.org/10.5829/idosi.mejsr.2012.12.6.2536

Ghavifekr, S., & Rosdy, W. A. W. (2015). Teaching and learning with technology: Effectiveness of ICT integration in schools. *International Journal of Research in Education and Science*, *1*(2), 175–191.

Gilster (1997). *Digital Literacy*. Wiley: Michigan, United States.

Goncalves, G., Oliveira, T., and Jesus, F. (2018) Understanding individual-level digital divide: Evidence of an African country. *Computers in Human Behaviour*, *87*, 276-291. https://doi.org/10.1016/j.chb.2018.05.039

Hair, J., Anderson, R., Tatham, R., & Black, W. (1998). *Multivariate Data Analysis* (5th ed.) Prentice Hall, Upper Saddle River, New Jersey.

Hair, J., Risher, J., Sarstedt, M., & Ringle, C. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hasan, B., and Ahmed, M. (2010) A path analysis of the impact of application-specific perceptions of computer self-efficacy and anxiety on technology acceptance. *Journal of Organisational and End User Computing*, *22*(3), 82-95. https://doi.org/10.4018/joeuc.2010070105

Herrero, A., San-Martín, H., and Garcia-De los Salmones, M. (2017). Explaining the adoption of social networks sites for sharing user-generated content: a revision of the UTAUT2. *Computers in Human Behavior*, *71*, 209–217. https://doi.org/10.1016/j.chb.2017.02.007

Hu, L.-t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Huang, J., Baptista, J., and Galliers, R. (2013). Reconceptualizing rhetorical practices in organizations: The impact of social media on internal communications. *Information and Management*. *50*(2-3), 112-124. https://doi.org/10.1016/j.im.2012.11.003

Huang, Y.-M. (2015). Exploring the factors that affect the intention to use collaborative technologies: The differing perspectives of sequential/global learners. *Australasian Journal of Educational Technology, 31*(3), 278-292. https://doi.org/10.14742/ajet.1868

Huffman, A. H., Whetten, J., & Huffman, W. H. (2013). Using technology in higher education: The influence of gender roles on technology self-efficacy. *Computers in Human Behavior*, *29*(4), 1779–1786. https://doi.org/10.1016/j.chb.2013.02.012.

Jang, M., Aavakare, M., Nikou, S., & Kim, S. (2021). The impact of literacy on intention to use digital technology for learning: A comparative study of Korea and Finland. *Telecommunications Policy*, *45*(7). DOI: https://doi.org/10.1016/j.telpol.2021.102154

Jaradat, M.-I. R. M. (2011). Exploring the factors that affecting intention to use mobile learning. *International Journal of Mobile Learning and Organisation*, *5*(2), 115–130. https://doi.org/10.1504/IJMLO.2011.041564.

Kang, M., Liew, B., Lim, H., Jang, J., & Lee, S. (2015). Investigating the Determinants of Mobile Learning Acceptance in Korea Using UTAUT2. In: Chen, G., Kumar, V., Kinshuk, Huang, R., Kong, S. (eds) *Emerging Issues in Smart Learning. Lecture Notes in Educational Technology*. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-44188-6_29

Kim, S. & Malhotra, N. (2005). A Longitudinal Model of Continued IS Use: An Integrative View of Four Mechanisms Underlying Post-Adoption Phenomena. *Management Science*, *51*(5), 741-755. https://doi.org/10.1287/mnsc.1040.0326

Kline, R. B. (2011). *Principles and practice of structural equation modelling* (3rd ed.). Guilford Press.

Knutsson, O., Blåsjö, M., Hållsten, S., & Karlström, P. (2012). Identifying Different Registers of Digital Literacy in Virtual Learning Environments. *Internet and Higher Education*, *15*(4), 237-246. https://doi.org/10.1016/j.iheduc.2011.11.002

Laakso, M. J., Kaila, E., & Rajala, T. (2018). ViLLE – collaborative education tool: Designing and utilizing an exercise-based learning environment. *Education and Information Technologies*, *23*(4), 1655–1676. https://doi.org/10.1007/s10639-017-9659-1

Limayem, M., Hirt, S., and Cheung, C. (2007). How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance. *MIS Quarterly*, *31*(4), 705-737. https://doi.org/10.2307/25148817

Lowenthal, J. (2010). Using Mobile Learning: Determinates Impacting Behavioral Intention. *American Journal of Distance Education*, *24*(4), 195-206. https://doi.org/10.1080/08923647.2010.519947

Marks, A., Al-Ali, M., Atassi, R., Abualkishik, A. Z., & Rezgui, Y. (2020). Digital Transformation in Higher Education: A Framework for Maturity Assessment. *International Journal of Advanced Computer Science and Applications, 11*(12), 504-513.

Martin, A., & Grudziecki, J. (2006). DigEuLit: Concepts and Tools for Digital Literacy Development. *Innovation in Teaching and Learning in Information and Computer Sciences, 5*(4), 249-267. https://doi.org/10.11120/ital.2006.05040249

Mohammadyari, S., and Singh, H. (2014). Understanding the effect of e-learning on individual performance: The role of digital literacy. *Computers and Education*, *82*, 11-25. https://doi.org/10.1016/j.compedu.2014.10.025

Morosan, C. and DeFranco, A. (2016). Co-creating value in hotels using mobile devices: A conceptual model with empirical validation. *International Journal of Hospitality Management*, *52*, 131-142. https://doi.org/10.1016/j.ijhm.2015.10.004

Ng, W. (2012). Can we teach digital natives digital literacy? *Computers and Education*, *59*(3), 1065–1078. https://doi.org/10.1016/j.compedu.2012.04.016.

Nikou, S. & Aavakara, M. (2021). An assessment of the interplay between literacy and digital Technology in Higher Education. *Education and Information Technologies*, *26*(5), 1-23. https://doi.org/10.1007/s10639-021-10451-0.

Nikou, S., Brännback, M., & Widén, G. (2018). The Impact of Multidimensionality of Literacy on the Use of Digital Technology: Digital Immigrants and Digital Natives. *Well-Being In The Information Society. Fighting Inequalities*, 117-133. https://doi.org/10.1007/978-3-319-97931-1_10

Prior, D. D., Mazanov, J., Meacheam, D., Heaslip, G., & Hanson, J. (2016). Attitude, digital literacy and self efficacy: Flow-on effects for online learning behavior. *Internet and Higher Education*, *29*, 91–97. https://doi.org/10.1016/j.iheduc.2016.01.001.

San Martin, H. & Herrero, A. (2012). Influence of the user's psychological factors on the online purchase intention in rural tourism: Integrating innovativeness to the UTAUT framework. *Tourism Management*, *33*(2), 341-350. https://doi.org/10.1016/j.tourman.2011.04.003

Sharif, A. & Raza, S. (2017). The Influence of Hedonic Motivation, Self-efficacy, Trust and Habit on Adoption of Internet Banking: A Case of Developing Country. *International Journal of Electronic Customer Relationship Management*, *11*(1), 1-22. https://doi.org/10.1504/IJECRM.2017.086750

Sung, H. N., Jeong, D. Y., Jeong, Y. S., & Shin, J. I. (2015). The Relationship among Self-Efficacy, Social Influence, Performance Expectancy, Effort Expectancy, and Behavioral Intention in Mobile Learning Service. *International Journal of u- and e- Service, Science and Technology*, *8*(9), 197-206. http://dx.doi.org/10.14257/ijunesst.2015.8.9.21

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research*, *6*(2), 144-176. https://doi.org/10.1287/isre.6.2.144

Thompson, R.L., Higgins, C.A. and Howell, J.M. (1991). Personal Computing: Toward a Conceptual Model of Utilization. *MIS Quarterly*, *15*(1), 125-143. http://dx.doi.org/10.2307/249443

Ting, Y. L. (2015). Tapping into students' digital literacy and designing negotiated learning to promote learner autonomy. *Internet and Higher Education*, *26*, 25–32. https://doi.org/10.1016/j.iheduc.2015.04.004

Venkatesh V, Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: toward a unified view. *MIS Quarterly*, *27*(3), 425–478.

Yamane, T. (1973). *Statistics: An Introductory Analysis*. 3rd Edition, Harper and Row, New York.