The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/1741-5659.htm

Received 26 August 2020
Revised 10 October 2020
23 October 2020
Accepted 26 October 2020

Students' adoption of e-learning in emergency situation: the case of a Vietnamese university during COVID-19

Nguyen Thi Thao Ho
Department of Management and Humanities, Universiti Teknologi PETRONAS, Seri Iskandar, Malaysia and FPT University, Hanoi, Vietnam

Subarna Sivapalan
Centre for Excellence in Teaching and Learning (CETaL), Universiti Teknologi PETRONAS, Seri Iskandar, Malaysia

Hiep Hung Pham
Center for Research and Practice on Education (RPE), Phu Xuan University, Hue, Vietnam

Lan Thi Mai Nguyen and Anh Thi Van Pham
FPT University, Hanoi, Vietnam, and

Hung Viet Dinh
University of Labour and Social Affairs, Hanoi, Vietnam

Abstract

Purpose – By using a technology acceptance model (TAM) on survey results collected from two member schools of a Vietnamese educational institution, this study aims to uncover the key factors that affect students' acceptance of e-learning during the Covid-19 period.

Design/methodology/approach – A bilingual questionnaire in English and Vietnamese was delivered. It was pre-tested on 30 participants before it was finalized. The authors first reviewed the measurement model and made adjustments to the theoretical TAM model. Then the adjusted TAM was used to investigate the relationships of the constructs in the model.

Findings – The results of the structural model show that computer self-efficacy (CSE) has a positive impact on perceived ease of use (PEOU). There is also a positive relationship between system interactivity (SI) and PEOU. Surprisingly, the authors documented that PEOU has no significant impact on students' attitudes (ATT). The results show that SI can moderately affect ATT. Finally, it is noted that the social factor (SF) directly affects the student's attitudes (ATT).

Research/limitations/implications – This study contains three limitations. First, as this study only focuses on undergraduate programs, readers should be careful in applying the findings and/or implications of this study to other education levels such as K-12, vocational training and postgraduate programs. Second, the findings are generated within the context of one type of e-learning, conducted via Google Meet. Therefore, future research is needed to provide further validation and comparison across other forms of e-learning. Finally, to further prevent the common bias problem, future research should use both five-point and seven-point Likert scales for the response options in the survey, as well as use negatively worded items. This will help prevent respondents from providing similar answers to all questions.

Originality/value – This study has both theoretical and practical implications. From a theoretical perspective, the study can provide a solid framework for similar studies. From a practical perspective, this

Interactive Technology and Smart Education
Vol. 18 No. 2, 2021
pp. 246-269

1741-5659
DOI 10.1108/ITSE-08-2020-0164

study offers implications for governments and universities in the process of adopting e-learning, given that the Covid-19 pandemic is currently in its second and more dangerous wave.

Keywords E-Learning, Universities, Covid-19, School closures, Technology acceptance model (TAM), Online teaching and learning, Learning during emergency

Paper type Research paper

Introduction

The Covid-19 pandemic has had a great impact on higher education worldwide. Covid-19 forced higher education institutions (HEIs) to halt traditional in-person learning. In response to an unprecedentedly long period of school closures, governments from around the world have used e-learning as a tool to ensure that schooling continued for students. However, several universities in developing countries do not have the full capacity to do that during Covid-19. At the same time, urgent preparation of online learning materials and lack of professional training for online teaching and learning might have affected the quality of online programs (Mohamedbhai, 2020).

Similarly, in accordance with the policy of the Vietnamese Ministry of Education and Training (MOET), the educational institution at which this study took place is among the first to adopt e-learning during the Covid-19 pandemic. Specifically, its Can Tho campus implemented e-learning as early as the second week right after the social distancing policy was released, followed by other campuses including Hanoi, Ho Chi Minh and Da Nang in the following week.

Particularly, for our analysis in this research, we used a case study of a HEI that used technology in teaching and learning in Vietnam. This educational institution was established in 1999 and headquartered in Hanoi. It is a member of a leading ICT corporation in Vietnam. The HEI was founded in 2006 with its vision: iGSM (i-Industry, G-Global, S-Smart Education and Mega). Its aim is to become a mega internationalized education system, which will meet the needs of society through state-of-the-art educational technology. Accordingly, it has implemented online learning in almost all programs. It provides diversified undergraduate programs in various majors including Business Administration, ICT, Graphic Design, Digital Marketing, Multimedia and Hospitality. As a member of a leading ICT corporation, the educational institution has had competitive advantages such as ICT infrastructures for online learning, long-term contracts with Coursera mass-operating online courses (MOOCs) and professional workshops on teaching and learning for lecturers. The institution also has many advantages including its year-long experience of implementing online learning in the form of MOOCs, amounting to one course per trimester. The second advantage is that both students and lecturers of the institution are familiar with technology, particularly laptops and internet connection, in their teaching and learning activities, due to the technology-based philosophy of the institution. Yet, it still faced a number of difficulties, including lack of specially designed course content for e-learning, lack of students' self-study skills, lack of official training programs for lecturers and challenges in running assessments during the final online exams.

Importantly, in accordance with the knowledge that the pandemic is still in a dangerous phase and school closures could possibly be extended, it is necessary to conduct a study to understand the factors that affect students' acceptance of e-learning during the Covid-19 pandemic. This study not only offers implications for governments and universities to better prepare for the move from traditional learning to e-learning during this pandemic, but also provides a good practice should there be a similar emergency in the future.

Impact of the Covid-19 pandemic to the higher education sector

It is evident that a long period of school closures can have a number of negative effects. School closures cause an interruption to learning. Extended school closures are also seen as a potential reason for the rise in student drop-out rates (UNESCO, 2020). Academic delays have also been found to have a relationship with the level of anxiety symptoms amongst students (Cao *et al.*, 2020). School closures can also possibly cause several negative effects for stakeholders. These include 'economic harm' for parents in charge of taking care of their children instead of working, economic loss for society caused by the decrease in the productivity of parents, and loss of education for children (Viner *et al.*, 2020).

In response to an unprecedentedly long period of school closures, governments around the world have taken to e-learning, as it is seen as a promising approach to continuing educational processes during school closures. E-learning provides students with considerable benefits and chances to learn anywhere and anytime (Baytiyeh, 2018). Therefore, during the current Covid-19 pandemic, e-learning has become the learning mode of choice in many countries.

At first, The Ministry of Education in China for instance had issued a policy on "Suspending Classes Without Stopping Learning" in March 2020 (Zhang *et al.*, 2020). Similarly, in the middle of March 2020, all Australian universities shifted from face to face classes to online classes (Kwan, 2020). On the other hand, the UK and the US universities have been late in tackling the Covid-19 outbreak across the country due to the late response of the two governments (Yamey and Weham, 2020). In the United States for example, 70% of lecturers have never taught online classes before (University of the Highlands and Islands, 2020). Similarly, it is noted that many UK universities are not prepared to address the effects of the coronavirus pandemic on students' education (Batty and Hall, 2020). For example, Professor Sir Tim O'Shea of Edinburgh University mentions that around 20 universities are qualified to deliver a number of "high-quality online courses" by the beginning of the new academic year in September 2020 (Batty and Hall, 2020).

It is evident that the Covid-19 pandemic brings not only opportunities but also challenges for institutions of higher learning (IHLs). Adedoyin and Soykan (2020) found that under the pressures of the Covid-19 pandemic, universities and other educational platforms quickly made a "digital transformation" of their educational activities. However, Ribeiro (2020) highlighted that quick "digital transformation" of the teaching and learning activities caused a burden on "logistical challenges" and "attitudinal modifications". It is also evident that the pandemic caused a negative impact on students' academic performance as many students were not ready to adopt e-learning. Similarly, a large number of lecturers were also not ready to deliver lectures effectively from home (Adedoyin and Soykan, 2020).

E-learning within the Vietnamese higher education sector

The online learning system in Vietnam had initially started as a distance learning model before it evolved into e-learning. In Vietnam in the early 1990s, two open universities (OUs) in Hanoi and Ho Chi Minh were founded and modeled after the Open University (OU) in the UK. Both OUs were initiated to respond to the demands of distance learning for those in rural regions (George, 2010). The two OUs provided distance learning programs for learners in rural regions of Vietnam (Pham and Ho, 2020). Following this, the institutions of higher education (IHEs launched undergraduate programs in the big cities and enrolled students aged 18 to 22 into the programs).

Since the late 1990s, access to computers has dramatically increased (Boymal *et al.*, 2007). Distance learning has consisted of DVDs/VCDs rather than e-learning, which mainly includes online courseware. Interestingly, only 2% (33.638) of the total HE students nationally (1,581,227) have been involved in "distance learning" (Pham and Ho, 2020) so far. There are several key reasons for this, namely:

- The current regulations of the Vietnamese Ministry of Education (MOE) only enable IHEs to run distance learning for formal courses.
- The quotas for distant students are rather limited as compared to the quotas for students in campuses.

Similarly, the adoption of educational technology generally, and e-learning particularly, into formal courses in Vietnam's IHEs is not popular. This situation is caused by both a lack of motivation to apply educational technology to academic activities, and the lack of policies enabling IHEs to integrate educational technology with formal courses systematically (Pham and Ho, 2020).

From the very beginning of the Covid-19 pandemic on January 23rd 2020, the Vietnamese Government implemented a very strict measure that required the closure of all schools nationwide to prevent the widespread of the Covid-19 virus. However, the decision of continued school closure was only released week by week. In response to this, the Vietnamese Ministry of Education and Training (MOET) decided to implement e-learning across schools and universities nationwide from March 26, 2020. In Vietnam, most HEIs were not well prepared for the implementation of e-learning during Covid-19. The first reason for this was that universities had a limited technology infrastructure and lacked an official process and prior experience with e-learning. Further, e-learning materials were poor, unstandardized, and not well controlled in terms of the quality of teaching and assessment. Second, from the learners' perspectives, there was limitation in equipment and internet infrastructure (especially in poor and remote areas of Vietnam) as well as a lack of necessary skills for e-learning. Third, e-learning at some universities also faced the risk of security assurance as students and teachers used free platforms and software (MOET, 2020).

Theoretical underpinning of study

The term e-learning has been widely used in education for several decades (Lee *et al.*, 2009). There are a variety of definitions of e-learning. Some researchers view e-learning as "the delivery of teaching materials via electronic media, such as Internet, Intranets, Extranets, satellite broadcast, audio/video tape, interactive TV, and CD-ROM" (Engelbrecht, 2005). Other researchers view e-learning as a "web based learning which uses web-based communication, collaboration, knowledge transfer, and training to add values to the individuals and the organizations" (Kelly and Bauer, 2003).

Based on the definitions used in the existing studies, this study defines e-learning as a Web-based learning, which uses Web-based communication, collaboration, multimedia, knowledge transfer and training to support learners' active learning without time and space barriers. Like any other educational technology, there are many strengths and weaknesses associated with the use of e-learning (Schroeder *et al.*, 2010). Although e-Learning helps to build community among learners, promote self-regulated learning, develop strong collaboration among learners and between learners and instructors, and improve problem-solving skills (Paechter *et al.*, 2010), it nevertheless increases the workload for both learners and instructors. Also, it is claimed to be less reliable than traditional learning in terms of peer feedback and collaborative activities assessment. Despite these weaknesses, e-learning systems have become an important part of delivering the modern university curriculum (Paechter *et al.*, 2010), let alone in emergencies like the pandemic of COVID-19.

Heutagogy theory and e-learning

Heutagogy is defined as the study of self-determined learning (Hase and Kenyon, 2000). In heutagogy, the role of human agency in the learning process is expanded. Thus, the learner is seen as, "the major agent in their own learning, which occurs as a result of personal experiences" (Hase and Kenyon, 2007). At the time that Hase and Kenyon (2000) first coined the term "heutagogy", technology and education were not efficient enough to support a self-determined approach of learning. Over decades, a different story of education is seen with social media, MOOCs and digital badges, which provide students with substantially more control over what they learn and how and where they learn it (Hase and Kenyon, 2013). Heutagogy can also provide learners with the skills and capacity that will help them better transition into the workforce (Blaschke and Hase, 2016) as employers today seek employees who are innovative, good at problem-solving and have good communication skills, and who are able to apply what they learn to real-life situations (Associates, 2013).

Several principles have been formulated from this theory, but this research only focuses on two principles concerning e-learning in the studied institution. First, this mode of learning requires a shift from teacher-centered to learner-centered experience, and it focuses on connection and collaboration with others rather than controlling the learning process (Hart, 2012). These learning activities are strongly supported by technology in the digital world. Specifically, social media has helped students to be involved in the process of building a learning model along with their teachers and classmates, resulting in a more learner-centered learning process (Cameron and Tanti, 2011). Second, it increases learners' capability. Capability refers to "the ability of being able to use the acquired competences in unfamiliar as well as in familiar circumstances" (Blaschke and Hase, 2016). Capability development is related to self-efficacy, communication, collaboration and positive values.

In general, the heutagogic approach to teaching and learning provides a holistic framework for developing self-determined learners, which is essential for online education.

Technology adoption model and hypothesis development

Previous studies show that learner satisfaction with e-learning is widely used to evaluate the effectiveness of e-learning (Eom *et al.*, 2006; Levy, 2007). The model which is commonly used to investigate learners' perception of e-learning is the technology acceptance model (TAM), which was proposed by Davis (1989). It suggests that the ease of use and usefulness of a technology affects users' intention to use it. Therefore, we can predict users' willingness to accept technology based on their perception by using the TAM model.

Despite the potential of e-learning as a tool to enhance education and training performance, its value will not be realized if users do not accept it as a learning tool. As e-learning uses information technology, TAM has been extensively used and extended for research in an e-learning context.

The technology acceptance model (TAM) developed by Davis (1989) has been used in various research studies, and therefore, it has become quite significant in the literature pertaining to technology acceptance (Chang *et al.*, 2017). A systematic review carried out by Al-Qaysi *et al.* (2020) reveals that the application of TAM in educational technology acceptance has proven to have superior benefits in comparison to other theoretical models. According to the theory, two personal beliefs namely "perceived usefulness" (PU) and "perceived ease of use" (PEOU) are affected by external and system-specific factors to predict attitudes towards using a technology. The attitude itself affects the behavioral intention to use a particular technology, which in turn, predicts the actual system use. Figure 1 shows the TAM model.

Previous research indicates that PU is a major determinant and predictor of intention to use computers in the workplace. In contrast, the impact of enjoyment on intention to use has not been examined (Davis *et al.*, 1992). As a result, perceived enjoyment (PE) was then added to the original TAM by Davis *et al.* (1992) as an important factor to predict computer acceptance and usage, and this is known as the extended TAM. PE refers to the degree to which "the activity of using the computer is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated" (Davis *et al.*, 1992, p. 1113). Essentially, PU and PEOU reflect the extrinsic motivational aspect of specific types of system usage, and PE usually reflects the intrinsic motivational aspect of specific types of system usage (Davis *et al.*, 1992).

Despite the additional benefits of the extended TAM over the original TAM, this study uses the original TAM for the following reasons. First, during an emergency situation resulting from the COVID-19 pandemic, e-learning is a vital solution for the continuation of schooling. Therefore, extrinsic motivation is the key driver of students' acceptance of e-learning, whilst intrinsic motivation is of less importance. Second, the original TAM model itself is a robust predictive model that is appropriate for different groups of technologies (Marangunić and Granić, 2015; Rissa, 2014). It has especially been used in many contexts and fields to investigate user acceptance of information technology (Salloum *et al.*, 2019). Importantly, we will focus on the implications for the studied institution regarding the implementation of e-learning in an emergency situation as well as provide insights for Vietnam and other countries.

The proposed research model has five exogenous variables: computer self-efficacy (CSE), interpersonal influence (INI), external influence (EXI), system interactivity (SI) and content feature (CF) and three endogenous variables: PEOU, PU and attitude (ATT) toward the use of e-learning system during the Covid-19 pandemic. In general, external variables can affect PU and PEOU, while PU and PEOU directly affect attitudes towards using the technology (ATT), and PU mediates the influence of PEOU on attitudes towards using the technology (Davis *et al.*, 1989).

Computer self-efficacy. CSE refers to people's judgment of their capabilities to perform particular tasks successfully (Bandura, 1977). In an e-learning context, many studies have proven that CSE has an impact on PEOU (Cheng, 2011). CSE has a positive influence on PEOU in e-learning contexts (Cheng, 2011; Punnoose, 2012). In their research, Cheng (2011) and Wu *et al.* (2010) state that one's confidence in using a computer properly may play an important role in affecting their self-assessment of the ease of accepting and using an e-learning system. The significant influences of CSE on PU have been empirically validated in the study of Ong *et al.* (2004). Additionally, the relationship between CSE and PEOU was based on a theoretical argument (Mathieson, 1991) and this was empirically examined to see whether a causal link exists between CSE and PEOU (Agarwal *et al.*, 2000). This suggests

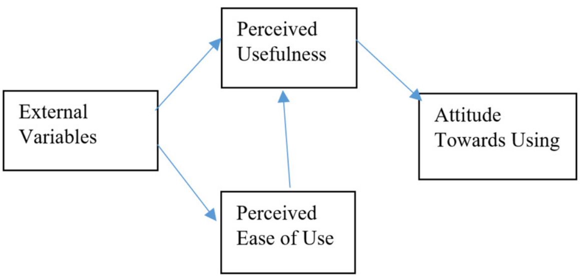

Figure 1. Theoretical technology acceptance model

that CSE has a significantly positive effect on the PEOU of e-learning. Thus, the first hypothesis of this study was formulated:

H1. CSE will positively affect the PEOU of the e-learning system.

Internal influence and external influence. These social factors (SF) are found to greatly affect user behavior (Cheng, 2011; Lee, 2006). INI refers to the influence of referents like friends, family members, colleagues, etc., and EXI refers to the influence of mass media reports or expert opinions (Bhattacherjee, 2000). Essentially, in an e-learning context, individuals are affected by the opinions of the referents that are important to them, and tend to incorporate the referents' beliefs into their belief that the system must be useful in executing its purpose (Lee, 2006). Davis *et al.* (1989) also notes that sometimes other people's commands score over the user's feelings and beliefs. These users take the aid of technology to obey such commands. Cheng (2011) finds that these SF positively influence individuals' attitudes towards using the e-learning system. Furthermore, Hsu and Lu (2004) report in their study that INI and EXI have a direct impact on the attitude toward technology adoption. Thus, the following hypotheses were formulated for this study:

H2a. INI will positively affect PU of the e-learning system.

H2b. INI will positively affect the attitudes towards using the e-learning system.

H2c. EXI will positively affect PU of the e-learning system.

H2d: EXI will positively affect the attitudes towards using the e-learning system.

System interactivity. SI refers to the interaction between instructors and learners, and the collaboration in learning that results from these interactions (Pituch and Lee, 2006). SI facilitates relationships between learners and lecturers (Sun and Hsu, 2013). The features of online interactivity will also enable lecturers to create online social tasks and manage learners' interest and their quality of learning (Rodríguez-Ardura and Meseguer-Artola, 2016). PEOU and PU were found to be affected by SI (Pituch and Lee, 2006; Shin, 2007). They show that the functionality and interactivity of the e-learning system can be beneficial for learners to stimulate their interest in learning; hence, learners can not only perceive that the e-learning system is easier to use, but also more useful for them to gain knowledge. Thus, the following hypotheses were formulated:

H3. SI will positively affect the PEOU of the e-learning system.

H4. SI will positively affect the PU of the e-learning system.

Content features. CFs are defined as the characteristics and presentation of course content and information (X. Zhang *et al.* n.d.). In e-learning contexts, CFs may include "text, hypertext, graphics, audio and video, computer animations and simulations, embedded tests, or multimedia information" (Wu *et al.*, 2010, p. 158). It has been found that students' positive perception of CFs might have an impact on their high levels of performance expectations (Wu *et al.*, 2010). The updated content, as compared to traditional learning methods, delivered in e-learning courses may lead students to feel that the e-learning system would provide them with a useful means of acquiring new knowledge (Lee *et al.*, 2009; Lee, 2006). Thus, the following hypothesis is formulated:

H5. CF will positively affect the PU of the e-learning system.

User beliefs and technology acceptance. PU is referred to as the degree to which a person believes that using a particular system will enhance his or her job performance (Chang and Tung, 2008). Several studies have shown that PU has a direct effect on attitudes towards using the e-learning system (Cheng, 2011; Liu *et al.*, 2009; Ngai *et al.*, 2007). Attitude refers to the degree to which the user is interested in specific systems; this has a direct effect on the intention to use those specific systems in the future (Davis *et al.*, 1989). The user will perceive the system to be useful if the system proves itself to be an effective way of performing tasks (Henderson and Divett, 2003). PEOU is defined as the degree to which a user believes that using a particular system will be easy to use (Davis, 1989). PEOU also directly affects attitudes towards using the e-learning system (Liu *et al.*, 2009; Ngai *et al.*, 2007; Stoel and Hye Lee, 2003). In addition, PU mediates the influence of PEOU on attitudes towards using the e-learning system *(Lee,* 2006*; Liu et al.* 2009; Ngai *et al.*, 2007; Stoel and Hye Lee, 2003). Thus, the following hypotheses were formulated:

H6a. PEOU will positively affect the PU of the e-learning system.

H6b. PEOU will positively affect the attitudes towards using the e-learning system.

H7. PU will positively affect the attitudes towards using the e-learning system.

Methodology

The researcher opted for the quantitative approach because this approach mainly involves the use of controlled questionnaires in which the response options are coded, as well as it allows for large numbers of respondents to be involved. Furthermore, the students are scattered all over the country, which made it easy to distribute online questionnaires to all student participants.

Data collection

A case study of a HEI in Vietnam that used technology in teaching and learning was used for our analysis. The studied educational institution was selected due to one of the author's long working experience, and sound understanding of the institution. At the same time, as the studied institution has campuses in different cities across Vietnam, it offers a good case study to understand the acceptance of e-learning among different students from different locations, and helps to avoid any geographical bias in our results.

We constructed our questionnaire using established items from prior literature (Cheng, 2011; Tran, 2016). Each item was revised and adjusted to fit the objective of this study. We adopt a five-point Likert scale for our analysis: (1) Strongly Disagree, (2) Disagree, (3) Neutral, (4) Agree, (5) Strongly Agree. This is to avoid confusion among the respondents, which can improve the quality of the responses. At the same time, it is documented that five, seven or ten-point scales are comparable for analytical purposes (Dawes, 2008). Our questionnaire was bilingual with both English and Vietnamese, which is included in Appendix 2 of this paper. We also used preventive measures to mitigate common method bias, following the guidelines by Rodríguez-Ardura *et al.* (2020) to collect survey responses from different campuses, within a different time period for each campus. We also kept the survey short and anonymous, while all questions were worded clearly and concisely.

The survey was pre-tested on 30 participants before it was finalized. We adjusted the questionnaire after the pre-test by removing items that caused a decrease in Cronbach alpha and ensured that Cronbach alphas were in an acceptable range (>0.8) (Peterson, 1994). Specifically, INI1 and PEOU1 were removed from the model. All participants of the pre-test process were then excluded from the final sample. We used Google form as the platform for our data collection. Our selection of this survey platform is based on several reasons. First, Google form allows unlimited number of surveys and respondents. Second, the responses and data of surveys are automatically collected in Google Spreadsheet (Vasantha Raju and Harinarayana, 2016). Third, it is convenient to use since the studied educational institution also uses Gmail as the official email system. The final survey was sent to 856 undergraduate students via their official email addresses under the studied institutions, across four campuses located in Hanoi, Can Tho, Ho Chi Minh and Danang. The survey was open from April 20th to April 30th 2020 after which we received 618 valid responses (72 % response rate). Table 1 summarizes the key characteristics of the final survey data.

Accordingly, the proportion of male and female respondents were relatively equivalent, which were 52.3% and 45.5%, respectively. 2.2% of the respondents refused to disclose their gender. In terms of school year, almost half of our samples were first year students, while the other half were divided into 27.5% of second year students, 12.8% third year students, and 11.3% final year students. Regarding the majority of the respondents, 36.2% were in IT students, 40.1% studied Business, and the rest were from other majors (including Language, Multimedia, and Graphic design). In our sample, 80.9% responded that the online learning experience during the Covid-19 pandemic period was a brand-new experience for them, while the remaining said they had experienced it before. Based on these statistics, we can rule out some potential biases in our results including gender bias, school year bias, and major bias.

Results

Measurement model

To review and assess the measurement model, we performed a two-step analysis. First, we performed Principal Component analysis to ensure the construct validity of the measures for

Characteristic	Respondents Frequency (n = 618)	(%)
Gender		
Male	281	45.5
Female	323	52.3
Prefer not to say	14	2.2
Year		
First year or foundation year	299	48.4
Second year	170	27.5
Third year	79	12.8
Final year	70	11.3
Major		
Information Technology (IT)	224	36.2
Business	217	40.1
Others	117	28.7
First time of completely online learning		
Yes	500	80.9
No	118	19.1

Notes: This Table reports the summary of the survey sample. The sample is classified by Gender, Year of schooling, Major, and whether they have prior experience with online learning

Table 1. Demographic and basic information of respondents

the studied variables. Since the sample size was larger than 350, we used the cut-off point of 0.3 (Hair *et al.*, 1998) as an acceptable factor loading that indicated satisfactory construct validity. We also used an eigenvalue of at least 1 and the rotation method of Varimax with Kaiser Normalization.

The results for the Principal Component analysis are reported in Table 2, with all factor loadings less than 0.3 omitted. The key results are summarized below:

- INI1, INI2, EXI1, EXI2 and EXI3 measure the same construct, therefore, are grouped into "SF".
- CF1, CF2, CF3, ATT1 measure two different constructs at the same time; and the difference in factor loadings for the two constructs are less than 0.3. These items are removed from the model.
- SI3, ATT2, ATT3 measure two different constructs at the same time; and the difference in factor loadings for the two constructs are more than 0.3. These items are kept in the model and they are deemed to measure the construct with the higher corresponding factor loading.
- PU1, PU2, PU3, PU4, ATT2, ATT3 measure the same construct, therefore, they are grouped up into "ATT - Attitude".

By performing the principal component analysis and group up items that measure the same construct, we can design our final model to its most reduced form, which helps avoid an over

			Component		
Item	1	2	3	4	5
CSE1				0.756	
CSE2				0.860	
CSE3				0.857	
INI2		0.737			
INI3		0.711			
EXI1		0.703			
EXI2		0.715			
EXI3		0.691			
SI1			0.815		
SI2			0.826		
SI3	0.338		0.712		
CF1	0.382	0.348	0.480		
CF2	0.530		0.466		
CF3	0.444	0.449			
PEOU2					0.865
PEOU3					0.878
PU1	0.799				
PU2	0.806				
PU3	0.740				
PU4	0.767				
ATT2	0.666	0.338			
ATT3	0.717	0.342			
ATT1	0.523	0.532			

Notes: This Table reports the rotated component matrix when performing principal analysts. The Rotation Method is Varimax with Kaiser Normalization. The Appendix provides a detailed description of the variables

Table 2. Principal component analysis - Rotated component matrix

identification problem (Matsunaga, 2010). Our adjusted model is illustrated in Figure 2, and the revised hypotheses are as follows:

*H1**. CSE will positively affect the PEOU of the e-learning system during the Covid-19 pandemic.

*H2**. SF will positively affect the attitudes towards using the e-learning system during the Covid-19 pandemic (ATT).

*H3**. SI will positively affect the PEOU of the e-learning system during the Covid-19 pandemic.

*H4**. SI will positively affect the attitudes towards using the e-learning system during the Covid-19 pandemic (ATT).

*H5**. PEOU will positively affect the attitudes towards using the e-learning system during the Covid-19 pandemic (ATT).

Figure 2 demonstrates the research model used in this study which is based on the TAM model.

In the second step, we performed a confirmatory factor analysis (CFA) on the revised measurement model and ran reliability tests (reported in Table 3). In accordance with Hair *et al.* (2010), all standardized loading estimates in the CFA model are above the acceptable threshold of 0.5 and statistically significant ($p < 0.05$). 16 out of 19 coefficients are higher than the ideal threshold of 0.7. In addition, CR and AVE of all constructs are above the minimum acceptable threshold 0.7 and 0.5 (Hair *et al.*, 2010; Holmes-Smith, 2001; Nunnally, 1978). These, together, ensure the measurement reliability and convergent validity of the model. MSV is lower than AVE for all constructs, and the square root of AVE (reported in the cross line) is higher than all the inter-construct correlations. These indicate a good discriminant validity (Fornell and Larcker, 1981; Hair *et al.*, 2010).

We also checked the model fit when performing the CFA for the measurement model. The results reported in Table 4 show that all criteria are within the acceptable level (Bagozzi and Yi, 1988; Byrne, 2010; Hair *et al.*, 2010). For example, Chi-squared = 397.193, df = 139, Chi-squared/df = 2.858, $p < 0.001$, GFI = 0.940, AGFI = 0.918, NFI = 0.953, TLI = 0.962, CFI = 0.969, and RMSEA = 0.055. Overall, this indicates that the proposed model has a good fit with the survey data.

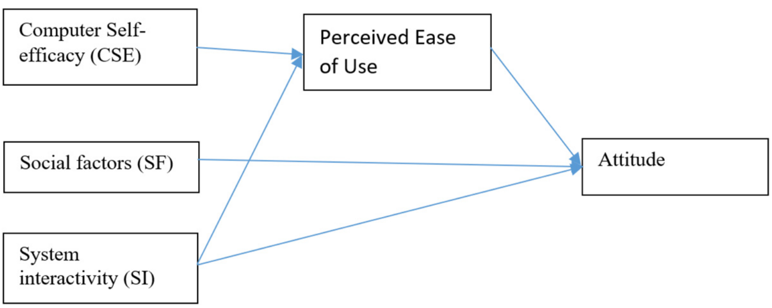

Figure 2.
Adjusted technology adoption model

Table 3. Confirmatory factor analysis

Relationship	Estimate	S.E.	C.R.	p-value	Significance
CSE3 ← CSE	1.000	0.789			
CSE2 ← CSE	1.093	0.905	0.053	20.612	***
CSE1 ← CSE	0.910	0.655	0.055	16.491	***
EXI3 ← EXI	1.000	0.752			
EXI2 ← EXI	1.063	0.871	0.050	21.414	***
EXI1 ← EXI	1.044	0.815	0.052	20.145	***
INI3 ← EXI	0.890	0.616	0.060	14.927	***
INI2 ← EXI	0.877	0.616	0.059	14.922	***
SI3 ← SI	0.846	0.780	0.038	22.072	***
SI2 ← SI	1.000	0.860			
SI1 ← SI	0.976	0.855	0.040	24.615	***
PEOU2 ← PEOU	1.000	0.958			
PEOU3 ← PEOU	0.961	0.893	0.039	24.413	***
ATT3 ← ATT	1.000	0.792			
ATT2 ← ATT	0.878	0.755	0.035	25.100	***
PU1 ← ATT	0.894	0.769	0.044	20.153	***
PU2 ← ATT	0.903	0.777	0.044	20.431	***
PU3 ← ATT	0.918	0.758	0.048	19.268	***
PU4 ← ATT	1.041	0.870	0.045	23.021	***

Notes: This Table reports the results of the confirmatory factor analysis. Appendix 1 provides a detailed description of the variables. ***represents significance levels of 0.1%

Table 4. Convergent and discriminant validity testing

Construct	CR	AVE	MSV	PEOU	CSE	EXI	SI	Attitude
PEOU	0.923	0.858	0.275	0.926				
CSE	0.830	0.624	0.285	0.484	0.790			
EXI	0.857	0.549	0.477	0.524	0.534	0.741		
SI	0.871	0.693	0.457	0.379	0.365	0.606	0.832	
ATT	0.907	0.621	0.477	0.486	0.442	0.691	0.676	0.788

Notes: This Table reports the results of the Convergent and Discriminant validity tests. CR: Composite Reliability, AVE: Average Variance Extracted, MSV: Maximum Shared Variance. The right part of the Table shows the Inter-construct Correlations with the crossline being the Squared root of AVE

Structural model

We next proceeded to run the structural model, as indicated in Figure 2. The indices represent the model fit for the structural model, as reported in Table 5, are as follows: Chi-squared = 489.4, df = 174, Chi-squared/df = 2.81, $p < 0.001$, GFI = 0.934, AGFI = 0.912, NFI = 0.949, TLI = 0.960, CFI = 0.967, and RMSEA = 0.054. The values of these indices are within the acceptable range as indicated in (Bagozzi and Yi, 1988; Byrne, 2010; Hair *et al.*, 2010). Thus, the structural model fits the survey data well.

We found that the CSE of students and the interactivity of the e-learning system (SI) positively affect the students' PEOU of the e-learning system during the Covid-19 period. However, our results show that PEOU has no significant impact on students' attitudes towards the use of e-learning during the Covid-19 period (ATT). In contrast, we documented that SF (i.e. the influence from people inside and out of the school) as well as SI can directly affect ATT, and the magnitude of the impact of SF on ATT is significant.

Hypothesis testing

Impact of external factors on student beliefs

The results of the structural modeling analysis are reported in Table 6. First, regarding the individual factor, the impact of CSE on PEOU is positive and statistically significant (b= 0.417, $p < 0.001$). Hence, *H1** is supported. Regarding system factor, SI also has a positive and statistically significant impact on PEOU (b= 0.238, $p < 0.001$), which supports *H3**. Based on these results, we noticed that the impact of CSE on PEOU is 1.75 times as much as the impact of SI on PEOU (0.417 compared to 0.238). This signifies the important role of students' computer skills in enhancing their adoption of e-learning during an emergency situation.

Student beliefs and technology acceptance

The results show that SF has a positive and significant impact on ATT (b = 0.768, $p <$ 0.001), thus *H2** is supported. The impact of SI on ATT is also significant (b = 0.239, $p <$ 0.001), thus *H4** is supported. However, the impact of PEOU on ATT is not significant ($p =$

Index	Result	Acceptable level
Chi-square	397.193	–
Degree of freedom	139	–
Chi-square/ Degree of freedom	2.858	<5
GFI	0.940	>0.9
AGFI	0.918	>0.8
NFI	0.953	>0.9
TLI	0.962	
CFI	0.969	>0.9
RMSEA	0.055	<0.08
PCLOSE	0.100	>0.05

Notes: This Table reports the results of multiple fit indices of the structural model. GFI: goodness of fit index, AGFI: Adjusted goodness of fit index, NFI: Bentler–Bonett normed fit index, TLI: Tucker–Lews index, CFI: comparative fix index, RMSEA: root mean square error of approximation

Table 5.
Results of multiple fit indices of the structural model

Construct	Estimated coefficient	*P*	Hypothesis
Dependent variable: PEOU			
CSE	0.417	***	supported
SI	0.238	***	supported
R^2	16%		
Dependent variable: Attitude			
SF	0.768	***	supported
SI	0.239	***	supported
PEOU	0.005	0.970	not supported
R^2	64.2%		

Notes: This Table reports the results of the structural equation model. Appendix 1 provides a detailed description of the variables. ***represents significance levels of 0.1%

Table 6.
Results of structural equation model

0.970), therefore, *H6** is not supported. Overall, out of the three variables, SF shows the strongest impact on ATT, where the impact is 3.21 times as much as the impact of SI on ATT (0.768 compared to 0.239). We can also interpret that if SF improves by one point, ATT will also improve by almost one point. These results suggest that SF (or the external encouragement to accept e-learning during the Covid-19 pandemic) plays a very important role in enhancing students' e-learning acceptance. Interestingly, we found that PEOU has no significant impact on ATT. While this result is not consistent with previous studies that show a direct relationship between PEOU and ATT (Liu *et al.*, 2009; Ngai *et al.*, 2007; Stoel and Hye Lee, 2003), this suggests that students' acceptance of e-learning in the context of an emergency situation is driven by different factors compared to that in a normal situation.

Table 7 provides a summary of the results from our tested hypotheses. The second column shows the hypotheses based on our original TAM model, while the third column shows the reviewed hypotheses after we performed the Principal Component Analysis and developed an adjusted TAM model. The last column reports our results from the tested hypotheses. Based on our summary, we have 7 hypotheses in the original model, two of which are dropped (*H5* and *H7*) and three are adjusted (*H2*, *H4*, *H6*) in the adjusted TAM model. Among the five hypotheses of the adjusted TAM, we found statistical evidence to support five of them (*H1*, *H2*, *H3*, *H4*) and reject one (*H6*).

Discussion

The results of the structural model show that CSE has a positive impact on PEOU. These findings align with previous conclusions by Cheng (2011), Punnoose (2012), Salloum *et al.* (2019) and Wu *et al.* (2010). It is reasonable that the level of CSE will positively affect the students' PEOU of the e-learning system, since all of the teaching and learning activities during the Covid-19 pandemic are performed online, with the use of a laptop or computer. Since the education institution under study is a member of one of the biggest ICT corporations with an educational philosophy of integrating technology in education, the CSE among the students is considered sufficient for the sudden implementation of e-learning in an emergency situation such as the Covid-19 pandemic. The second principle of heutagogy describes capability as "the ability of being able to use the acquired competences in unfamiliar as well as in familiar circumstances" (Blaschke and Hase, 2016). In the case of the present study, CSE is considered as the capability. Therefore, CSE makes students familiar

Hypothesis	TAM	Adjusted TAM	Status
H1	CSE (+) PEOU	CSE (+) PEOU	Supported
H2-a	INI (+) PU	SF (+) ATT	Supported
H2-b	INI (+) ATT		
H2-c	EXI (+) PU		
H2-d	EXI (+) ATT		
H3	SI (+) PEOU	SI (+) PEOU	Supported
H4	SI (+) PU	SI (+) ATT	Supported
H5	CF (+) PU	Dropped	NA
H6-a	PEOU (+) PU	PEOU (+) ATT	Not supported
H6-b	PEOU (+) ATT		
H7	PU (+) ATT	Dropped	NA

Notes: This Table provides a summary of the hypotheses in our theoretical model and adjusted model. The Table also reports the results of hypothesis testing. Appendix 1 provides a detailed description of the variables

Table 7. Summary of hypothesis testing results

with using the e-learning system pre and post COVID. This aligns with three studies that also mention that the learners applied the newly acquired skills in unfamiliar learning contexts (Agonács and Matos, 2019). Consequently, it is implied that the students' development of capability is necessary as universities implement new approaches to teaching and learning in the future. More than that, this result might be a good signal for the academic management of educational institutions to review the academic programs and consider increasing online components in their programs post COVID. Importantly, it is also implied that the university management should review the institution's involvement within CSE factors to develop and implement the digital transformation of educational activities effectively.

In addition, there is also a positive relationship between SI and PEOU, which is similar to the findings by Pituch and Lee (2006) and Shin (2007). Accordingly, the interaction between lecturers and students, and among students themselves are important during the period of e-learning since students can seek help from their lecturers and/or classmates whenever they have difficulties in e-learning. The ability to effectively interact with other users within an e-learning system will therefore transfer into the perception of ease of use among students. The principle of heutagogy mentions "learner centered and learner-determined learning" as the learner is mainly accounted for determining what to learn (Blaschke and Hase, 2016). This theory is suitable for this case as the role of active learner is crucial to e-learning implementation. Additionally, the finding of Putistina *et al.* (2019) notes that learners' autonomy can be developed through interaction inside and outside the classroom. Therefore, universities in general and this educational institution in particular should use an e-learning system that has effective communication tools. At the same time, the institution should review and redesign its learning materials to enable more time and activities for both in-class and online mutual interaction. More importantly, it is also implied for university management to evaluate and improve both the system and MOOCs courses more effectively in a post Covid-19 period.

Surprisingly, we have documented that PEOU has no significant impact on ATT. Although this insignificant result does not support our hypothesis, it is not surprising since similar results have been documented in previous studies including Silva *et al.* (2018) and Aldhmour and Sarayrah (2016). In our case, this no-impact result is reasonable given the fact that students at the studied educational institution are familiar with the use of computers and the internet in their daily routine as well as in-class learning. Therefore, their PEOU of e-learning systems will have no big impact on their attitudes towards the emergency use of e-learning systems during the Covid-19 pandemic. However, this result does not align with the findings of previous studies which show that PEOU directly affects attitudes towards using the e-learning system (Liu *et al.*, 2009; Ngai *et al.*, 2007; Stoel and Hye Lee, 2003).

Furthermore, the study of Deepwell and Malik (2008) highlighted that difficulty with ICT equipment might be a factor that has an impact on attitudes towards using technologies in learning. This might enable the educational institution to conduct further studies to explore whether there might be other factors that have a greater impact on the attitudes toward MOOCs in a post Covid-19 era. Importantly, it is also implied that university management should seriously take heed of students' attitudes by the time they plan to implement digital transformation on teaching and learning activities in the future.

The results also show that SI can directly affect ATT, although the magnitude of the impact is only moderate ($b = 0.239$). Since we have combined our items for PU and ATT, this finding supports the conclusion by Cheng (2011) and Shin (2007) which indicate that the ability to effectively interact with other users within an e-learning system can enhance students' PU of the system, which is essentially equivalent to their attitudes towards the use of e-learning during the Covid-19 pandemic. This result suggests that to ensure the success of an urgent e-learning implementation, it is helpful to enhance the interactivity of an e-learning system by, for example, offering a better communication system, allowing out-of-class consulting hours, or adding automated help function. Importantly, to sustain the MOOCs post Covid-19 era, the university management should prioritize the system by ensuring the technological facilities work well to serve the implementation of MOOCs.

Lastly, we documented that SF directly affects ATT, with the coefficient of 0.768, representing a relatively large impact. SF refers to both INI (the influence from lecturers, classmates, and friends) and EXI (the influence from news, experts, and mass media). Based on our findings, these two types of influence are the only factors that affect the attitudes of students towards (or their acceptance of) the implementation of e-learning during the Covid-19 pandemic. Altogether, given the large and significant magnitude of the impact of SF on ATT, it is highly recommended that social influence is enhanced to improve students' acceptance of e-learning in a similar situation of emergency. Accordingly, both universities and society need to implement various channels to communicate the benefits of e-learning as a situational replacement for face-to-face lectures during the extended period of school closures. The influence can be from, but not limited to, lecturers, students who are key opinion leaders (KOLs), experts, and mass media. This result also implies that promoting social influence is necessary not only for the e-learning implementation during the Covid-19 pandemic, but also for the MOOCs post-COVID. It is suggested that this educational institution can provide training courses to students to promote a positive improvement in the attitudes of students towards e-Learning (Salloum *et al.*, 2019). More importantly, the university management should deliver a key message to their students that digital transformation in teaching and learning activities such as online learning and blended learning is a must, responding to the changes of Industrial Revolution (IR) 4.0 post-Covid-19 era. Especially during the second wave of Covid-19, if the university continues to be closed, the university management should have virtual meetings to connect with students, as well as have specific actions to support students to deal with the academic and psychological issues that could result from learning online.

Conclusion

From a theoretical perspective, this study aims to evaluate the implementation of e-learning during the Covid-19 period within the Vietnamese higher education context through the quantification and evaluation of the impact of various external variables on the success of the implementation of e-learning. It is suggested that a solid framework for similar future research be conducted. From a practical perspective, this study provides implications for governments and universities in the process of implementing e-learning given that the Covid-19 pandemic is seeing its second and more dangerous wave. It is necessary that more emphasis be placed in communicating the benefits of e-learning via a wide variety of channels as well as enhancing the interactivity of e-learning systems. This practice is helpful for both current and future situations.

This study contains three limitations. First, since this study only focuses on undergraduate programs, readers should be careful in applying the findings and/or implications of this study to other education levels such as K-12, vocational training, and postgraduate programs. Second, our findings are generated within the context of one type of e-learning, conducted via Google Meet. Therefore, future research is needed to provide further validation and comparison across other forms of e-learning. Finally, to further prevent the common bias problem, future research should use both five-point and seven-point Likert scales for the response options in the survey, as well as use negatively worded items. This will help prevent respondents from providing similar answers to all questions.

References

Adedoyin, O.B. and Soykan, E. (2020), "Covid-19 pandemic and online learning: the challenges and opportunities", *Interactive Learning Environments*, pp. 1-13, available at: https://doi.org/10.1080/10494820.2020.1813180

Agarwal, R., Sambamurthy, V. and Stair, R.M. (2000), "The evolving relationship between general and specific computer self-efficacy – an empirical assessment", *Information Systems Research*, Vol. 11 No. 4, pp. 418-430.

Agonács, N. and Matos, J.F. (2019), "Heutagogy and self-determined learning: a review of the published literature on the application and implementation of the theory", *Open Learning: The Journal of Open, Distance and e-Learning*, Vol. 34 No. 3, pp. 223-240, available at: https://doi.org/10.1080/02680513.2018.1562329

Aldhmour, F. and Sarayrah, I. (2016), "An investigation of factors influencing consumers' intention to use online shopping: an empirical study in South of jordan", *The Journal of Internet Banking and Commerce*, Vol. 21 No. 2.

Al-Qaysi, N., Mohamad-Nordin, N. and Al-Emran, M. (2020), "A systematic review of social media acceptance from the perspective of educational and information systems theories and models", *Journal of Educational Computing Research*, Vol. 57 No. 8, pp. 2085-2109.

Associates, H.R. (2013), "It takes more than a major: employer priorities for college learning and student success", *Liberal Education*, Vol. 99 No. 2.

Bagozzi, R.P. and Yi, Y. (1988), "On the evaluation of structural equation models", *Journal of the Academy of Marketing Science*, Vol. 16 No. 1, pp. 74-94.

Bandura, A. (1977), "Self-efficacy: toward a unifying theory of behavioral change", *Psychological Review*, Vol. 84 No. 2, pp. 191-215, available at: https://doi.org/10.1037/0033-295X.84.2.191

Batty, D. and Hall, R. (2020), "No campus lectures and shut student bars: UK universities' £1bn struggle to move online", The Observer, available at: www.theguardian.com/education/2020/apr/25/degrees-of-separation-can-universities-adapt-in-the-rush-to-online-learning

Baytiyeh, H. (2018), "Online learning during post-earthquake school closures", *Disaster Prevention and Management: An International Journal*, Vol. 27 No. 2, pp. 215-227, available at: https://doi.org/10.1108/DPM-07-2017-0173

Bhattacherjee, A. (2000), "Acceptance of e-commerce services: the case of electronic brokerages", *IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans*, Vol. 30 No. 4, pp. 411-420, available at: https://doi.org/10.1109/3468.852435

Blaschke, L.M. and Hase, S. (2016), "Heutagogy: a holistic framework for creating Twenty-First-Century self-determined learners", Available at: https://doi.org/10.1007/978-3-662-47724-3_2

Boymal, J., Martin, B. and Lam, D. (2007), "The political economy of internet innovation policy in vietnam", *Technology in Society*, Vol. 29 No. 4, pp. 407-421, available at: https://doi.org/10.1016/j.techsoc.2007.08.003

Byrne, B.M. (2010), *Structural Equation Modeling with AMOS: basic Concepts, Applications, and Programming (Multivariate Applications Series)*, *Taylor and Francis Group*: *New York, NY 396*, p. 7384.

Cameron, L. and Tanti, M. (2011), "Students as learning designers: using social media to scaffold the experience", *E-Learning Papers*, Vol. 27, pp. 1-6.

Cao, W., Fang, Z., Hou, G., Han, M., Xu, X., Dong, J. and Zheng, J. (2020), "The psychological impact of the COVID-19 epidemic on college students in China", *Psychiatry Research*, Vol. 287, p. 112934, available at: https://doi.org/10.1016/j.psychres.2020.112934

Chang, S.C. and Tung, F.C. (2008), "An empirical investigation of students' behavioural intentions to use the online learning course websites", *British Journal of Educational Technology*, pp. 71-83, available at: https://doi.org/10.1111/j.1467-8535.2007.00742.x

Chang, C.T., Hajiyev, J. and Su, C.-R. (2017), "Examining the students' behavioral intention to use e-learning in Azerbaijan? The general extended technology acceptance model for E-learning approach", *Computers and Education*, Vol. 111, pp. 128-143, available at: https://doi.org/10.1016/j.compedu.2017.04.010

Cheng, Y.M. (2011), "Antecedents and consequences of e-learning acceptance", *Information Systems Journal*, Vol. 21 No. 3, pp. 269-299, available at: https://doi.org/10.1111/j.1365-2575.2010.00356.x

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, pp. 319-340, available at: https://doi.org/10.2307/249008

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1989), "User acceptance of computer technology: a comparison of two theoretical models", *Management Science*, Vol. 35 No. 8, pp. 982-1003, available at: https://doi.org/10.1287/mnsc.35.8.982

Davis, F.D., Bagozzi, R.P. and Warshaw, P.R. (1992), "Extrinsic and intrinsic motivation to use computers in the workplace 1", *Journal of Applied Social Psychology*, Vol. 22 No. 14, pp. 1111-1132.

Dawes, D.J. (2008), "Do data characteristics change according to the number of scale points used? An experiment using 5-Point, 7-Point and 10-Point scales", *International Journal of Market Research*, Vol. 50 No. 1, Available at: https://doi.org/10.1177/147078530805000106

Deepwell, F. and Malik, S. (2008), "On campus, but out of class: an investigation into students' experiences of learning technologies in their self-directed study", *ALT-J*, Vol. 16 No. 1, pp. 5-14, available at: https://doi.org/10.1080/09687760701850166

Engelbrecht, E. (2005), "Adapting to changing expectations: post-graduate students' experience of an e-learning tax program", *Computers and Education*, Vol. 45 No. 2, pp. 217-229.

Eom, S.B., Wen, H.J. and Ashill, N. (2006), "The determinants of students' perceived learning outcomes and satisfaction in university online education: an empirical investigation", *Decision Sciences Journal of Innovative Education*, Vol. 4 No. 2, pp. 215-235.

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50.

George, E.S. (2010), "Higher education in vietnam 1986–1998: Education in transition to a new era?", *Reforming Higher Education in Vietnam*, pp. 31-49, available at: https://doi.org/10.1007/978-90-481-3694-0_3

Hair, J.F., Black, B., Babin, B.J. and Anderson, R.E. (2010), *Multivariate Data Analysis: Global Edition*, 7th edn. Pearson London.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. and Tatham, R.L. (1998), *Multivariate Data Analysis*, 3th edition, Prentice Hall New York, NY, Vol. 5.

Hart, J. (2012), "Informal and social learning", The Really Useful Elearning Instruction Manual: Your Toolkit for Putting Elearning into Practice, pp. 107-123.

Hase, S. and Kenyon, C. (2000), "From andragogy to heutagogy", Ulti-BASE In-Site.

Hase, S. and Kenyon, C. (2007), "Heutagogy: a child of complexity theory", *Complicity: An International Journal of Complexity and Education*, Vol. 4 No. 1.

Hase, S. and Kenyon, C. (2013), *Self-Determined Learning: Heutagogy in Action*, A&C Black London.

Henderson, R. and Divett, M.J. (2003), "Perceived usefulness, ease of use and electronic supermarket use", *International Journal of Human-Computer Studies*, Vol. 59 No. 3, pp. 383-395, available at: https://doi.org/10.1016/S1071-5819(03)00079-X

Holmes-Smith, P. (2001), *Introduction to Structural Equation Modeling Using LISREL, ACSPRI-Winter Training Program, Perth.*

Hsu, C.L. and Lu, H.P. (2004), “Why do people play on-line games? An extended TAM with social influences and flow experience”, *Information and Management*, Vol. 41 No. 7, pp. 853-868, available at: https://doi.org/10.1016/j.im.2003.08.014

Kelly, T.M. and Bauer, D.K. (2003), “Managing intellectual capital – via e-learning – at cisco”, In *Handbook on Knowledge Management*, Springer, New York, NY pp. 511-532.

Kwan, C. (2020), “Australian universities begin moving classes online to tackle COVID-19 outbreak”, Available at: www.zdnet.com/article/australian-universities-begin-moving-classes-online-to-tackle-covid-19-outbreak/

Lee, Y. (2006), “An empirical investigation into factors influencing the adoption of an e-learning system”, *Online Information Review*, Vol. 30 No. 5, pp. 517-541, available at: https://doi.org/10.1108/14684520610706406

Lee, B.C., Yoon, J.O. and Lee, I. (2009), “Learners’ acceptance of e-learning in South Korea: theories and results”, *Computers and Education*, Vol. 53 No. 4, pp. 1320-1329, available at: https://doi.org/10.1016/j.compedu.2009.06.014

Levy, Y. (2007), “Comparing dropouts and persistence in e-learning courses”, *Computers and Education*, Vol. 48 No. 2, pp. 185-204.

Liu, S.H., Liao, H.L. and Pratt, J.A. (2009), “Impact of media richness and flow on e-learning technology acceptance”, *Computers and Education*, Vol. 52 No. 3, pp. 599-607, available at: https://doi.org/10.1016/j.compedu.2008.11.002

Marangunić, N. and Granić, A. (2015), “Technology acceptance model: a literature review from 1986 to 2013”, *Universal Access in the Information Society*, Vol. 14 No. 1, pp. 81-95.

Mathieson, K. (1991), “Predicting user intentions: comparing the technology acceptance model with the theory of planned behavior”, *Information Systems Research*, Vol. 2 No. 3, pp. 173-191.

Matsunaga, M. (2010), “How to factor-analyze your data right: Do’s, don’ts, and how-to’s”, *International Journal of Psychological Research*, Vol. 3 No. 1, pp. 97-110, available at: https://doi.org/10.21500/20112084.854

MOET (2020), “Đại học tiên phong đẩy mạnh chuyển đổi số giáo dục”, Available at: https://moet.gov.vn/tintuc/Pages/phong-chong-nCoV.aspx?ItemID=6615

Mohamedbhai, G. (2020), “COVID-19: What consequences for higher education?”, University World News. Available at: www.universityworldnews.com/post.php?story=20200407064850279

Ngai, E.W.T., Poon, J.K.L. and Chan, Y.H.C. (2007), “Empirical examination of the adoption of WebCT using TAM”, *Computers and Education* , Vol. 48 No. 2, pp. 250-267, available at: https://doi.org/10.1016/j.compedu.2004.11.007

Nunnally, J.C. (1978), *Psychometric Theory*, McGraw-Hill New York, NY.

Ong, C.S., Lai, J.Y. and Wang, Y.S. (2004), “Factors affecting engineers’ acceptance of asynchronous e-learning systems in high-tech companies”, *Information and Management*, Vol. 41 No. 6, p. 795-804, available at: https://doi.org/10.1016/j.im.2003.08.012

Paechter, M., Maier, B. and Macher, D. (2010), “Students’ expectations of, and experiences in e-learning: their relation to learning achievements and course satisfaction”, *Computers and Education*, Vol. 54 No. 1, pp. 222-229.

Peterson, R.A. (1994), “A Meta-analysis of Cronbach’s coefficient alpha”, *Journal of Consumer Research*, Vol. 21 No. 2, pp. 381-391, available at: https://doi.org/10.1086/209405

Pham, H.H. and Ho, T.T.H. (2020), “Toward a ‘new normal’ with e-learning in Vietnamese higher education during the post COVID-19 pandemic”, *Higher Education Research and Development*, pp. 1-5, available at: https://doi.org/10.1080/07294360.2020.1823945

Pituch, K.A. and Lee, Y. (2006), “The influence of system characteristics on e-learning use”, *Computers and Education*, Vol. 47 No. 2, pp. 222-244, available at: https://doi.org/10.1016/j.compedu.2004.10.007

Punnoose, A.C. (2012), "Determinants of intention to use eLearning based on the technology acceptance model", *Journal of Information Technology Education: Research*, Vol. 11 No. 1, pp. 301-337.

Putistina, O.V., Kvasyuk, E.N. and Savateeva, O.V. (2019), "Interaction and autonomy in foreign language and culture studies", *Journal of History Culture and Art Research*, Vol. 8 No. 2, pp. 13-25, available at: https://doi.org/10.7596/taksad.v8i2.2067

Ribeiro, R. (2020), "How university faculty embraced the remote learning shift", Technology Solutions That Drive Education, available at: https://edtechmagazine.com/higher/article/2020/04/how-university-faculty-embraced-remote-learning-shift

Rissa, J. (2014), "An empirical study on the e-learning acceptance among the Finnish labor".

Rodríguez-Ardura, I. and Meseguer-Artola, A. (2016), "E-learning continuance: the impact of interactivity and the mediating role of imagery, presence and flow", *Information and Management*, Vol. 53 No. 4, pp. 504-516.

Rodríguez-Ardura, I., Meseguer-Artola, A., Rodríguez-Ardura, I. and Meseguer-Artola, A. (2020), "Editorial: how to prevent, detect and control common method variance in electronic commerce research", *Journal of Theoretical and Applied Electronic Commerce Research*, Vol. 15 No. 2, Available at: https://doi.org/10.4067/S0718-18762020000200101

Salloum, S.A., Qasim Mohammad Alhamad, A., Al-Emran, M., Abdel Monem, A. and Shaalan, K. (2019), "Exploring students' acceptance of E-Learning through the development of a comprehensive technology acceptance model", *IEEE Access*, Vol. 7, pp. 128445-128462, available at: https://doi.org/10.1109/ACCESS.2019.2939467

Schroeder, A., Minocha, S. and Schneider, C. (2010), "The strengths, weaknesses, opportunities and threats of using social software in higher and further education teaching and learning", *Journal of Computer Assisted Learning*, Vol. 26 No. 3, pp. 159-174.

Shin, D.H. (2007), "User acceptance of mobile internet: implication for convergence technologies", *Interacting with Computers*, Vol. 19 No. 4, pp. 472-483, available at: https://doi.org/10.1016/j.intcom.2007.04.001

Silva, A.G., Canavari, M. and Sidali, K.L. (2018), "A technology acceptance model of common bean growers' intention to adopt integrated production in the Brazilian Central region", *Die Bodenkultur: Journal of Land Management, Food and Environment*, Vol. 68 No. 3, pp. 131-143.

Stoel, L. and Hye Lee, K. (2003), "Modeling the effect of experience on student acceptance of web-based courseware", *Internet Research*, Vol. 13 No. 5, pp. 364-374, available at: https://doi.org/10.1108/10662240310501649

Sun, J.N. and Hsu, Y.C. (2013), "Effect of interactivity on learner perceptions in web-based instruction", *Computers in Human Behavior*, Vol. 29 No. 1, pp. 171-184.

Tran, K.N.N. (2016), "The adoption of blended E-learning technology in vietnam using a revision of the technology acceptance model", *Journal of Information Technology Education*, Vol. 15

UNESCO (2020), "Adverse consequences of school closures", available at: https://en.unesco.org/covid19/educationresponse/consequences

University of the Highlands and Islands (2020), "COVID-19: higher education opportunities in a changing world", 10 June available at: www.onlinestudies.com/article/covid-19-higher-education-opportunities-in-a-changing-world/

Vasantha Raju, N. and Harinarayana, N.S. (2016), "Online survey tools: a case study of Google forms", *National Conference on "Scientific, Computational and Information Research Trends in Engineering*.

Viner, R.M., Russell, S.J., Croker, H., Packer, J., Ward, J., Stansfield, C., Mytton, O., Bonell, C. and Booy, R. (2020), "School closure and management practices during coronavirus outbreaks including COVID-19: a rapid systematic review", *The Lancet Child and Adolescent Health*, Vol. 4 No. 5, pp. 397-404, available at: https://doi.org/10.1016/S2352-4642(20)30095-X

Wu, J.H., Tennyson, R.D. and Hsia, T.-L. (2010), "A study of student satisfaction in a blended e-learning system environment", *Computers and Education*, Vol. 55 No. 1, pp. 155-164, available at: https://doi.org/10.1016/j.compedu.2009.12.012

Yamey, G. and Weham, C. (2020), "Why the U.S. and U.K. Failed their coronavirus responses |", Time. available at: https://time.com/5861697/us-uk-failed-coronavirus-response/

Zhang, X., Keeling, K. and Pavur, R. (2020), "Information quality of commercial web site home pages: an explorative analysis", p. 13.

Zhang, W., Wang, Y., Yang, L. and Wang, C. (2020), "Suspending classes without stopping learning: China's education emergency management policy in the COVID-19 outbreak", *Journal of Risk and Financial Management*, Vol. 13 No. 3, p. 55, available at: https://doi.org/10.3390/jrfm13030055

Appendix 1

Variable	Variable name	Definition
ATT	Attitude	The degree to which the user is interested in specific systems, which has a direct effect on the intention to use those specific systems in the future (Davis *et al.*, 1989)
CF	Content feature	The characteristics and presentation of course content and information (Zhang *et al.*, 2020)
PEOU	perceived ease of use	The degree to which a user believes that using a particular system will be free of effort (Davis, 1989)
INI	interpersonal influence	The influence of referents like friends, family members, colleagues, etc. and experienced persons considered by individuals in performing a behavior (Bhattacherjee, 2000)
EXI	external influence	The influence of mass media reports, expert opinions and non-personal information considered by individual in performing a behavior (Bhattacherjee, 2000)
SI	System interactivity	The interaction between instructors and learners, and the collaboration in learning that results from these interactions (Pituch and Lee, 2006)
PU	perceived usefulness	The degree to which a person believes that using a particular system will enhance his or her job performance (Chang and Tung, 2008)
CSE	Computer self-efficacy	People’s judgment of their capabilities to perform particular tasks successfully (Bandura, 1977)

Table A1. Variable definition

Appendix 2

Survey questions

SECTION 1: PERSONAL INFORMATION

1. Your gender?

Male

Female

Prefer not to say

2. What year are you in?

First year or foundation year

Second year

Third year

Final year

3. What is you major?

Information Technology (IT)

Business administration

Others

4. Is this the first time that you have undertaken a course completely via online learning?

Yes

No

SECTION 2: TAM

Question 1:

Participants responded to the given statements using the 5-point Likert scale: (1) Strongly Disagree, (2) Disagree, (3) Neutral, (4) Agree, (5) Strongly Agree

Computer self-efficacy (CSE)	• CSE1: I could complete my learning activities via an online learning system if I had never used an online learning system like this before. • CSE2: I could complete my learning activities via an online learning system if I had only the system manuals for reference. • CSE3: I could complete my learning activities via an online learning system if I had seen someone else using it before trying it myself.

Question 2:

Participants responded to the given statements using the 5-point Likert scale: (1) Strongly Disagree, (2) Disagree, (3) Neutral, (4) Agree, (5) Strongly Agree.

Interpersonal influence (INI)	• INI1: My lecturer thinks that I should study online during Covid-19 period. • INI2: My classmates think that I should study online during Covid-19 period. • INI3: My friends think that I should study online during Covid-19 period.
External influence (EXI)	• EXI1: I read/see news reports that studying online is a good way of learning during Covid-19 period. • EXI2: Expert opinions depict a positive sentiment for using online learning during Covid-19 period. • EXI3: Mass media reports convince me to use online learning during Covid-19 period.

(*continued*)

Question 3:

Participants responded to the given statements using the 5-point Likert scale: (1) Strongly Disagree, (2) Disagree, (3) Neutral, (4) Agree, (5) Strongly Agree.

System interactivity (SI)	• SI1: The online learning system enables interactive communication between the lecturer and learners. • SI2: The online learning system enables interactive communication among learners. • SI3: The communicational tools in the online learning system are effective.
Content Feature (CF)	• CF1: The current content of the course is redesigned to fit online learning during Covid-19 period. • CF2: The instruction delivery of content in the online course during Covid-19 period is easily understandable • CF3: The related teaching and learning activities in the online course during Covid-19 period is suitable and appropriate.

Question 4:

Participants responded to the given statements using the 5-point Likert scale: (1) Strongly Disagree, (2) Disagree, (3) Neutral, (4) Agree, (5) Strongly Agree.

Perceived ease of use (PEOU)	• PEOU1: Interacting with the online learning system does not require a lot of my mental effort. • PEOU2: I find the online learning system easy to use. • PEOU3: It is easy to become skillful at using the online learning system.
Perceived usefulness (PU)	• PU1: Using the online learning system improves my learning performance during Covid-19 period. • PU2: Using the online learning system promotes my learning effectiveness during Covid-19 period. • PU3: Using the online learning system gives me greater autonomy and flexibility over learning during Covid-19 period. • PU4: I find the online learning system useful and comfortable in my learning during Covid-19 period.
Attitude	• ATT1: Using the online learning system during Covid-19 period is a good idea. • ATT2: The online learning system provides an attractive learning environment during Covid-19 period. • ATT3: Overall, I like using the online learning system during Covid-19 period.

Corresponding author
Nguyen Thi Thao Ho can be contacted at: nguyen_20000147@utp.edu.my