Print ISSN: 2288-4637 / Online ISSN 2288-4645
doi:10.13106/jafeb.2021.vol8.no10.0385

The Effect of Perceived Risk and Technology Self-Efficacy on Online Learning Intention: An Empirical Study in Vietnam

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Received: June 30, 2021 Revised: September 09, 2021 Accepted: September 17, 2021

Abstract

In an effort to find ways to increase the effectiveness of online education, literature and empirical study based on the Technology Acceptance Model (TAM) have addressed a variety of questions, including perceived ease of use (PEU) and perceived usefulness (PU). After TAM, extensive studies have focused on the impact of extrinsic factors on PEU and PU, including Self-efficacy and Perceived Risk. This study aims to analyze the direct, indirect, and moderating effects of Self-efficacy and Perceived Risk on Online Learning Intention (OLI). Data was collected through a survey method from 472 students studying at universities in Vietnam. The collected data was analyzed using the PLS-SEM technique to test the hypotheses. The findings reveal that Technology Self-Efficacy influences the intention to take online courses both directly and indirectly through Perceived Ease of Use and Perceived Usefulness. Besides, Perceived Risk COVID-19 also has a positive effect on online learning intention, and plays a role as a moderating variable on the impact of PU on OLI. These findings suggest that students will have a stronger intention to study online when they are confident in their ability to use technology. When they believe in their ability to use technology, their online learning intention will also increase.

Keywords: Technology Self-Efficacy, Perceived Risk COVID-19, Perceived Usefulness, Perceived Ease of Use, Online Learning Intention

JEL Classification Code: I20, I23, I24, M10, M19

1. Introduction

The impact of information technology on human life is enormous and its role in education is also extremely important, especially in the context of the global COVID-19 pandemic. Around the world, many educational institutions have temporarily closed. Some universities have also postponed or canceled all campus activities to minimize gatherings thereby reducing the spread of COVID-19. During this quarantine due to the COVID-19 pandemic, it is essential to change the educational service, convert the teaching mode to online mode (Ambarwati et al., 2020; Park & Lee, 2021).

In an effort to find ways to increase the effectiveness of online education, literature and empirical study based on the Technology Acceptance Model (TAM) have addressed a variety of questions, including perceived ease of use (PEU) (Kim et al., 2008) and perceived usefulness (PU) (Maheshwari, 2021). After TAM, extensive studies have focused on the impact of extrinsic factors on PEU and PU, including Self-efficacy (Lee et al., 2006) and Perceived Risk. Bandura (1986) defined self-efficacy as the belief in one's capabilities to organize and execute the courses of action required to manage prospective situations. Technology Self-Efficacy (TSE) is defined as the level of confidence students have in using technology for learning (Cai et al., 2019). People with higher Technology Self-Efficacy (TSE) are less likely to worry about technology usability and tend to perform better on technology-related tasks (Downey & Kher 2015).

In the process of studying Online Learning Intention (OLI), especially during the COVID-19 pandemic, Perceived Risk (PR) is also a factor that deserves attention. Most previous studies suggest that the impact of PR on behavior is negative (Marafon et al., 2018). However, because COVID-19 can be transmitted through close contact

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with infected individuals, the perceived risk associated with its transmission is expected to have a positive impact on university students' intention to study online. The COVID-19 transmission can appear through close contact with infected individuals (Guan et al., 2020). As university students become more aware of the usefulness of online learning during the COVID-19 period, the more they intend to study online. However, during the continuing global COVID-19 outbreak, the more these students realize that the risk of COVID-19 transmission through direct person-to-person contact is extremely high, the higher their intention to study online. With that argument, in this study, we use Perceived Risk COVID-19 both as an independent variable affecting OLI and as a moderator between PU and OLI.

In the face of the COVID-19 outbreak, educational institutions in general and universities, in particular, may need to start paying attention to online teaching methods and include them in the curricula for the future. Therefore, it is necessary to understand the opinions of learners and explore learners' tendencies towards online teaching methods (Bali & Liu, 2018). For students to adopt and succeed in online learning, besides the skills and knowledge required, it is essential to identify other factors that influence their intention to study online (Brahmasrene & Lee, 2012). In that context, this paper aims to study the online learning intention of university students in the future, through factors such as Perceived Risk, specifically the risk associated with the transmission of PR COVID-19, PEU, TSE, and the relationship between these factors.

2. Literature Review

2.1. Technology Acceptance Model – TAM

Based on the theory of reasonable action (TRA), Davis (1986) developed the Technology Acceptance Model (TAM) which is more specifically related to predicting the acceptability of an information technology system. TAM is an information systems theory that models how users come to accept and use technology. This model is determined by two main factors: PU and PEU. The final version of TAM hypothesized that PEU not only affects directly but also indirectly through PU, the intention to use (Davis et al., 1989).

2.2. Online Learning Intention (OLI)

The intention is a representation of the willingness to perform a behavior. The Theory of Reasoned Action (Ajzen & Fishbein, 1975) and the Theory of Planned Behavior (Ajzen, 1991) are two very widely used theories in explaining human behavior through their intentions. Face-to-face learning, e-learning, distance learning, and online learning are different types of learning environments available. Online learning is a form of learning that is "completely online" in which learners do not go to class but learn completely outside the classroom (Oblinger & Oblinger, 2005). In this study, online learning intention is the willingness to participate in online courses**.**

2.3. Perceived Ease of Use (PEU), Perceived Usefulness (PU), and Online Learning Intention (OLI)

PU is defined as the degree to which a person believes that using a certain system will increase his or her job performance. According to TAM, PEU not only affects directly but also indirectly through PU online learning intention (Davis et al., 1989). The intention to use technology, such as online money transfer services (Noreen et al., 2021) or E-learning (Park, 2009) was found to be positively correlated with PEU and PU. According to Huang et al. (2020), PEU is responsible for 64% of the difference in college students' behavioral intentions. Based on TAM and together with the above arguments, the following hypotheses are proposed:

H1: *Perceived Ease of Use has a positive effect on Online Learning Intention.*

H2: *Perceived Ease of Use has a positive effect on Perceived Usefulness.*

H3: *Perceived Usefulness has a positive impact on Online Learning Intention.*

2.4. Technology Self-Efficacy (TSE) and Online Learning Intention (OLI)

Self-efficacy refers to an individual's belief in his or her capacity to execute behaviors necessary to produce specific performance attainments. The self-efficacy of technology is derived from the concept of self-efficacy defined by Bandura (1986), according to which self-efficacy is defined as a belief in one's ability to take the necessary actions in controlling situations. In the context of online learning, TSE refers to a factor that reflects students' views and levels of confidence in using technology for learning (Cai et al., 2019), i.e. the ability to use technology without worrying about any problems. It also estimates the user's ability to use technological inputs to achieve desired outcomes (Bailey et al., 2017; Cebeci et al., 2020).

In the online learning environment, TSE is linked to learners' belief in the ability to use technology in learning. Some students believe that using technology in learning is easily achievable, however, there are also students who think that it is difficult to learn how to use technology to serve their learning process (Bailey et al., 2017). Many previous studies have demonstrated an association between self-efficacy and PEU (Davis, 1989; Mathieson, 1991; Venkatesh & Davis, 2000; Lee, 2006; Al-Gahtani, 2016). Thanks to self-efficacy, individuals can assess how easy or difficult it is to use technology to perform a particular task (Purnomo & Lee, 2013). A meta-analysis by Abdullah and Ward (2016) on TAM theory through a review of 107 studies showed that self-efficacy is the best explanatory factor for PEU and has a strong impact on PU. This is also tested in the study of Rezaei et al. (2020). With those analyses, the following hypotheses are formed:

H4: *Technology Self-Efficacy has a positive effect on Perceived Ease of Use.*

H5: *Technology Self-Efficacy has a positive effect on Perceived Usefulness.*

H6: *Technology Self-Efficacy has a positive impact on Online Learning Intention.*

2.5. Perceived Risk (PR) and Online Learning Intention (OLI)

The concept of PR was first introduced by Bauer (1960), who defined perceived risk as the risk that consumers actively perceive because they do not understand product information. PR is a multidimensional structure, including many types of risks depending on the type of product or service (Kassim & Ramayah, 2015), or many risk aspects such as financial risk, physical risk, social risk, time loss risk, and psychological risk (Forsythe & Shi, 2003). The research of Maser and Weiermair (1998) mentioned another type of risk that of disease risk, and this is the type of risk that is of interest in the context of this study. In this study, the perceived risk of disease risk refers to students' concerns about COVID-19 when interacting with classmates or teachers in a face-to-face learning setting, and their fear of contracting COVID-19 through face-to-face communication.

In many of the consumer behavior studies, the negative effects of PR are often highlighted, such as in the context of travel (Rittichainuwat & Chakraborty, 2009), mobile money services (Noreen et al., 2021), or online banking (Kassim & Ramayah, 2015; Marafon et al., 201). Having direct contact with a large number of people when going to school increases the likelihood of COVID-19 infection. Therefore, the students' intention to learn online will be stronger if they perceive a higher risk of COVID-19 infection. Furthermore, the more these students are aware of the significant risk of COVID-19 transmission through direct person-to-person contact, the more likely they are to study online. With that argument, in this study, in addition to the direct effect on OLI, PR COVID-19 was used as a moderator variable between PU and OLI. Therefore, the following research hypotheses are stated:

H7: *Perceived Risk COVID-19 positively impacts Online Learning Intention.*

H8: *Perceived Risk COVID-19 moderates the effect of Perceived Usefulness on Online Learning Intention.*

The proposed research model is shown in Figure 1.

3. Research Method

3.1. Measures

The proposed research model includes five elements: PEU, PU, PR COVID-19, TSE, and OLI. The PEU and PU scales were inherited from the TAM of Davis et al. (1989). COVID-19 PR was measured using three observed variables from Olya and Al-Ansi (2018) and adjusted for the COVID-19 context. TSE is measured by four observed variables inherited from related studies (Bandura, 1986; Ozturk et al., 2016; Nikou & Economides, 2017; Chao, 2019; Ukpabi et al., 2021). OLI was measured using four observed variables adapted from Aji et al. (2020). All observed variables were designed to measure respondents' opinions with a 5-point Likert scale, a type of psychometric response scale in which responders specify their level of agreement to a statement typically in five points: (1) Strongly disagree; (2) Disagree; (3) Neither agree nor disagree; (4) Agree; (5) Strongly agree. PLS-SEM (Partial Least Squares Structural Equation Modeling) technique is used to test the hypotheses in the proposed research model.

3.2. Data Collection

This is a study on students' intention to study online, so the data is collected from students of universities in Vietnam. Due to the ongoing COVID-19 situation, the survey questionnaires were delivered to respondents via an online form. A total of 550 survey questionnaires were sent to students studying at universities that have implemented online teaching programs in Ho Chi Minh City. After completing data collection, the questionnaire was manually checked and those that did not meet the requirements were

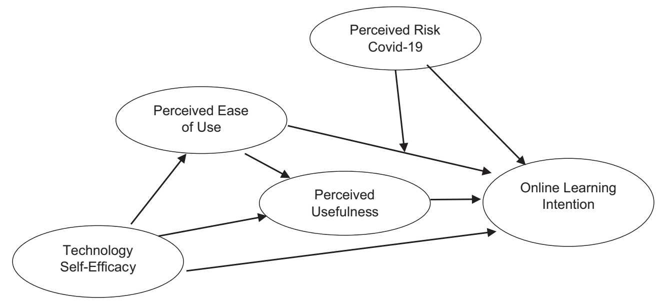

Figure 1: Research Model

discarded. 472 students (85.8% of the respondents) submitted responses with qualified answers. In which, 55.1% are male students and 44.9% are female students; 22% of first-year students; 25.8% of 2nd-year students; 31.7% of 3rd-year students; 20.5% final year students.

4. Results

4.1. Measurement Model

First, the measurement model is evaluated for internal consistency and convergent validity (Table 1). Internal consistency reliability was assessed through composite reliability (CR) or Cronbach's alpha index. If these indicators are greater than 0.7, the scale is considered good (Hair et al., 2017). Convergence value is evaluated through outer loading (greater than 0.7) and Average Extracted Variance (AVE) index (greater than 0.5).

Table 1 shows that all scales have Cronbach's alpha values that meet the standards (more than 0.7), and that composite reliability CR and AVE of all structures are greater than the minimum acceptable thresholds of 0.7 and 0.5, respectively (Henseler et al., 2016; Henseler, 2017). The outer loading of TSE4 (0.697) is between 0.6 and 0.7, below the threshold value (0.7). However, since the composite reliability and AVE values of TSE are higher than 0.7 and 0.5, respectively, the TSE4 value can still be retained (Hair et al., 2017). To test the discriminant validity, the study used the Heterotrait-Monotrait Ratio (HTMT) method recommended by Henseler et al. (2016).

From the results in Table 2, the HTMT ratio from 0.477 to 0.793 (ranged from 0.190 to 0.85) indicates that the index meets discriminant validity (Nitzl, 2016; Henseler et al., 2016).

To test the structural model estimation, the adjusted R^2 value is considered. As shown in Figure 2, the adjusted R^2 value of OLI is 48.5% (greater than 30%), which is considered good enough in social research (Arya et al., 2019).

4.2. Testing of Hypotheses

With a sample size of 5000 people, we used the Bootstrapping technique. The results are shown in Table 3 as follows.

From the results in Table 3, hypotheses H1, H2, H3, H4, H5, and H6 are supported, showing that PEU, PU and TSE of students have a positive impact on OLI. These factors have values of 0.391 (p = 0.000), 0.338 (p = 0.000), 0.282 (p = 0.000), 0.463 (p = 0.000), 0.360 (p = 0.000) and 0.107 (p = 0.023). In addition, with β = 0.099, p = 0.047, PR COVID-19 of students also positively affects OLI, hence, H7 is supported. Thus, all research hypotheses are supported.

Further analyzes were performed to evaluate the mediating effects of PEU and PU on the relationship between TSE and OLI. Using the Bootstrapping method with 5000 iterations, the indirect and total effects are shown in Table 4.

The final step is to examine the moderating role of PR. The results in Table 5 below demonstrated that PR COVID-19 of students moderates the strength of the mediating effects of PEU and PU on the relationship between TSE and OLI.

5. Conclusion and Limitations

The results of the research model test show that TSE both directly and indirectly through PEU and PU affects OLI. These findings are consistent with the previous conclusions of Park (2009), Huang et al. (2020), Abdullah and Ward (2016), and Rezaei et al. (2020). It can be seen that students will form a stronger intention to study online when they are confident in their ability to use technology. When they believe in their ability to use technology, these students find it easy and really useful to use online learning especially in the context of COVID-19, and this increases their online learning intention.

The study results also show that there is a positive effect of PR COVID-19 on OLI. Outbreaks of COVID-19 may cause concern among students about catching COVID-19 through contact with people who have the disease. This finding is consistent with the findings of Aji et al. al (2020) who examined the positive effect of PR COVID-19 on the intention to use cryptocurrency, and also provided an alternative while previous studies suggested that PR has a negative influence on intention, such as in the context of travel (Rittichainuwat & Chakraborty, 2009), online banking (Kassim & Ramayah, 2015; Marafon et al., 2018), or mobile money services (Noreen et al., 2021). In addition, PR COVID-19 also plays a moderating role in the impact of PU on OLI. This can be explained by the fact that the higher university students' perceptions of the usefulness of online learning during the COVID-19 period, the more they will intend to study online (in the context of COVID-19), and the stronger their intention to study online will become as they become aware of the high risk of COVID-19 transmission from person to person.

With the above study results, it can be seen that the COVID-19 pandemic can be an opportunity for universities to implement online learning into their training programs. To deploy and attract students to this new form of learning, universities must emphasize the risks of COVID-19 infection as well as students' confidence in their ability to use technology in ways that are familiar to them in their daily lives, so that they can see the ease of use of the

Table 1: Constructs' Factor Loadings, Consistency Reliability, and AVE

Dimensions and Items	Item Code	Factor Loading	Cronbach's α	CR	AVE
Online Learning Intention (OLI)			**0.765**	**0.850**	**0.587**
I will use online courses during the COVID-19 pandemic	OLI1	0.742			
I prefer using online courses during the COVID-19 pandemic	OLI2	0.765			
In the future, I will use online courses for my studies	OLI3	0.788			
I will likely recommend the online courses to my friends	OLI4	0.768			
Perceived Ease of Use (PEU)			**0.733**	**0.830**	**0.551**
Interacting with the online learning system does not require much of my mental effort.	PEU1	0.717			
The online learning system is easy to use for me.	PEU2	0.794			
It is easy to become skillful at using the online learning system.	PEU3	0.752			
For me, how to use the e-learning system is very clear and easy to understand	PEU4	0.703			
Perceived Risk (PR)			**0.863**	**0.916**	**0.784**
I am worried to get infected by coronavirus when using online courses during COVID-19	PR1	0.877			
I am not comfortable having face-to-face courses during COVID-19	PR2	0.881			
I am afraid to get infected by coronavirus when using online courses during COVID-19	PR3	0.898			
Perceived Usefulness (PU)			**0.724**	**0.845**	**0.644**
Using the online learning system improves my learning performance during the COVID-19 period.	PU1	0.796			
Using the online learning system promotes my learning effectiveness during the COVID-19 period.	PU2	0.817			
I find the online learning system useful and comfortable in my learning during the COVID-19 period.	PU4	0.795			
Technology Self-Efficacy (TSE)			**0.734**	**0.832**	**0.555**
I am confident of using online learning even if there is no one around to show me how to do it	TSE1	0.775			
I am confident of using online learning even if I have never used such a system before	TSE2	0.749			
I am confident of using online learning even if I have only the software manuals for reference	TSE3	0.771			
I am confident that I have the skills, experience, and knowledge required for an online course	TSE4	0.679			

online learning system and improve their perception of its usefulness, resulting in more plans to participate.

This study has shown what students consider when deciding to study online, including TSE, PR COVID-19, PEU, and PU. However, this study only assessed students from universities in Vietnam. To get a broader view of the factors affecting students' intention to study online, further research can be done with students in different regions, as well as comparing the online learning intention of students across different age groups or income levels.

Table 2: Discriminant Validity using Heterotrait-Monotrait Ratio (HTMT)

Variables	OLI	PEU	PR	PU	TSE
Online Learning Intention (OLI)					
Perceived Ease of Use (PEU)	0.793				
Perceived Risk (PR)	0.542	0.477			
Perceived Usefulness (PU)	0.769	0.681	0.708		
Technology Self-Efficacy (TSE)	0.612	0.602	0.558	0.694	

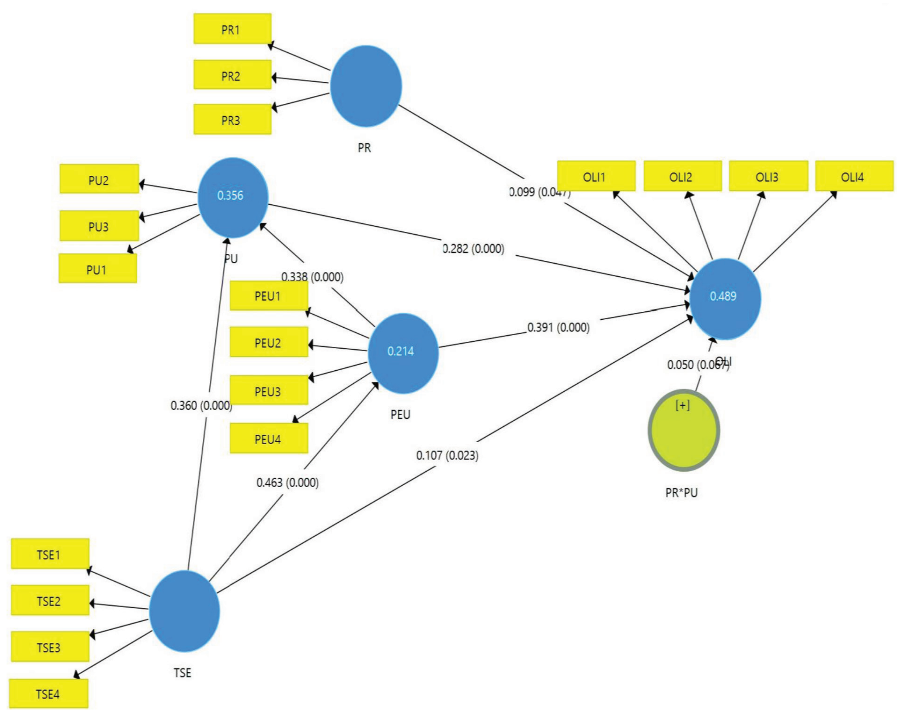

Figure 2: Structural Model with Bootstrap Values

Table 3: Hypothesis Results

Hypotheses	Proposal Effect	Path Coefficients for Direct Effect	*P*-value	Results
H1: PEU → OLI	+	0.391	0.000***	Supported
H2: PEU → PU	+	0.338	0.000***	Supported
H3: PU → OLI	+	0.282	0.000***	Supported
H4: TSE → PEU	+	0.463	0.000***	Supported
H5: TSE → PU	+	0.360	0.000***	Supported
H6: TSE → OLI	+	0.107	0.023**	Supported
H7: PR → OLI	+	0.099	0.047**	Supported

Notes: OLI: Online Learning Intention; PEU: Perceived Ease of Use; PR: Perceived Risk; PU: Perceived Usefulness; TSE: Technology Self-Efficacy.
****p* value significant at level 0.005; ***p* value significant at level 0.05; **p* value significant at level 0.1.

Table 4: Mediation Effect

Hypotheses	Path	Path Coefficients	*P*-value	Confidence Intervals Bias Corrected	
				Lower Confidence Level	Upper Confidence Level
Indirect effects	TSE → PEU → OLI	0.181	0.000	0.138	0.227
	PEU → PU → OLI	0.095	0.000	0.058	0.143
	TSE → PEU → PU → OLI	0.044	0.000	0.027	0.069
	TSE → PU → OLI	0.101	0.000	0.061	0.149
	TSE → PEU → PU	0.156	0.000	0.111	0.209
Total effects	TSE → OLI	0.326	0.000	0.266	0.389

Notes: OLI: Online Learning Intention; PEU: Perceived Ease of Use; PR: Perceived Risk; PU: Perceived Usefulness; TSE: Technology Self-Efficacy.

Table 5: Moderation Effect

Hypotheses	Path	Path Coefficients	*P*-value	Results
H8: PR*PU→OLI	PR and PU → OLI	0.05	0.067*	Supported

Notes: OLI: Online Learning Intention; PR: Perceived Risk.
***p value significant at level 0.005; **p value significant at level 0.05; *p value significant at level 0.1.

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