Hindawi
Human Behavior and Emerging Technologies
Volume 2023, Article ID 6128584, 10 pages
https://doi.org/10.1155/2023/6128584

Research Article

Students' Online Learning Adoption during an Emergency Situation: Integrating the Self-Determination and Perceived Risk Theories

Sheng-Ju Chan,[1] **Thi Xuan Nong**,[2,3] **and Thi Thanh Truc Nguyen**[4]

[1]*Graduate Institute of Education, National Chung Cheng University, Taiwan*
[2]*The Educational Leadership and Management Development of the College of Education, National Chung Cheng University, Taiwan*
[3]*Thai Nguyen University of Agriculture and Forestry, Vietnam*
[4]*Ho Chi Minh City Open University, Vietnam*

Correspondence should be addressed to Thi Xuan Nong; nongthixuan@tuaf.edu.vn

Received 28 August 2023; Revised 1 December 2023; Accepted 16 December 2023; Published 26 December 2023

Academic Editor: Pinaki Chakraborty

By integrating self-determination theory and perceived risk theory, the current research proposes a new model to predict students' online learning adoption during an emergency situation such as the COVID-19 pandemic. More specifically, it is aimed at exploring how online communication self-efficacy, online learning belonging, and perceived risk predict students' online learning adoption. A printed questionnaire was developed to collect data from 487 Vietnamese students using a quota sampling method. After missing data and outliers were removed, 450 questionnaires were found to be usable for data analysis. SMARTPLS version 3.2.2 was employed to analyze PLS-SEM and test the proposed hypotheses. The study found that online communication self-efficacy and perceived risk both have direct effects on students' online learning adoption as well as indirect effects through the partial mediating role of online learning belonging. Our study also explored that perceived risk does not play a moderation in the association between online learning belonging and students' online learning adoption. These findings fill important gaps in the literature and provide some implications for academicians, governments, educators, and parents in fostering students' adoption of online learning.

1. Introduction

The effects of the COVID-19 pandemic have been significant across various societal domains, including the field of education [1, 2]. In an effort to curb the spread of the virus as well as protect students, many schools and universities were forced to temporarily close their physical campuses and transition to online learning near the onset of the pandemic in order to continue their educational programs [3, 4]. Since then, the rapid increase in online learning that took place during the period of school closures has prompted researchers to examine students' experiences and attitudes towards this mode of education.

Before the COVID-19 pandemic, research on online learning centered on topics such as the impact of information technology [5, 6] and course design [7], instrument creation [8], and student adoption with e-learning courses [9–12]. These studies, which focused on a standard educational setting, mostly used traditional models such as the technology acceptance model (TAM), the theory of planned behavior (TPB), the theory of reasoned action (TRA), or the unified theory of acceptance and use of technology (UTAUT). Their focus was to investigate the direct effects of factors such as perceived ease of use [10], performance expectancy, effort expectancy, hedonic motivation, and habit on students' technology adoption intention or behavior [12].

Since the outbreak of the pandemic, a few studies have been conducted on the efficacy of online learning during the period of school closures as well as afterwards. For example, Nong et al. [1] conducted a study on the impact of vaccinations on students' online learning intention. The authors proposed a moderated mediation model with perceived invulnerability playing a mediating role and the students' age having a moderating role. However, the study focused only on students' intrinsic motivation and did not consider external factors. Pham and Ho [13] conducted a study on the "new normal" of e-learning in Vietnamese higher education post-COVID-19, examining the policies of the Vietnamese government regarding the integration of e-learning into higher education. To the best of our knowledge, the study investigating students' attitudes towards e-learning during the COVID-19 pandemic was conducted by Ho et al. [3]. However, the theoretical framework used in this study was the technology acceptance model (TAM), which may be suitable for studies on technology adoption, but insufficient for exploring other potential antecedents of e-learning during and after the height of the pandemic.

To overcome these limitations, many researchers have integrated traditional theories, such as TAM, TRA, TPB, and UTAUT, and contextual-related theories, including protection motivation theory (PMT) and perceived risk theory (PRT). For example, Doan [14] integrated TAM and PRT, and Nguyen and Tang [4] integrated TAM and PMT to explore antecedents of students' online learning intention in the COVID-19 context. Although these studies considered various factors related to the research context, such as perceived severity, perceived vulnerability, and perceived risk (PR), they did not pay attention to internal factors related to student competence, such as online communication self-efficacy (OCSE) and online learning belonging (OLB). Given the sudden shift to online learning that took place, it is important to understand intrinsic and extrinsic motivations that promote students' adoption of this learning mode.

Based on these research gaps, and in response to the call to expand self-determination theory (SDT), a widely accepted theory of motivation, with other suitable theories or frameworks [15], the current study integrates SDT and PRT in the context of the COVID-19 pandemic, to propose a moderated-mediation model exploring determinants of students' online learning adoption (SOLA) through the mediation of OLB and moderation of PR. The integration of self-determination and perceived risk theories offers a unique and crucial perspective on the factors that influence students' decisions to adopt or reject online learning in this global emergency situation. By exploring the interplay between SDT and PRT in students' online learning adoption during the height of the COVID-19 pandemic, the current study is aimed at filling an important gap in the literature. The findings of this study can provide valuable insights for governments, educators, policymakers, and parents as they work to support students' continued education during challenging times. Toward this end, the current study proposes the following research questions (RQs):

RQ1: what are the determinants of students' online learning adoption during an emergency situation, and how do they differ in predictive power?

RQ2: does online learning belonging mediate the relationships between, on the one hand, online communication self-efficacy and perceived risk and, on the other, students' online learning adoption?

RQ3: does perceived risk moderate the relationship between online learning belonging and students' online learning adoption?

2. Literature Review

2.1. Theoretical Background

2.1.1. Self-Determination Theory. SDT is a comprehensive theory of human motivation and personality that emphasizes the importance of the basic psychological need for autonomy, competence, and relatedness for psychological well-being and healthy development [16–18]. According to SDT, when these three basic psychological needs are satisfied, people tend to be more motivated and engaged in their activities. Furthermore, SDT also suggests that people are more likely to participate in activities that align with their intrinsic motivations and values. Students who are intrinsically motivated to learn and value education, for example, are more likely to engage and motivate themselves in their learning activities [19].

In the online learning context, the theory suggests that students who feel autonomous in their learning process, connected to others in their online learning community, and competent in their online learning skills are more likely to be motivated and engaged in their online learning experience [20, 21]. SDT is suitable for the present study for several reasons. First, SDT provides a theoretical framework for understanding students' motivations for adopting online learning during a crisis situation, such as the COVID-19 pandemic, by highlighting the role of personal autonomy and competence in promoting engagement and well-being. Second, SDT has been widely tested and validated in various educational settings and has been found to be a strong predictor of students' engagement and academic performance [21].

Therefore, the present study incorporates SDT to provide a deeper understanding of the psychological factors that influence students' adoption of online learning during an emergency situation and to help researchers identify the strategies that can promote autonomy, relatedness, and competence in online learning. Two factors, namely, OCSE and OLB, are used as indicators of these psychological determinants since they are known as intrinsic motivators that promote students' adoption of online learning.

2.1.2. Perceived Risk Theory. Bauer [22] was the first to propose the concept of PRT, in which PR was defined as an individual's perception of risk, representing subjective opinions or value judgments in the presence of multiple objective threats within uncertain situations. In the context of this study, PR specifically denotes students' perceptions of the severity of the COVID-19 pandemic. Various previous research works have highlighted that a heightened level of perceived risk can impact human attitudes and behavioral intentions toward the adoption of preventive measures.

Additionally, differences in perceived risk have been identified as drivers for changes in human behavior [4, 23].

In the context of online learning, the theory suggests that students' perceptions of the risks and benefits associated with online learning will influence their decision to adopt it during an emergency situation such as the COVID-19 pandemic. For example, students may perceive the benefits of online learning as including not only flexibility and convenience but also a reduced infection risk of COVID-19 [4]. The present study adopts PRT as one of the theoretical lenses for studying online adoption for the following reasons: first, since PR is known as an extrinsic motivator that alters students' perceptions of the transition from face-to-face to online learning, PRT provides a theoretical framework for understanding how students' perceptions of risk might influence their behavior. Second, PRT has been widely tested and validated in various educational settings and has been found to be a strong predictor of students' adoption of technology [14, 24].

By integrating PRT with SDT, the present study provides a model for studying both the intrinsic and extrinsic factors that influence students' adoption of online learning during an emergency situation such as the COVID-19 pandemic. This integration contributes to fill important gaps in the existing literature.

2.2. Hypothesis Development

2.2.1. Online Communication Self-Efficacy, Online Learning Belonging, and Online Learning Adoption. OCSE refers to students' beliefs in their ability to effectively communicate and use technology in online environments by asking questions, expressing emotion, and discussing ideas [25, 26], whereas OLB refers to students' sense of connectedness and integration in the online learning community [27]. Based on SDT, we argue that students' confidence in their ability to communicate effectively online will influence their sense of belonging in the online learning environment. Stated otherwise, we predict that students with a high level of OCSE will be more likely to feel a strong sense of belonging in this environment. The reason is that these students are better equipped to participate in online communication and form relationships with their peers and instructors [25]. Previous studies support these arguments. As Kim and Park [28] found, a positive relationship exists between OCSE and online social presence, which is a key aspect of online learning belonging. The authors also indicated that those with a higher level of OCSE were more likely to participate in online discussions, collaborate with their peers, and form relationships in the online learning environment, leading to a stronger sense of belonging [28]. Additionally, Strayhoen [29] found that students feel more confident participating in online activities if they have abilities and skills in online communication, that is, a high level of OCSE.

Previous studies have also linked high levels of OCSE to positive outcomes in online learning, such as increased participation and engagement [25, 28, 30], and several studies have demonstrated that a lack of OCSE may lead to a higher dropout rate in the online learning environment [25, 30–32]. The reason for the latter finding is that students lack opportunities to interact with others in an online learning environment and can, therefore, become socially isolated, bored, and uninterested in the online courses [25, 30, 33]. Regarding the former finding, OCSE has been demonstrated to be a predictor of online learning satisfaction [30], which increases students' engagement and participation [34, 35]. It follows that it plays a crucial role in enhancing online education, serving as a pivotal element for academic success in distance learning [31, 32].

Another important determinant of success in distance education is a strong sense of belonging in the online environment. Previous studies have linked OLB with increased engagement, motivation, and academic performance [29, 36, 37]. These studies argue that a sense of belonging can help students succeed by lowering psychological distress and the concomitant risk of developing mental health problems by increasing engagement, motivation, and participation [29, 36, 37]. Research has demonstrated that a sense of belonging serves as a potent source of resilience for students, fortifying them against disengagement from active participation in the learning process [38]. Peacock et al. [39] indicated that fostering a sense of belonging in the online learning environment may provide a means of improving students' experiences and attainment while also lowering attrition rates. Based on these arguments, we argue that a sense of online learning belonging will foster online learning adoption and mediate the relationship between OCSE and SOLA. Hence, the following hypotheses are proposed:

H1: online communication self-efficacy has a positive effect on students' online learning belonging.

H2: online communication self-efficacy has a positive effect on students' online learning adoption.

H3: online learning belonging has a positive effect on students' online learning adoption.

H4: online learning belonging mediates the relationship between online communication self-efficacy and students' online learning adoption.

2.2.2. Perceived Risk, Online Learning Belonging, and Online Learning Adoption. In the context of the COVID-19 pandemic, several researchers have applied PRT to explore the role of PR in predicting human behavioral changes [4, 14, 24]. Although the relationship of PR and OLB has not been explored in previous studies, the perception of risk associated with COVID-19 has proven to be an external factor that drives students to adopt a learning method like online learning [40, 41]. In addition, although previous studies have shown that students almost always prefer face-to-face learning to online learning, this preference has changed in the COVID-19 pandemic situation. In the face of the complicated evolution of the epidemic and its high level of risk, students quickly adapted to the online environment and felt more familiar with online learning than ever before [40, 41]. As Nguyen and Tang [4] indicated, the perception of severe danger in face-to-face environments led to changes in students' attitude and perceptions of online learning. From these observations, we argue that PR will foster OLB, as the following hypothesis states.

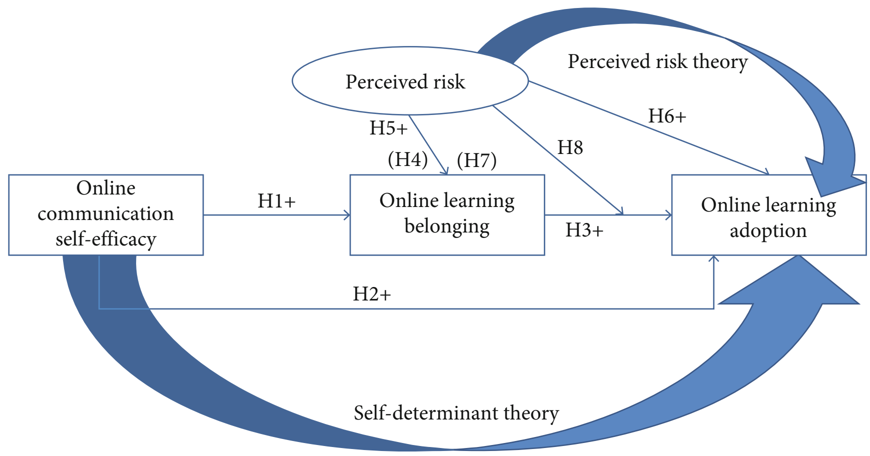

Figure 1: Research model. Note: mediating effect hypotheses are in parentheses.

H5: perceived risk has a positive effect on online learning belonging.

Several prior studies using PRT to explore human behavior in pandemics have indicated that the situation's severity is the main factor contributing to protection motivation and the subsequent adoption of avoidance behavior. The negative effects of public relations are frequently highlighted in consumer behavior studies, such as in the context of travel [42], mobile financial services [43], and e-government [44]. In the context of online learning, Doan [14] has also indicated that PR fosters students' online learning intentions because school attendance puts students in direct contact with many people, which increases their chances of contracting COVID-19. It follows that if students perceive a heightened risk of COVID-19 infection, their desire to learn online will be stronger. This risk may be perceived as high if students are made aware of the possibility of COVID-19 transmission through direct person-to-person contact [4, 14]. In addition, Procentese et al. [45] have found that in an emergency situation like COVID-19, a sense of belonging protects against academic stress and contributes to higher retention rates in online learning. Based on these findings, we argue that OLB can be a mediator in the association between PR and SOLA. The following hypotheses test these relationships:

H6: perceived risk has a positive effect on students' online learning adoption.

H7: online learning belonging mediates the relationship between perceived risk and students' online learning adoption.

2.2.3. Perceived Risk as a Moderator. Several studies have shown that people's attitudes and behavior intentions can change in response to exposure to heightened levels of risk, and that variations in risk perception can lead to variations in people's actual behavior [4]. Moreover, those who are highly attuned to potential danger are more likely to be proactive about preventing harm to themselves [46]. At the beginning of the pandemic, online learning was proposed to lower the risk of contracting COVID-19 in schools and in the community [4, 14]. Based on this rationale and the abovementioned studies on OLB, we contend that students with a higher level of OLB will adopt online learning more readily and that this receptivity will be further bolstered when they have a higher level of risk perception. The following hypothesis expresses this expectation.

H8: the relationship between online learning belonging and students' online learning adoption will be stronger among students with a high level of risk perception.

Figure 1 shows the research model for this study.

3. Methodology

3.1. Instrument Development. Drawing from prior research, we developed a survey questionnaire. After a thorough examination of the literature, we identified studies employing analogous constructs and modified them to align with the parameters of the present study. Given that the initial constructs were in English, two English teachers were engaged to translate the questionnaire into Vietnamese, with an additional two English teachers enlisted for a backward translation process to safeguard the instrument's validity. Subsequently, three education experts were invited to evaluate the questionnaire. Following this, ten Vietnamese students were recruited to complete the questionnaire to ensure its face validity. Ultimately, a printed version of the questionnaire was prepared for data collection.

The printed questionnaire includes three parts. The first one contains one question in which respondents were asked to indicate whether they participated in online learning during the COVID-19 pandemic. Those participants who responded "yes" in this section proceeded to the subsequent stage. Four demographic questions, including participants' gender, age, grade, and location, were comprised in the second section. The third one assesses the following four main factors of the current research.

OCSE measures students' perceptions of their ability to effectively communicate and use technology in an online environment, consisting of three items revised by Thongsri et al. [26]. For example "I feel confident in using online tools (email, discussion) to effectively communicate with others."

OLB measures students' sense of connectedness and integration in the online learning community, including four items adapted from Hazel et al. [47] and Yorke [48], for example, "In the COVID-19 period, most days, I look forward to take part in online classes."

SOLA measures students' willingness to adopt online learning in the COVID-19 situation, including four items revised by Nguyen and Tang [4] and Thongsri et al. [26], for example, "I would like to take online-learning courses during the COVID-19 period."

PR measures students' perception regarding the risk of the COVID-19 pandemic, including six items revised by Nguyen and Borazon [44]. For example, "I find COVID-19 has a high infection rate."

All of the constructs in this study utilized self-report scales employing a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), and demonstrated an initial Cronbach's alpha value exceeding 0.7 [49].

3.2. Pilot Test. A pilot survey with 73 respondents was performed prior to the official survey to ensure that participants could comprehend and respond to the questionnaire easily. Moreover, the data obtained from this survey was employed to assess the feasibility of the translation and calculate Cronbach's alpha value. The findings indicate that all principal constructs exhibit a Cronbach's alpha value surpassing the 0.7 threshold.

3.3. Data Collection and Procedure. The printed questionnaire was directly distributed to 487 students in five universities placed in Ho Chi Minh City, Vietnam, from November 29^{th} to December 19^{th}, 2022. A quota sampling method was used to recruit participants from a population of around 20,000 students. Following this, data was imported into SPSS 22 software. After removing 29 missing data cases and 8 outliers, a total of 450 valuable cases were used for further investigation. Table 1 presents the respondents' demographic information.

3.4. Data Analysis Strategy. For testing outliers, normal distribution, and generating descriptive statistics, the SPSS 22 software was employed. Instances with z scores exceeding ± 3.29 ($p < .001$) were identified as outliers during the examination of univariate normality [50]. Using this approach, 8 outliers were identified and subsequently eliminated from the dataset.

In addition, common method bias is often identified as the primary contributor to measurement errors in behavioral sciences. These errors could arise from factors such as a consistency motif, illusory correlations, implicit theories, leniency biases, and acquiescence. To identify potential bias, the study utilizes Harman's single factor test, wherein all items are loaded into a single un-rotated factor solution in exploratory factor analysis to evaluate the variance explained by this singular component. It is crucial that this singular component accounts for less than 50% of the variance in order to address and minimize potential bias. Our findings reveal a total variance for the single factor of 36.17%, which is below the 50% threshold recommended by Podsakoff et al. [51]. Consequently, the present study is deemed free of common method bias. In simpler terms, the results indicate that the factor with the highest variance (36.17%) does not take the majority of the variance. As a result, variances associated with measurement error do not compromise the validity of the study's findings [44]. Finally, SMARTPLS 3.2.2 software was employed to test PLS-SEM.

Table 1: Participant's demographic information.

Measure	Class	Frequency	Percent
Gender	Male	222	49.3
	Female	228	50.7
Age	18-20	223	49.6
	21 and above	227	50.4
Grade	First year	115	25.6
	Second year	121	26.9
	Third year	106	23.6
	Fourth year	96	21.3
	More than four years	12	2.7
Location	Urban	228	50.7
	Rural	222	49.3
Total		450	100

Table 2: Descriptive statistics ($N = 450$).

Constructs	Min-max	Mean	SD
OCSE	1.0-5.0	3.90	0.78
OLB	1.0-5.0	3.76	0.79
PR	1.0-5.0	3.94	0.73
SOLA	1.0-5.0	4.08	0.68

4. Findings

4.1. Descriptive Statistics. Before advancing to further analyses, descriptive statistics were scrutinized. Table 2 displays descriptive statistics for the study constructs.

4.2. Measurement Model Evaluation. To evaluate the convergent validity and reliability of the measures, Cronbach's alpha (>0.7), outer loadings (>0.7), composite reliability (CR > 0.7), and average variance extracted (AVE > 0.5) were employed, following the recommendations of Fornell and Larcker [52]. Additionally, discriminant validity was assessed using the heterotrait–monotrait (HTMT) correlation ratio (<0.90) as suggested by Garson [53] and Hair et al. [49]. Table 3 presents Cronbach's alpha value, outer loadings, CR, and AVE of the latent variables in the current study.

Cronbach's alpha for factors ranges from 0.842 to 0.879, which is higher than 0.70 but lower than 0.95, as shown in Table 3 [49]. Furthermore, the outer loadings of all items are higher than 0.7. All of the latent variables have a CR ranging from 0.891 to 0.917. Finally, the AVE values for all latent variables fall within the range of 0.578 to 0.766. Overall, the measurement models in the study exhibit robust

Table 3: Outer loadings, Cronbach's alpha, CR, and AVE of latent variables.

Constructs	Item coding	Outer loading	Cronbach's alpha	CR	AVE
OCSE	OCSE1	0.871	0.848	0.908	0.766
	OCSE2	0.859			
	OCSE3	0.895			
OLB	OLB1	0.812	0.842	0.894	0.679
	OLB2	0.874			
	OLB3	0.758			
	OLB4	0.846			
PR	PR1	0.745	0.854	0.891	0.578
	PR2	0.801			
	PR3	0.773			
	PR4	0.740			
	PR5	0.780			
	PR6	0.717			
SOLA	SOLA1	0.814	0.879	0.917	0.734
	SOLA2	0.872			
	SOLA3	0.881			
	SOLA4	0.859			

convergent validity. Moreover, the HTMT ratio results presented in Table 4 are below the 0.90 threshold, indicating satisfactory discriminant validity [49, 53].

4.3. Structural Model Evaluation

4.3.1. Lateral Collinearity Assessment. Multicollinearity was checked prior to evaluate the structural model, and the inner VIF values were computed to rule out multicollinearity. Hair et al. [49] proposed that the inner VIF values should be lower than 5, and the present research discovered VIF values ranging from 1.053 to 1.282, falling within the recommended range, indicating that there was no issue of multicollinearity in the data in the present study.

4.3.2. Hypothesis Testing. Bootstrapping is a method for assessing and testing the significance of a model. The T-statistics value gauges the significance of path coefficients [54]. Table 5 displays the PLS-SEM results, indicating that the data substantiated all direct and indirect effects, with the exception of moderating hypotheses.

As can be seen from Table 5, all direct effect hypotheses were supported, and OLB is a mediator in the association between OCSE and SOLA as well as in the relationship between PR and SOLA. However, the moderator of PR in the association between OLB and SOLA was not supported, and the result model is depicted in Figure 2.

4.3.3. Comparing Predictive Power of Predictors. To assess and compare the predictive power of antecedents in the research model, the F-square value was utilized in the present study. As per Cohen [55], the recommended benchmarks for F-square and R-square were as follows:

Table 4: HTMT (heterotrait–monotrait ratio).

Constructs	OCSE	OLB	PR	SOLA
OCSE	—			
OLB	0.448	—		
PR	0.324	0.351	—	
SOLA	0.488	0.661	0.390	—

F-square: 0.02 (small), 0.15 (medium), and 0.35 (large); R-square: 0.02 (weak), 0.13 (moderate), and 0.26 (substantial). The comparative predictive power among antecedents is detailed in Table 6.

Table 6 shows that antecedents could explain 40% of the variance in dependent variable (SOLA). This value is substantial [55], while 19% of the variance of OLB could be explained by predictors in the research model (moderate). Furthermore, OLB has the highest predictive power (0.26) in the research model, more than a medium effect size suggested by Cohen [55], while the interaction effect of PR*OLB has the lowest predictive power (0.00) for SOLA.

5. Discussion

5.1. Determinants with Direct Relationships and the Relative Impact of These Determinants on SOLA. Based on the integration of SDT and PRT in a united model, our research findings revealed that OCSE, OLB, and PR are all antecedents of SOLA during an emergency situation such as the COVID-19 pandemic. Interestingly, OCSE was demonstrated to have a positive effect on OLB. This relationship is consistent with the perspective of SDT, which supposes that students who feel autonomous in their learning process, connected to others in their online learning community, and competent in their online learning skills are more likely to be motivated and engaged in their online learning experience [20]. In addition, OCSE was found to have a positive effect on SOLA. The finding is in line with previous studies, which maintain that a lack of OCSE may result in a higher dropout rate in an online learning environment and that a higher level of OCSE correlates with positive outcomes in online learning, such as increased participation and engagement [25, 28, 30].

Additionally, our findings also identified a positive relationship between OLB and SOLA. This is consistent with previous research indicating that a sense of belonging provides students with a powerful source of resilience, strengthening them against disengagement from actively participating in their learning [38]. OLB also assists students in succeeding by reducing psychological stress and the risk of developing mental health problems, which in turn increases engagement, motivation, and participation [29, 36, 37].

Furthermore, our findings indicated that PR positively affects both OLB and SOLA. This can be explained by PRT, which states that in an emergency situation, attitudes and behavioral intentions can change, depending on a person's perception of the level of risk the pandemic poses. Although previous research has indicated a positive association between PR and SOLA [4, 14], an interesting finding

Table 5: Hypothesis testing results ($^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$).

Hypothesis	Relationship	Beta	T value	P values	Decision
Direct relationships					
H1	OCSE→OLB	0.325	5.468	***	Supported
H2	OCSE→SOLA	0.212	3.046	**	Supported
H3	OLB→SOLA	0.448	6.345	***	Supported
H5	PR→OLB	0.215	4.002	***	Supported
H6	PR→SOLA	0.144	2.111	*	Supported
Indirect relationships					
H4	OCSE→OLB→SOLA	0.146	4.773	***	Supported
H7	PR→OLB→SOLA	0.096	2.980	**	Supported
Moderating relationships					
H8	PR*OLB→SOLA	0.002	0.025	>0.05	Not supported

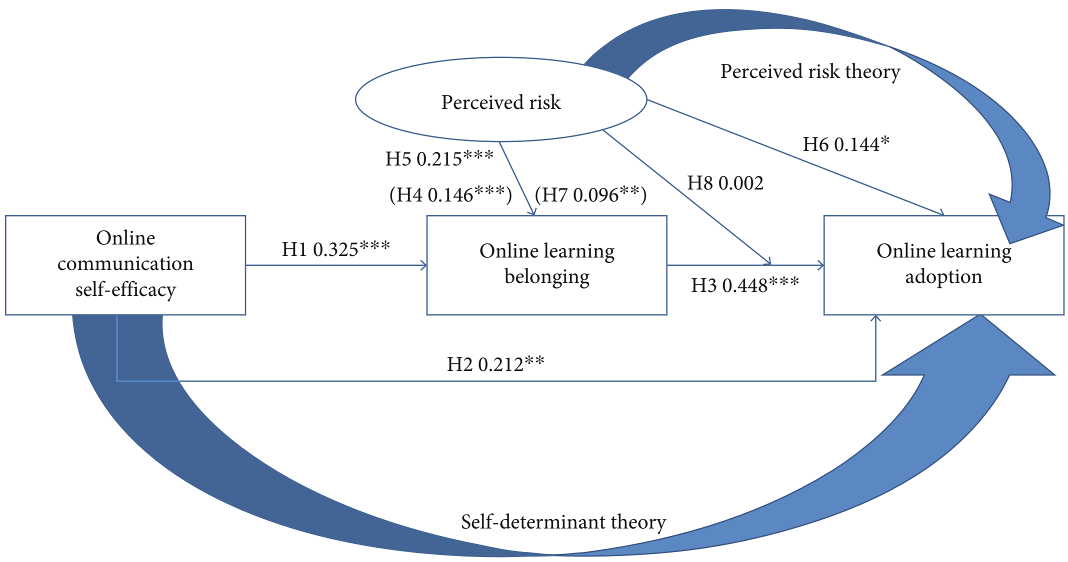

Figure 2: Structural model. Note: coefficients for mediating effects are in parentheses. $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table 6: Comparing predictive power among antecedents.

Predictors	Outcome variables	R-square (>0.02) [55]	F-square (>0.02) [55]
OCSE	SOLA	0.40	0.06
OLB			0.26
PR			0.03
PR*OLB			0.00
OCSE	OLB	0.19	0.12
PR			0.05

"*" means the "interaction effect" between PR and OLB.

from our research was the discovery of a positive relationship between PR and OLB. In the situation of the COVID-19 pandemic, heightened levels of OLB correlating with greater PR were able to change students' attitudes and perceptions of online learning. The reason is that students were more motivated to adopt and feel comfortable with online learning in the face of the pandemic's complicated evolution and ongoing risk factor [4, 40, 41].

A comparison of the determinants' predictive power revealed that OLB has the highest predictive power, whereas the interaction effect of PR*OLB has the lowest predictive power for SOLA. This finding demonstrates that a sense of belonging provides students with a powerful source of resilience, strengthening them against disengagement from effective participation in online learning [38].

5.2. The Mediating Role of Online Learning Belonging. Our study established a partial mediation of OLB in the association between OCSE and SOLA. This mediating role is explained as follows: students' abilities and skills in an online communication environment foster a sense of belonging that promotes their adoption of online learning [39]. More precisely, when students have a high level of OCSE in online communication, they feel confident to participate in online activities, which translates as a sense of belonging. Such students find it easier to accept online learning [29, 36, 37, 56].

Moreover, the study also showed that OLB partially mediates the association between PR and SOLA. This is explained by the emergency situation of the COVID-19 pandemic. In this situation, PR promotes students' belonging in an online learning environment [40, 41], thereby increasing their intention to participate in and adopt online learning. The result is that PR has a near-significant impact on students' intentions to study online [4].

5.3. The Moderation of Perceived Risk. Although PR was indicated to have a direct effect on OLB and SOLA, the expected interaction effect between PR and OLB in the relationship between OLB and SOLA was not supported in the present study. The reason may be that in the COVID-19 context, online learning was known as a preventative measure of COVID-19 infection in school environments; it was also a required measure in Vietnam where the pandemic situation is complex. As a result, the relationship between OLB and SOLA did not vary among students according to their level of PR.

6. Conclusions

6.1. Theoretical Implications. This study is one of the pioneers in integrating SDT and PRT to explore SOLA. It, thus, represents a response to the call of Ryan and Deci [15], SDT's founders, to expand SDT with other suitable theories or frameworks [15] to form a unified research model. In this study, our research provided new insights (see Figure 2) for predicting SOLA in an emergency situation. The findings indicate that the addition of PRT to the SDT model can enhance its ability to account for contextual factors when predicting individuals' behavior in emergency situations.

The present study filled research gaps by exploring both intrinsic and extrinsic motivators of students' online learning adoption in an emergency situation. The two internal factors investigated were OCSE and OLB, whereas the external factor was PR. The study revealed that OLB partially mediates the relationship between OCSE and SOLA as well as the relationship between PR and SOLA. These findings constitute new insight into the mechanism, whereby OCSE and PR impact SOLA, especially in the context of online learning and the COVID-19 pandemic.

6.2. Practical Implications. Our study found that OCSE has a positive effect on both OLB and SOLA, indicating a need for students to develop online communication skills and abilities by accessing and familiarizing themselves with technology devices and the network environment prior to the adoption of online learning. Facilitating this development is the responsibility of both schools and students' families. The current study also revealed that a contextual factor, namely PR, has a positive effect on OLB as well as SOLA. Therefore, to boost students' adoption of and participation in online learning in an emergency situation, it is critical that educators and governments broaden and diversify their broadcasting of the dangers of COVID-19 and other emergencies. The information disseminated needs to include preventive measures to increase students' awareness and caution, increasing the likelihood that they will actively adopt and participate in online learning.

Lastly, since OLB was found to have the highest predictive power for SOLA, educators and policymakers should pay attention and give priority to fostering OLB in students. Encouraging self-discipline, providing a sense of comfort, and communicating the need for respect in the online learning environment may increase students' sense of belonging within this environment, thereby increasing their adoption of online learning.

6.3. Limitations and Suggestions for Further Study. The present study adopted a quota sampling method, which may introduce bias into the results. Hence, it is recommended that future studies consider the use of a random sampling method to enhance the validity of the findings. Another limitation of the present study is its reliance on self-report scales, which may have led to common method biases also influencing the research findings. We, therefore, encourage future research to collect data from multiple sources to help reduce the likelihood of common method biases. Besides, there are also useful theories, like PMT, that can be used in an emergency situation to predict students' online learning adoption. Hence, for further studies, researchers may consider PMT like a contextual theory for online learning adoption in the emergency situation and compare the results obtained by both contextual-related theories (such as PRT and PMT). Finally, since the moderating role of PR was not established in our study, future studies may want to investigate its role further.

Abbreviations

AVE:	Average variance extracted
CR:	Composite reliability
H:	Hypothesis
OCSE:	Online communication self-efficacy
OLB:	Online learning belonging
PMT:	Protection motivation theory
PR:	Perceived risk
PRT:	Perceived risk theory
RQ:	Research question
SDT:	Self-determination theory
SOLA:	Students' online learning adoption
TAM:	Technology acceptance model
TPB:	Theory of planned behavior
TRA:	Theory of reasoned action
UTAUT:	Unified theory of acceptance and use of technology.

Data Availability

The primary data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors have disclosed no potential conflicts of interest concerning the authorship and/or publication of this article.

Authors' Contributions

Sheng-Ju Chan (National Chung Cheng University, Taiwan) contributed to the methodology, data validity, and writing. Thi Xuan Nong (National Chung Cheng University, Taiwan; Thai Nguyen University of Agriculture and Forestry, Vietnam) contributed to the methodology, data validity, data analysis, and writing. Thi Thanh Truc Nguyen (Ho Chi Minh City Open University, Vietnam) contributed to the data collection and data coding.

References

[1] T. X. Nong, H. T. Nguyen, and T. T. T. Nguyen, "The effect of perceived vaccination on students' online learning intentions: a moderated mediation model," *Human Behavior and Emerging Technologies*, vol. 2022, Article ID 9387583, 9 pages, 2022.

[2] S. Rashid and S. S. Yadav, "Impact of COVID-19 pandemic on higher education and research," *Indian Journal of Human Development*, vol. 14, no. 2, pp. 340–343, 2020.

[3] N. T. T. Ho, S. Sivapalan, H. H. Pham, L. T. M. Nguyen, A. T. V. Pham, and H. V. Dinh, "Students' adoption of e-learning in emergency situation: the case of a Vietnamese university during COVID-19," *Interactive Technology and Smart Education*, vol. 18, no. 2, pp. 246–269, 2020.

[4] H. T. Nguyen and C. W. Tang, "Students' intention to take e-learning courses during the COVID-19 pandemic: a protection motivation theory perspective," *The International Review of Research in Open and Distributed Learning*, vol. 23, no. 3, pp. 21–42, 2022.

[5] O. W. Adejo, I. Ewuzie, A. Usoro, and T. Connolly, "E-learning to m-learning: framework for data protection and security in cloud infrastructure," *International Journal of Information Technology and Computer Science*, vol. 10, no. 4, pp. 1–9, 2018.

[6] A. Y. Alsabawy, A. Cater-Steel, and J. Soar, "IT infrastructure services as a requirement for e-learning system success," *Computers & Education*, vol. 69, pp. 431–451, 2013.

[7] C. Goh, C. Leong, K. Kasmin, P. Hii, and O. Tan, "Students' experiences, learning outcomes and satisfaction in e-learning," *Journal of E-learning Knowledge Society*, vol. 13, no. 2, 2017.

[8] F. Martin, D. U. Bolliger, and C. Flowers, "Design matters: development and validation of the online course design elements (OCDE) instrument," *The International Review of Research in Open Distributed Learning*, vol. 22, no. 2, pp. 46–71, 2021.

[9] Y. Duan, Q. He, W. Feng, D. Li, and Z. Fu, "A study on e-learning take-up intention from an innovation adoption perspective: a case in China," *Computers & Education*, vol. 55, no. 1, pp. 237–246, 2010.

[10] Q. Hammouri and E. Abu-Shanab, "Exploring factors affecting users' satisfaction toward e-learning systems," *International Journal of Information and Communication Technology Education*, vol. 14, no. 1, pp. 44–57, 2018.

[11] Y.-C. Lee, "The role of perceived resources in online learning adoption," *Computers & Education*, vol. 50, no. 4, pp. 1423–1438, 2008.

[12] A. Tarhini, R.'. Masa'deh, K. A. al-Busaidi, A. B. Mohammed, and M. Maqableh, "Factors influencing students' adoption of e-learning: a structural equation modeling approach," *Journal of International Education in Business*, vol. 10, no. 2, pp. 164–182, 2017.

[13] H.-H. Pham and T.-T.-H. Ho, "Toward a 'new normal' with e-learning in Vietnamese higher education during the post COVID-19 pandemic," *Higher Education Research Development*, vol. 39, no. 7, pp. 1327–1331, 2020.

[14] T. T. T. Doan, "The effect of perceived risk and technology self-efficacy on online learning intention: an empirical study in Vietnam," *The Journal of Asian Finance, Economics Business Management Studies: An International Journal*, vol. 8, no. 10, pp. 385–393, 2021.

[15] R. M. Ryan and E. L. Deci, *Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness*, Guilford Publications, 2017.

[16] T. K. F. Chiu, "Student engagement in K-12 online learning amid COVID-19: a qualitative approach from a self-determination theory perspective," *Interactive Learning Environments*, vol. 31, no. 6, pp. 3326–3339, 2023.

[17] E. L. Deci and R. M. Ryan, "The "what" and "why" of goal pursuits: human needs and the self-determination of behavior," *Psychological Inquiry*, vol. 11, no. 4, pp. 227–268, 2000.

[18] N. R. Salikhova, M. F. Lynch, and A. B. Salikhova, "Adult learners' responses to online learning: a qualitative analysis grounded in self-determination theory," *Eurasia Journal of Mathematics, Science Technology Education*, vol. 17, no. 10, article em2011, 2021.

[19] N. B. Mendoza, Z. Yan, and R. B. King, "Supporting students' intrinsic motivation for online learning tasks: the effect of need-supportive task instructions on motivation, self-assessment, and task performance," *Computers & Education*, vol. 193, article 104663, 2023.

[20] M. Gagné and E. L. Deci, "Self-determination theory and work motivation," *Journal of Organizational Behavior*, vol. 26, no. 4, pp. 331–362, 2005.

[21] M. S. Rosli, N. S. Saleh, A. M. Ali, and S. Abu Bakar, "Self-determination theory and online learning in university: advancements, future direction and research gaps," *Sustainability*, vol. 14, no. 21, article 14655, 2022.

[22] R. A. Bauer, "Consumer behavior as risk taking," in *Proceedings of the 43rd National Conference of the American Marketing Assocation*, Chicago, Illinois, June 1960.

[23] W. Hong, R.-D. Liu, Y. Ding, J. Hwang, J. Wang, and Y. Yang, "Cross-country differences in stay-at-home behaviors during peaks in the COVID-19 pandemic in China and the United States: the roles of health beliefs and behavioral intention," *International journal of environmental research public Health Nutrition*, vol. 18, no. 4, p. 2104, 2021.

[24] S. Sarosa, "The effect of perceived risks and perceived cost on using online learning by high school students," *Procedia Computer Science*, vol. 197, pp. 477–483, 2022.

[25] C. Peechapol, J. Na-Songkhla, S. Sujiva, and A. Luangsodsai, "An exploration of factors influencing self-efficacy in online learning: a systematic review," *International Journal of Emerging Technologies in Learning*, vol. 13, no. 9, p. 64, 2018.

[26] N. Thongsri, C. Chootong, O. Tripak, P. Piyawanitsatian, and R. Saengae, "Predicting the Determinants of Online Learning Adoption during the COVID-19 Outbreak: A Two-Staged Hybrid SEM-Neural Network Approach," *Interactive Technology Smart Education*, vol. 18, no. 3, pp. 362–379, 2021.

[27] S. Manca and M. Ranieri, "Is Facebook still a suitable technology-enhanced learning environment? An updated critical review of the literature from 2012 to 2015," *Journal of Computer Assisted Learning*, vol. 32, no. 6, pp. 503–528, 2016.

[28] K. J. Kim and H. Park, “An exploration of learner's perceptions of online teaching and learning,” *Journal of Educational Technology Development and Exchange*, vol. 1, no. 1, pp. 1–14, 2007.

[29] T. L. Strayhorn, *College Students’ Sense of Belonging: A Key to Educational Success for All Students*, Routledge, 2018.

[30] D. Shen, M.-H. Cho, C.-L. Tsai, and R. Marra, “Unpacking online learning experiences: online learning self-efficacy and learning satisfaction,” *The Internet and Higher Education*, vol. 19, pp. 10–17, 2013.

[31] H. Street, “Factors influencing a learner’s decision to drop-out or persist in higher education distance learning,” *Online Journal of Distance Learning Administration*, vol. 13, no. 4, pp. 1–5, 2010.

[32] W. Taipjutorus, S. Hansen, and M. Brown, “Investigating a relationship between learner control and self-efficacy in an online learning environment,” *Journal of Open, Flexible Distance Learning*, vol. 16, no. 1, pp. 56–69, 2012.

[33] N. Bergdahl, “Engagement and disengagement in online learning,” *Computers & Education*, vol. 188, article 104561, 2022.

[34] I. H. Mohd, N. Hussein, A. H. Aluwi, and M. K. Omar, “Enhancing students engagement through blended learning satisfaction and lecturer support,” in *2016 IEEE 8th International Conference on Engineering Education (ICEED)*, Kuala Lumpur, Malaysia, December 2016.

[35] S. Sarkar, S. Sharma, and S. Raheja, “Implementation of blended learning approach for improving anatomy lectures of phase I MBBS students–learner satisfaction survey,” *Advances in Medical Education and Practice*, vol. 12, pp. 413–420, 2021.

[36] E. Kahu, K. Nelson, and C. Picton, “Student interest as a key driver of engagement for first year students,” *Student Success*, vol. 8, no. 2, pp. 55–66, 2017.

[37] L. A. J. Kirby and C. L. Thomas, “High-impact teaching practices foster a greater sense of belonging in the college classroom,” *Journal of Further and Higher Education*, vol. 46, no. 3, pp. 368–381, 2022.

[38] D. Pendergast, J. Allen, G. McGregor, and M. Ronksley-Pavia, “Engaging marginalized, “at-risk” middle-level students: a focus on the importance of a sense of belonging at school,” *Education Sciences*, vol. 8, no. 3, p. 138, 2018.

[39] S. Peacock, J. Cowan, L. Irvine, and J. Williams, “An exploration into the importance of a sense of belonging for online learners,” *The International Review of Research in Open and Distance Learning*, vol. 21, no. 2, pp. 18–35, 2020.

[40] A. Besser, G. L. Flett, and V. Zeigler-Hill, “Adaptability to a sudden transition to online learning during the COVID-19 pandemic: understanding the challenges for students,” *Scholarship of Teaching and Learning in Psychology*, vol. 8, no. 2, pp. 85–105, 2022.

[41] J. Zhou and Q. Zhang, “A survey study on US college students’ learning experience in COVID-19,” *Education Sciences*, vol. 11, no. 5, p. 248, 2021.

[42] S. M. Sánchez-Cañizares, L. J. Cabeza-Ramírez, G. Muñoz-Fernández, and F. J. Fuentes-García, “Impact of the perceived risk from COVID-19 on intention to travel,” *Current Issues in Tourism*, vol. 24, no. 7, pp. 970–984, 2021.

[43] C. Yan, A. B. Siddik, N. Akter, and Q. Dong, “Factors influencing the adoption intention of using mobile financial service during the COVID-19 pandemic: the role of FinTech,” *Environmental Science and Pollution Research*, vol. 30, no. 22, pp. 61271–61289, 2021.

[44] H. T. Nguyen and E. Q. Borazon, “Drivers of e-government use during the COVID-19 pandemic: the case of Vietnam,” *Online Information Review*, vol. 47, no. 5, pp. 838–861, 2022.

[45] F. Procentese, V. Capone, D. Caso, A. R. Donizzetti, and F. Gatti, “Academic community in the face of emergency situations: sense of responsible togetherness and sense of belonging as protective factors against academic stress during COVID-19 outbreak,” *Sustainability*, vol. 12, no. 22, p. 9718, 2020.

[46] T. Wise, T. D. Zbozinek, G. Michelini, C. C. Hagan, and D. Mobbs, “Changes in risk perception and self-reported protective behaviour during the first week of the COVID-19 pandemic in the United States,” *Royal Society Open Science*, vol. 7, no. 9, article 200742, 2020.

[47] C. E. Hazel, G. E. Vazirabadi, and J. Gallagher, “Measuring aspirations, belonging, and productivity in secondary students: validation of the student school engagement measure,” *Psychology in the Schools*, vol. 50, no. 7, pp. 689–704, 2013.

[48] M. Yorke, “The development and initial use of a survey of student ‘belongingness’, engagement and self-confidence in UK higher education,” *Assessment Evaluation in Higher Education*, vol. 41, no. 1, pp. 154–166, 2016.

[49] J. F. Hair, C. M. Ringle, and M. Sarstedt, “PLS-SEM: indeed a silver bullet,” *Journal of Marketing Theory and Practice*, vol. 19, no. 2, pp. 139–152, 2011.

[50] B. G. Tabachnick, L. S. Fidell, and J. B. Ullman, *Using Multivariate Statistics (Vol. 5)*, Pearson, Boston, MA, 2007.

[51] P. M. Podsakoff, S. B. MacKenzie, J.-Y. Lee, and N. P. Podsakoff, “Common method biases in behavioral research: a critical review of the literature and recommended remedies,” *Journal of Applied Psychology*, vol. 88, no. 5, pp. 879–903, 2003.

[52] C. Fornell and D. F. Larcker, “Structural equation models with unobservable variables and measurement error: algebra and statistics,” *Journal of Marketing Research*, vol. 18, no. 3, pp. 382–388, 1981.

[53] G. D. Garson, *Partial Least Squares: Regression & Structural Equation Models*, Statistical Associates Publishing, Asheboro, 2016.

[54] C. M. Ringle, D. Da Silva, and D. Bido, “Structural equation modeling with the SmartPLS,” *Brazilian Journal of Marketing*, vol. 13, no. 2, pp. 56–73, 2014.

[55] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*, Routledge, 2013.

[56] A. Razzaq, Y. T. Samiha, and M. Anshari, “Smartphone habits and behaviors in supporting students self-efficacy,” *International Journal of Emerging Technologies in Learning*, vol. 13, no. 2, 2018.