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# Students' Intention to Take E-Learning Courses During the COVID-19 Pandemic: A Protection Motivation Theory Perspective

**Hoai Than Nguyen[1] and Chia Wei Tang[2]**
*[1]National Sun Yat-sen University, Taiwan; [2]Graduate Institute of Educational Administration and Policy, National Chengchi University, Taiwan*

## Abstract

This study proposes a new model for integrating the protection motivation theory (PMT) with the technology acceptance model (TAM) to explore factors affecting students' intention to attend e-learning courses during the COVID-19 pandemic. A total of 432 valid responses to an online questionnaire were received from freshmen students studying in universities in Vietnam and Taiwan. Structural equation modeling was used to evaluate the proposed research model and test the hypotheses, and model evaluation reflected a good fit between the data and the proposed research model. Differences between perceived vulnerability, perceived severity, and intention to take e-learning courses across two countries were also established, suggesting that both the TAM and the PMT should be considered for use in studies related to technology adoption in the pandemic context. The factors influencing students' intentions to take online courses can be quite varied when different educational settings are considered; therefore, a more contextual understanding of students' e-learning intentions during pandemic times should be carefully examined. Suggestions for governments and policy makers are also proposed.

*Keywords*: e-learning, COVID-19, protection motivation theory (PMT), technology acceptance model (TAM), Vietnam, Taiwan

# Introduction

E-learning refers to "web-based learning which uses web-based communication, collaboration, knowledge transfer, and training to add values to the individuals and the organizations" (Kelly & Bauer, 2003, p.511). It is considered one of the most effective forms of distance learning and an effective solution for lifelong learning because it is based on modern technology using the Internet (Gurcan et al., 2021; Ho et al., 2020). Not only are lectures provided in e-learning, as they have been via previous platforms, such as distance learning through DVDs/video CDs or television, but e-learning also allows teachers and learners to interact with one another online (Rana & Lal, 2014).

When COVID-19 occurred, use of e-learning was widely considered worldwide (Favale et al., 2020). In the education sector, e-learning has increasingly become one of the mandatory requirements for educational institutions in many countries during the pandemic (Pham & Ho, 2020; Radha et al., 2020) because authorities assume that in COVID-19 time, teaching and learning methods need to be adjusted to satisfy social distancing requirements (Gohiya & Gohiya, 2020). E-learning has thus become a key method for teaching and learning in many education systems (Pham & Ho, 2020), and information technology—including medical declaration applications and electronic vaccination certificates—has been one of the most effective tools for fighting the pandemic (Sathish et al., 2020).

Studies of e-learning domains have been quite diverse, including some on the impact of information infrastructure (Adejo et al., 2018; Alsabawy et al., 2013), some on instrument development (Martin et al., 2021), and some on student adoption of and satisfaction with e-learning courses (Hammouri & Abu-Shanab, 2018; Tarhini et al., 2017). Such studies often take place in a normal context based on the technology acceptance model (TAM) (Davis, 1985) and its expanded versions, such as the theory of planned behavior (Ajzen, 1991) and the theory of reasoned action (Fishbein & Ajzen, 1977). Moreover, they mainly focus on exploring the direct effects of factors such as ease of use (Hammouri & Abu-Shanab, 2018), course design (Goh et al., 2017), performance expectations, effort expectations, hedonic motivation, habits (Tarhini et al., 2017), and technology adoption intentions or behaviors.

While some recent studies have taken place in a COVID-19 context, they have focused only on aspects such as technology products (Alqahtani & Rajkhan, 2020), government policy adjustment (Pham & Ho, 2020), students' satisfaction with e-learning (Gohiya & Gohiya, 2020), parents' perceptions and students' experiences of e-learning (Hamaidi et al., 2021), and barriers and challenges (Favale et al., 2020; Radha et al., 2020). For example, Pham and Ho (2020) studied the post COVID-19 "new normal" with e-learning in Vietnamese higher education, focusing on reviewing the Vietnam government's response and policies seeking to put e-learning at the center of higher education in the future.

Ho et al.'s study (2020) is to our knowledge the only study that has explored factors of students' attitudes toward e-learning in the COVID-19 context. The theoretical framework adopted in that study is still TAM, and while TAM can be appropriate for studies on technology adoption or e-learning behavior, at the critical time of the COVID-19 pandemic, other theoretical frameworks are likely be necessary for exploring other potential antecedents for e-learning. Protection motivation theory (PMT) is one such framework to be considered (Wang et al., 2019). Based on PMT, van der Weerd et al. (2011) argue that a community's inclination to accept protective measures can be influenced by a high level of risk perception. Therefore, the current study incorporated PMT and TAM concurrently to expand our current understanding of e-learning motivational factors. To shed more light on the complex dynamic of the antecedent of students' e-learning intentions, this study compared the perspectives of higher education students from Vietnam and Taiwan who had experienced different COVID-19 conditions and histories of e-learning in higher education.

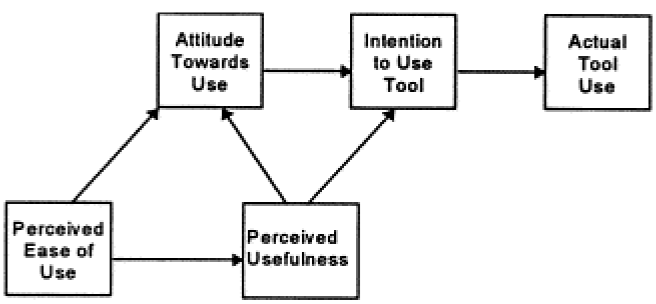
# Literature Review

## The Technology Acceptance Model

The TAM was developed by Davis in 1985. In this model, two personal beliefs—perceived usefulness (PU) and perceived ease of use (PEOU)—affect both attitude about and behavioral intention to use a new technology. PU, defined as the degree to which a person believes that their work performance or quality of life will be enhanced by using a particular system (Davis et al., 1989), mediates relationships between PEOU and attitude toward technology. E-learning is the particular system examined in this study, and the degree to which a user believes that using a specific system will be simple is defined as the PEOU (Davis et al., 1989). Attitude toward technology consists of a user's degree of interest in a particular system that directly affects the intention to use that system and mediates the association between PU and the intention to use technology (Davis et al., 1989). In this study, this refers to students' attitude toward e-learning (ATEL). The version of TAM advanced by Dishaw and Strong (1999; Figure 1) consists of four main constructs: PEOU, PU, attitude toward technology, and intention to use technology.

**Figure 1**

*The Technology Acceptance Model*




*Note*. From "Extending the Technology Acceptance Model with Task–Technology Fit Constructs," by. M. T. Dishaw and D. M. Strong, 1999, *Information & Management*, *36*(1), p.10 x (https://doi.org/10.1016/S0378-7206(98)00101-3). Copyright 1999 by Elsevier Science B.V.

Because of its significant implications, TAM has become a popular model for use in studies on adoption of new technology system in various contexts and domains, including education and e-learning (Cheng, 2011; Ho et al., 2020; Liu et al., 2009). Al-Qaysi et al. (2020) provide a systematic review revealing that this model has brought about more significant benefits than others. Prior studies on educational technology acceptance suggest that we can predict users' willingness to adopt technology by application of the TAM to their perceptions. For example, the mediation effect of PU on the interaction between PEOU and attitude, as well as the mediation of attitude on the effect of PU and intention, has also been established in previous studies (Lee et al., 2009; Liu et al., 2009; Ngai et al., 2007; Zhang et al., 2014). The TAM and several other studies also indicate that PU directly affects both attitude and intention to take e-learning courses (ITTELC) (Cheng, 2011; Liu et al., 2009). This study aims to examine whether these effects occur similarly in an e-learning context in the presence of COVID-19. The following hypotheses were proposed:

- H1.1: PEOU has a positive effect on PU.
- H1.2: PEOU has a positive effect on ATEL.
- H2: PU mediates the relationship between PEOU and ATEL.
- H3.1: PU has a positive effect on ATEL.
- H3.2: PU has a positive effect on ITTELC.
- H3.3: ATEL has a positive effect on ITTELC.
- H4: ATEL mediates the relationship between PU and ITTELC.

## E-Learning in the COVID-19 Context: The Relevance of PMT

PMT was first advanced by Rogers in 1975 to explore fear-based appeals and how individuals cope with them. The main content of the theory is that protection motivation stems from cognitive appraisal of a threatening situation as dangerous, serious, and likely to happen, combined with the belief that a recommended coping behavior can contribute to effectively preventing this risk. This theory has been regarded as the most useful in predicting people's intentions to engage in protective action (Anderson & Agarwal, 2010). In the original model, PMT includes both coping appraisal and threat appraisal, with threat appraisal involving both severity and vulnerability (Meso et al., 2013).

This theory was initially used extensively in studies in the health sector, in social cognition, and in social psychology (Ifinedo, 2012), and it was subsequently expanded for predicting human behavior intention in areas such as information systems (Hanus & Wu, 2016), food science (Pang et al., 2021), and education (Meso et al., 2013; Singh et al., 2011). In studies on human behavioral intention, the cognitive appraisal process, including determination of perceived severity and perceived vulnerability, was considered the source of protective motivation: a change in attitude seen first as protection motivation (Conner & Norman, 2015) followed by intention to perform the behavior (Chenoweth et al., 2009).

Perceived vulnerability (PV) refers to the probability that the threat will occur if there is no change in existing behavior or no application of adaptive behavior (Lee & Larsen, 2009). In this study, PV reflects student assessment of the possibility of COVID-19 infection if e-learning is not available. Perceived severity (PS), defined as students' assessment of the severity of the threat, in this study refers to student assessment of the severity of the COVID-19 pandemic.

Several prior studies that used PMT to understand human behavior during pandemics and epidemics have indicated a situation's severity as being one of the main motivators that creates protection motivation (Bish & Michie, 2010), and protection motivation leads to adopting avoidance behaviors (Sharifirad et al., 2014). Especially in the COVID-19 context, many scholars have taken PMT as a foundation theory for their own work (e.g., Al-Rasheed, 2020; Bashirian et al., 2020; Prasetyo et al., 2020; Rather, 2021). In a study related to the COVID-19 pandemic, Prasetyo et al. (2020) demonstrate that PV and PS have direct effects on individual attitudes, with their subsequent attitude influencing their related behavioral intention. Scholars have suggested benefits of applying the aforementioned behavioral change principles to motivate people toward desirable behavior to help control the COVID-19 pandemic (West et al., 2020). In this study, we applied PMT theory in an e-learning context, assuming both PS and PV influence student ATEL and ITTELC. Consequently, we further proposed the following hypotheses:

- H5.1: PV has a positive effect on ATEL.
- H5.2: PS has a positive effect on ATEL.
- H5.3: PV has a positive effect on ITTELC.
- H5.4: PS has a positive effect on ITTELC.
- H6.1: ATEL mediates the relationship between PV and ITTELC.
- H6.2 ATEL mediates the relationship between PS and ITTELC.

## The COVID-19 Pandemic and E-Learning in Vietnam and Taiwan Higher Education

Vietnam and Taiwan have both been regarded as successful models in the fight against COVID-19 in Asia (Shokoohi et al., 2020). Specifically, between March 2020 and May 2021, Vietnam reported 5,306 COVID-19 cases (Ministry of Health, 2021a), while Taiwan reported 1,244 cases. However, during the current study period, Taiwan was facing a violent outbreak of COVID-19. According to the Taiwan Centers for Disease Control (2021), as of June 27, Taiwan reported 14,634 cases (about 0.061% of the population) and 632 deaths, an approximate 12 times increase since those recorded in May 2021. For various reasons, Taiwan also encountered many difficulties obtaining vaccines. At this time, the Taiwan government decided to establish a nationwide Level 3 alert, after which the general public began to take the pandemic more seriously. Also, under Ministry of Education instruction, nationwide schools for the very first time exclusively adopted online learning in May 2021. Influence of the national program for e-learning meant that e-learning had been a familiar tool in Taiwanese higher education since 2003 (Chang et al., 2009). In short, although appropriate equipment and teacher knowledge of e-learning had been established before the pandemic, in-person classes were preferred until the May 2021 COVID-19 outbreak.

Conversely, during the same period, although the COVID-19 pandemic in Vietnam had begun to explode as of June 27, 2021 with Vietnam reporting 15,643 cases (approximately 0.016% of population), an approximate three times increase in cases occurred since those reported in May 2021. Nationwide, the situation was perceived as being under control, and the general public was relatively incautious about the pandemic (Ministry of Health, 2021b). While distance learning was also required in Vietnam by the Ministry of

Education and Training during this period, e-learning had not become a widely accepted method of teaching and learning, and higher education institutions (HEIs) were not well-prepared to apply e-learning in the emerging COVID-19 context (Ho et al., 2020).

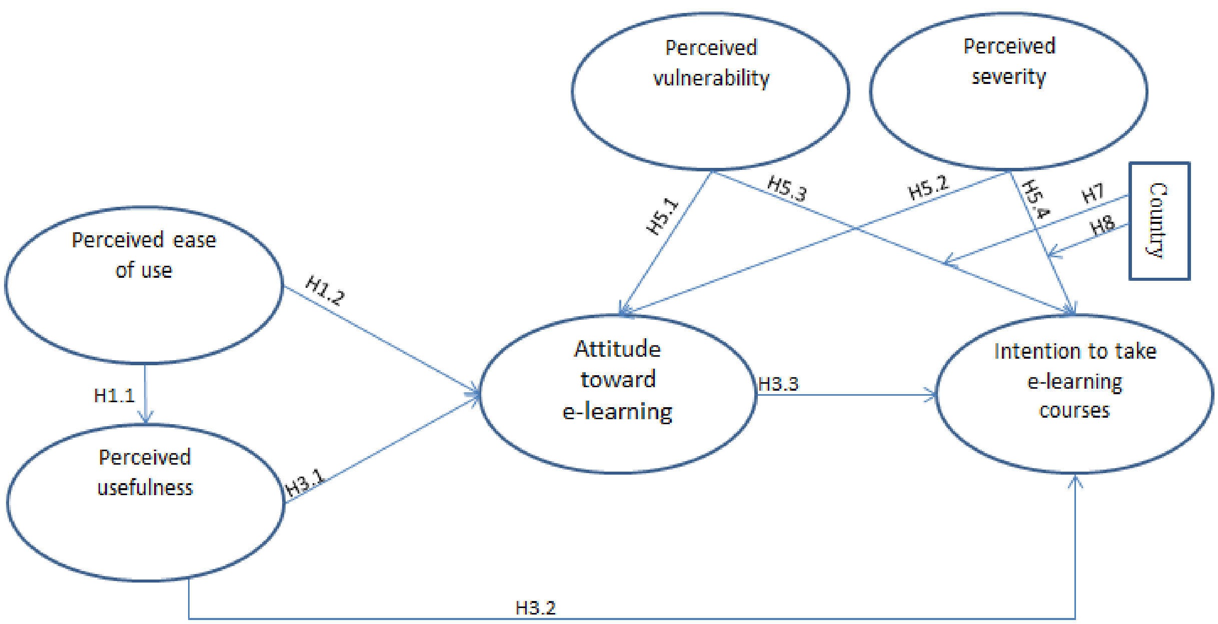
According to PMT, given the difference with respect to the COVID-19 situation in the two countries as illustrated above, students in Taiwan perceived the pandemic as more serious and thus increased their ITTELC. The following hypotheses were proposed:

- H7: PV affects ITTELC more for Taiwanese students than Vietnamese students.
- H8: PS affects ITTELC more for Taiwanese students than Vietnamese students.

Figure 2 illustrates the research model.

**Figure 2**

*Research Model*




*Note*. PV = perceived vulnerability; PS = perceived severity; PEOU = perceived ease of use; PU =perceived usefulness; ATEL = attitude toward e-learning; ITTELC = intention to take e-learning courses.

# Methodology

A questionnaire survey of students studying in universities in Vietnam and Taiwan was conducted. SurveyCake was used as a platform for data collection, and the questionnaire was distributed between June 10 and the July 4, 2021. Data were processed and analyzed via SPSS version 20 and AMOS version 20.

## Participants

Data were collected from first-year students studying in Vietnamese and Taiwanese universities. Convenience sampling was used; two top-ranked universities, with total student populations of 7,000 to 9,000, were selected from each country. The online questionnaire was distributed to the undergraduate students individually by e-mails by each university's office of academic affairs. After careful data cleaning (removal of outliers and those with incomplete answers), 432 out of 462 responses were deemed usable. Participant information is summarized in Table 1.

**Table 1**

*Participants' Demographic Information*

| Measure | Items | Frequency | % |
|---|---|---|---|
| Gender | Male | 176 | 40.7 |
| | Female | 256 | 59.3 |
| Country | Vietnam | 224 | 51.9 |
| | Taiwan | 208 | 48.1 |
| Total | | 432 | 100.0 |

## Measure

A survey questionnaire with six subscales was developed. The first subscale, PV of COVID-19, included five items adapted from Prasetyo et al. (2020) and Boyraz et al. (2020). The PS of the COVID-19 pandemic subscale consisted of six items adapted from Li et al. (2020) and Prasetyo et al. (2020). The PU subscale comprised four items adapted from Cheng (2011) and Ho et al. (2020). The remaining sections measuring PEOU (4 items), ATEL (4 items), and ITTELC (4 items) were revised from Khan et al. (2021) and Cheng (2011). All six sections measure constructs of this study employed an item scale ranging from 1 (strongly disagree) to 5 (strongly agree), and these six constructs reflected original Cronbach's alpha ($\alpha$) values exceeding the threshold of 0.7 (PV [$\alpha = 0.908$], PS [$\alpha = 0.84$], PU [$\alpha = 0.93$], PEOU [$\alpha = 0.84$], ATEL [$\alpha = 0.92$], ITTELC [$\alpha = 0.97$]).

# Findings

## Measurement Model Evaluation

To evaluate the measurement model, we checked the reliability and convergent and discriminant validity of measures using criteria and methods proposed by Fornell and Larcker (1981). To check for convergent validity, an individual item factor loading should be greater than 0.50, the average variance extracted (AVE) should be greater than 0.50, and the composite reliability (CR) of all constructs should be greater than 0.80. Table 2 shows that all three conditions were met, establishing the measurement model's convergent validity. Cronbach's α was also used to confirm data reliability, and as indicated in Table 2, the α value for all constructs exceeded the permissible minimum value of 0.7 (Mortelmans et al., 2008).

**Table 2**

*Results of Confirmatory Factor Analysis, Reliability Test, and Convergent Validity Analysis*

| Construct | Items | Estimate | Average variance extracted (AVE > 0.5) | Composite reliability (CR > 0.8) | Cronbach's α (> 0.7) |
|---|---|---|---|---|---|
| Perceived vulnerability | PV1 | 0.694 | 0.510 | 0.839 | 0.838 |
| | PV2 | 0.683 | | | |
| | PV3 | 0.737 | | | |
| | PV4 | 0.716 | | | |
| | PV5 | 0.740 | | | |
| Perceived severity | PS1 | 0.723 | 0.503 | 0.858 | 0.857 |
| | PS2 | 0.779 | | | |
| | PS3 | 0.715 | | | |
| | PS4 | 0.669 | | | |
| | PS5 | 0.732 | | | |
| | PS6 | 0.627 | | | |
| Perceived usefulness | PU1 | 0.666 | 0.602 | 0.857 | 0.853 |
| | PU2 | 0.809 | | | |
| | PU3 | 0.774 | | | |
| | PU4 | 0.842 | | | |
| Perceived ease of use | PEOU1 | 0.777 | 0.546 | 0.824 | 0.801 |
| | PEOU2 | 0.516 | | | |
| | PEOU3 | 0.801 | | | |
| | PEOU4 | 0.821 | | | |
| Attitude toward e-learning | ATEL1 | 0.739 | 0.582 | 0.847 | 0.843 |
| | ATEL2 | 0.835 | | | |
| | ATEL3 | 0.676 | | | |
| | ATEL4 | 0.792 | | | |
| Intention to take e-learning courses | ITTELC1 | 0.745 | 0.653 | 0.883 | 0.881 |
| | ITTELC2 | 0.830 | | | |
| | ITTELC3 | 0.842 | | | |
| | ITTELC4 | 0.813 | | | |

*Note*. PV = perceived vulnerability; PS = perceived severity; PU =perceived usefulness; PEOU = perceived ease of use; ATEL = attitude toward e-learning; ITTELC = intention to take e-learning courses.

To test discriminant validity, we applied the method of comparing the square root of the AVE for each given construct with the associated correlation values proposed by Fornell and Larcker (1981). The diagonal values in Table 3 are the square roots of AVE higher than the values in their respective rows and columns, indicating a good level of discriminant validity. This suggests that the measurement model is of satisfactory reliability and validity.

**Table 3**

*Results of Discriminant Validity Analysis for Measurement Model*

| Construct | PV | PS | PU | PEOU | ATEL | ITTELC |
|---|---|---|---|---|---|---|
| PV | **0.714** | | | | | |
| PS | 0.119 | **0.709** | | | | |
| PU | 0.154 | 0.331 | **0.776** | | | |
| PEOU | 0.209 | 0.190 | 0.183 | **0.739** | | |
| ATEL | 0.206 | 0.340 | 0.445 | 0.610 | **0.763** | |
| ITTELC | 0.347 | 0.375 | 0.479 | 0.423 | 0.640 | **0.808** |

*Note*. The bolded diagonal values in Table 3 are the square roots of AVE. PV = perceived vulnerability; PS = perceived severity; PU =perceived usefulness; PEOU = perceived ease of use; ATEL = attitude toward e-learning; ITTELC = intention to take e-learning courses.

## Results of the Structural Model

As indicated in Table 4, the model fit statistics are all at satisfactory levels, indicating a good fit between the data and the proposed research model.

**Table 4**

*Summary of Model Fit Statistics for Structural Models*

| Model fit statistics | Suggested value | Observed value |
|---|---|---|
| Chi-square/*df* | < 2.00 | 1.823 |
| Comparative fit index | > 0.90 | 0.955 |
| Goodness of fit index | > 0.90 | 0.914 |
| Normed fit index | > 0.90 | 0.906 |
| Non-normed fit index | > 0.90 | 0.949 |
| Root mean square error of approximation | < 0.05 or < 0.08 | 0.044 |

## Results of Hypotheses Testing

Table 5 summarizes the results of path analysis and hypothesis test results. Each proposed direct effect was significant except for H5.1. The results indicate that PV affects students' intentions to take e-learning courses but not their attitudes toward e-learning.

**Table 5**

*Results of Hypothesis Testing for Direct Effects*

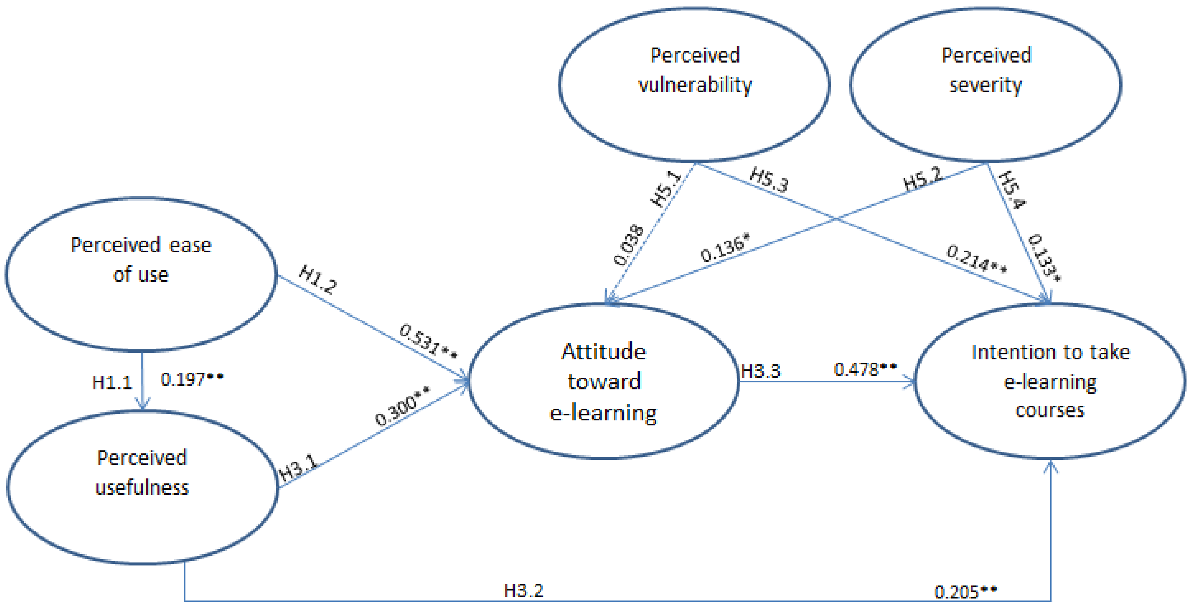
| Hypotheses (direct paths) | Standardized path coefficients | *t* | *p* | Result |
|---|---|---|---|---|
| H1.1: PEOU → PU | 0.197 | 3.470 | < 0.001 | Accepted |
| H1.2: PEOU → ATEL | 0.531 | 9.212 | < 0.001 | Accepted |
| H3.1: PU → ATEL | 0.300 | 5.964 | < 0.001 | Accepted |
| H3.2: PU → ITTELC | 0.205 | 4.035 | < 0.001 | Accepted |
| H3.3: ATEL →ITTELC | 0.478 | 7.989 | < 0.001 | Accepted |
| H5.1: PV → ATEL | 0.038 | 0.824 | > 0.05 | Rejected |
| H5.2: PS → ATEL | 0.136 | 2.890 | < 0.01 | Accepted |
| H5.3: PV → ITTELC | 0.214 | 4.549 | < 0.001 | Accepted |
| H5.4: PS → ITTELC | 0.133 | 2.853 | < 0.01 | Accepted |

*Note*. PEOU = perceived ease of use; PU =perceived usefulness; ATEL = attitude toward e-learning; ITTELC = intention to take e-learning courses; PV = perceived vulnerability; PS = perceived severity.

Significant structural relationships between the variables in the research model and the standardized path coefficients are shown in Figure 3.

**Figure 3**

*Structural Model*




*Note.* * $p < 0.01$. ** $p < 0.001$.

To examine the significance of the proposed mediation effect, a bootstrapping approach using 1,000 resamples with a 95% confidence interval was used. As shown in Table 6, only H6.1 was rejected, suggesting that PV only directly influences individual intentions to take e-learning courses, and attitudes toward e-learning do not play a mediating role in the association.

**Table 6**

*Results of Hypothesis Testing for Mediation Effect*

| Hypotheses (indirect paths) | Standardized path coefficients | $p$ | Result |
|---|---|---|---|
| H2: PEOU → PU → ATEL | 0.059 | < 0.01 | Accepted |
| H4: PU → ATEL → ITTELC | 0.143 | < 0.01 | Accepted |
| H6.1: PV →ATEL → ITTELC | 0.018 | > 0.05 | Rejected |
| H6.2: PS →ATEL → ITTELC | 0.065 | < 0.05 | Accepted |

*Note*. PEOU = perceived ease of use; PU =perceived usefulness; ATEL = attitude toward e-learning; ITTELC = intention to take e-learning courses; PV = perceived vulnerability; PS = perceived severity.

Table 7 shows that the total effect of three TAM factors on ITTELC (ATEL = 0.478, PU = 0.348, PEOU = 0.322) was slightly higher than that of the PMT factors (PV = 0.232, PS = 0.198). For TAM factors, the total effect of PU on ITTELC is larger, while for PMT factors, the total effect of PV is stronger than that of PS.

**Table 7**

*Antecedents' Effect on ITTELC*

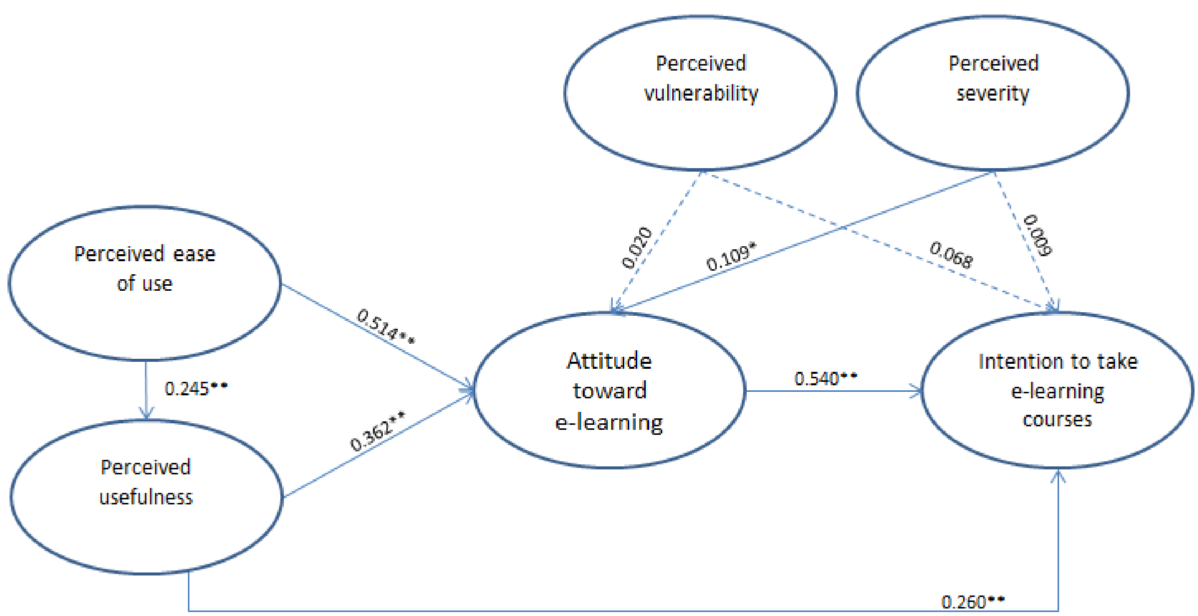
| Antecedents | | Direct effect | Indirect effect | Total effect |
|---|---|---|---|---|
| TAM factors | PEOU | n.s. | 0.322 | 0.322 |
| | PU | 0.205 | 0.143 | 0.348 |
| PMT factors | PS | 0.133 | 0.065 | 0.198 |
| | PV | 0.214 | 0.018 | 0.232 |

*Note.* ITTELC = intention to take e-learning courses; TAM = technology acceptance model; PEOU = perceived ease of use; n.s. = nonsignificant; PU = perceived usefulness; PMT= protection motivation theory; PV = perceived vulnerability; PS = perceived severity.

The structural model results for the two countries are shown in Figures 4 and 5. Taiwan's model shows greater PS and PV effects on ITTELC but lower PU effect on ITTELC. Table 8 shows the effect of PU, PS, PV, and PEOU on ITTELC in the two countries. Specifically, as the "Total effect" column suggests, two PMT factors (PS, PV) have stronger effects on ITTELC in Taiwan than they do in Vietnam. In contrast, PU affects ITTELC more significantly in Vietnam than in Taiwan.

**Figure 4**

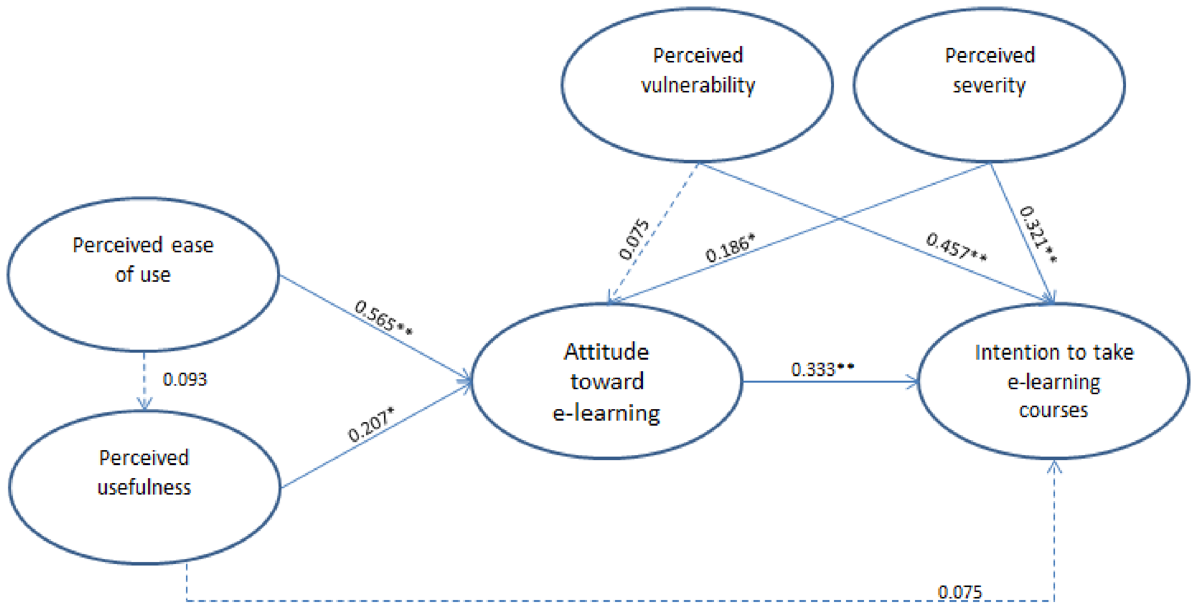
*Structural Model of Vietnam*




Note. * $p < 0.05$. ** $p < 0.001$.

**Figure 5**

*Structural Model of Taiwan*




*Note*. * $p < 0.05$. ** $p < 0.001$.

**Table 8**

*Antecedents' Effect on ITTELC Between Vietnam and Taiwan Model*

| Antecedents | | Direct effect | Indirect effect | Total effect |
|---|---|---|---|---|
| TAM factors | PEOU | n.s. (n.s.) | 0.389 (0.202) | 0.389 (0.202) |
| | PU | 0.260 (0.075) | 0.195 (0.069) | 0.455 (0.144) |
| PMT factors | PS | 0.009 (0.321) | 0.059 (0.062) | 0.068 (0.383) |
| | PV | 0.068 (0.457) | — (—) | 0.068 (0.457) |

*Note*. Coefficients for Taiwan are in parentheses. ITTELC = intention to take e-learning courses; TAM = technology acceptance model; PEOU = perceived ease of use; n.s. = nonsignificant; PU =perceived usefulness; PMT = protection motivation theory; PS = perceived severity; PV = perceived vulnerability.

To further test H7 and H8, a chi-square difference test was used to examine whether the hypothesized path coefficients were significantly different. As Table 9 indicates, there is a significant difference in the path coefficients between PV, PS, and ITTELC in the Taiwan and Vietnam models. Specifically, the path coefficients of these effects are significantly higher for Taiwan; thus, H7 and H8 were supported.

**Table 9**

*Multigroup Analysis of Paths from PV and PS to ITTELC Between Taiwan and Vietnam*

| Paths to compare | $X^2$ | *df* | $\Delta X^2$ from base model | Path coefficients | Result of hypothesis testing |
|---|---|---|---|---|---|
| Unconstrained base model[a] | 896.925 | 576 | | | |
| Constrained paths[b] | | | | | |
| H7: PV → ITTELC | 915.574 | | 18.649* | 0.068 (0.457*) | Accepted |
| H8: PS → ITTELC | 909.101 | | 12.176* | 0.007 (0.321*) | Accepted |

*Note.* [a] Paths for the two countries groups were allowed to be freely estimated. [b] The path specified was constrained to be equal across the two countries groups. Coefficients for Taiwan are in parentheses. * $p$ < 0.001.

# Discussion and Conclusion

The TAM has long been seen as a valid theoretical framework for explaining students' attitudes and intentions with regard to e-learning (Al-Qaysi et al., 2020; Baby & Kannammal, 2020; Cheng, 2011; Mohammadi, 2015), but one recent study conducted in the COVID-19 context reflects a contradictory result (Ho et al., 2020). It seems that in the context of the current pandemic, in addition to TAM factors, other influential factors also require attention.

To shed more light on the complexity of students' online learning intention, this PMT-based study incorporated two additional factors—PV and PS—along with TAM factors. The researchers chose two countries with different COVID-19 pandemic situations for study. Our findings echo those of previous studies on relationships between PV, PS, and human behavioral intention in other noneducational settings (Chenoweth et al., 2009; Prasetyo et al., 2020). If perceived risk of the disease is higher, people will more easily accept protection measures such as adopting e-learning courses. This suggests that it is essential to build people's awareness of the serious nature of the disease. To this end, governments should strengthen and diversify forms of advertising about the dangers of COVID-19 as well as other emergency situations in the future; they should also enumerate prevention measures to boost people's awareness and caution. Educators and policy makers should enhance student risk perception in terms of severity and vulnerability of the pandemic or other emergent situations, so they are more spontaneous and cooperative in accepting e-learning classes.

Our analysis also shows that the dynamics of the study variables evolved when we separately examined the whole data set and the two countries using the proposed model. While the TAM and PMT factors were significant in predicting ITTELC, PS also had a positive effect on ATEL and ITTELC, while PV only had a positive direct effect on ITTELC and did not affect attitudes toward e-learning. While the total effect of TAM factors was also slightly higher than that of the PMT factors, the picture changed when we compared the results from Vietnam and Taiwan. In Vietnam, TAM factors worked quite well in explaining ITTELC, but PMT factors were either insignificant (PV) or had an indirect effect on ITTELC (PS). Conversely, the Taiwan results presented a completely different picture. Specifically, TAM factors had only an indirect effect on

ITTELC, while PMT factors had a much stronger effect on ITTELC. As Denzin (2017) has argued, nuances in data might be different if collected at different times, in different places, and from different people, with such differences possibly due to a different pandemic condition and information and communication technology education traditions in the two countries.

As mentioned in the literature review section, this study was conducted after a more violent outbreak of COVID-19 in Taiwan but not in Vietnam. This was exacerbated by the fact that the number of new cases in Taiwan was on the rise, coupled with difficulties encountered in accessing vaccines during this period. Another factor was that Taiwanese students seemed to be more cautious about the COVID-19 pandemic because of their previous experience with the SARS outbreak in 2003 (Liang et al., 2021). Prasetyo et al. (2020) shows that when the levels of PV and PS increase, people tend to change their attitudes and behaviors with respect to adopting protective measures. Similarly, while the COVID-19 situation in Taiwan was more serious than it was in Vietnam during the research period, the effect of PS and PV on ITTELC was higher for Taiwanese students than for Vietnamese students.

On the other hand, differences in the level of e-learning readiness between the two countries also played a role in the results. E-learning had become a popular method in HEIs; it had become a familiar tool in teaching and learning in Taiwan since the national program for e-learning was initiated in 2003 (Chang et al., 2009). On the other hand, since incorporating e-learning into formal courses was less common for HEIs in Vietnam (Ho et al., 2020), the need to enhance Vietnamese students' perceived view of e-learning's ease and helpfulness had a greater effect on their ITTELC than it did for Taiwanese students. Therefore, more focus should be placed on the Vietnam Ministry of Education and Training broadcasting the benefits of e-learning through a variety of channels and in different contexts. Moreover, to establish students' e-learning usage habits, HEIs should also consider expanding the use of online courses in their academic programs even under normal circumstances. Governments should also invest in technology infrastructure to improve e-learning use in HEIs so that students can become accustomed to using e-learning and comfortably take e-learning courses when necessary.

In summary, the theoretical implication of this study is that it provides a new perspective for integrating PMT and TAM and exploring factors affecting student intentions to take e-learning courses in an emergency situation such as the COVID-19 pandemic. This responds to the call of Ho et al. (2020) for further research to determine whether other factors have a stronger impact on attitudes and intentions to use e-learning throughout the COVID-19 era. In addition, the mediating role of student ATEL with respect to relationships between PS and ITTELC was also established by our study.

Our cross-country comparison also shed light on the condition of PMT and TAM factor effects on students' ITTELC, and this is also important as a practical implication of our findings. Our analysis shows that a more contextual understanding of students' e-learning intentions should be carefully examined during a pandemic and that factors for ITTELC can vary in different educational settings. Therefore, educators and policy makers should clearly define the context of e-learning implementation to identify the necessary antecedents that contribute to improving an individual's intention to accept e-learning. Accordingly, educators and policy makers in Vietnam, Taiwan, and other countries are advised to develop strategies with variable emphasis among TAM and PMT factors that have different roles in different countries' settings.

## Limitations and Suggestions for Further Study

There are some limitations to this study. First, since we employed the convenience sampling method, the study reflects limitations in sample representation. Second, since this study did not consider external factors to TAM that could also be relevant in predicting students' intension for e-learning, we suggest that future studies could adopt random sampling methods to make samples suitably representative. The current research model could also be tested with participants from other countries that represent varied contexts in order to generate more insights. Multigroup analysis could also be applied to examine whether other important demographic variables could be used in interpreting the model, such as type of education, level of education, students' major, and so forth. Finally, a more theoretical framework might complement the TAM and PMT and provide a more comprehensive picture of our understanding of the factors influencing students' inclinations toward e-learning.

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