Predicting Continuous Intention to Use e-Learning Platforms among University Students: An Integrated Model

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***Abstract*—The current study explores Continuous Intention (CI) to use electronic learning (e-learning) as an educational tool among university students through the prism of a post-pandemic theoretical framework. Despite e-learning technology's latest launch in academia, very little has been done to evaluate its effects. To examine what factors impact the continuous intention to use E-learning, this paper contemplates incorporating the Technology Acceptance Model (TAM) with Self-Determination Theory (SDT). University students were asked to fill out questionnaire forms that were designed to gather data for the proposed model. This study employed a linear Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. The empirical results indicated that perceived usefulness and autonomy are significant predictors of the continued intention to use E-learning in the Thai context. Contrarily, the CI was unaffected by Perceived ease of use. Overall, theoretical and practical ramifications are addressed.**

***Keywords*—continuous intention, e-learning, technology acceptance model, self-determination theory, higher education, Partial Least Squares Structural Equation Modeling (PLS-SEM)**

I. Introduction

Higher education is always evolving due to new technologies and globalization. Most Higher Education Institutions (HEIs) of all sizes and forms struggle to compete by improving their technology capabilities [1, 2]. Recently, there have been many changes to the scene of the higher education sector within and beyond the pandemic [3]. Many HEIs in East Asia, including Thailand, have transitioned to E-learning [4, 5]. The challenge that COVID-19 poses to HEIs in Asian countries is profound. Recently, many higher education systems have been forced to take the learning process and other operations remotely. This path results in innovative strategies to cross digital gaps and overwhelm other issues [6].

The Thai government has taken extensive preventative measures to help keep COVID-19 from spreading further [7]. Temporary school and university closures are among these procedures, necessitating an online platform to ensure that students' learning progresses while the institutions are closed [8]. However, e-learning platforms provide an alternative and conducive setting for group learning. Teachers may engage with their students and exchange class materials online, which makes learning available to students no matter where they are or what device they are using [3]. Through an entirely e-learning method during the pandemic, university students were able to continue their academic pursuits [9]. Internet-based educational platforms like Moodle, websites, and free communication platforms like Google Classroom and Zoom meetings have been used by several universities in Thailand to deliver learning content [7]. Professors with social media can communicate with their learners more easily than ever before [10]. In addition, significant efforts are made to increase student and instructor technology literacy. To overcome this unique scenario (i.e., the move to e-learning), universities have grown more aware of the need for E-learning to address other pressing educational issues vital to the Thai educational future [4].

Moreover, E-learning platforms give students an entirely new learning experience that seamlessly connects with their peers and the content [11, 12]. A familiar form of online earning is applications (apps) downloaded on a mobile device and accessed through a wireless network [13]. According to Yeap, Ramayah and Soto-Acosta [14], the rapid development of E-learning technology can transform traditional education into a modern direction. E-learning represents solving numerous educational issues [15]. First and foremost, it allows students to learn at their own pace without the constraints of traditional classrooms. Second, it encourages teamwork. As a third benefit, it allows students to participate in formal education outside the classroom and access learning resources without time limits [11]. As a bonus, students can take part in online discussions, exchange resources, and pose questions at any time [16].

Although most university students are reluctant to use e-learning platforms, especially after universities open onsite classes, they continue to use e-learning platforms for internet browsing and gaming for educational purposes [17, 18]. The educational system still faces many challenges, such as high dependence on learning through rote rather than through exploration, lack of student interaction, and total dependence on the teacher in transferring the information to the students [19]. Therefore, research on what motivates students to continue using e-learning and its advantages is required. Also, issues with using e-learning during the pandemic cannot reflect the normal situation. During the pandemic, universities employed remote checking-in and online question-and-answer systems to ensure students attended and participated in daily courses. Aside from that, learners' positive behavioral intention to use and feedback on the learning experience is not guaranteed because online-based courses are mandatory [3]. Till now, there are no techniques to gauge their continuous intention toward the instructor's

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teaching and e-learning platforms.

Furthermore, there is still a gap in the research on non-voluntary e-learning acceptance in social emergencies like the pandemic. There is a dearth of research on university students' continuous intention to utilize non-voluntary e-learning during and after the outbreak, especially in underdeveloped countries like Thailand, where e-learning was not well accepted in universities before the pandemic. Several research studies have examined Thai students' perceptions of e-learning [4, 7, 8, 20]. However, little research has been undertaken on online students' behavior after the pandemic, so little is known about how their behavior influences outcomes. Hence, this study fills the gaps by examining the factors influencing learners' continuous intention to use e-learning platforms. This study will increase students' willingness to learn using E-learning and help policymakers improve their strategies and resources.

Consequently, this study fills the gaps by examining the factors influencing learners' continuous intention to use e-learning. This study will help increase students' continuous intention to learn using e-learning and help policymakers improve their strategies and resources. Partial least squares structural equation modeling (PLS-SEM) is used to determine what factors must be present for CI to be successful [21, 22]. Hence, this study gives practitioners useful insight and substantially improves our theoretical knowledge of E-learning applications in classrooms. This research adds to the existing body of knowledge by combining Self-Determination Theory (SDT) with the Technology Acceptance Model (TAM). It sheds light on what influences university students' continuous intention to use e-learning. Finally, this study aims to fill a gap in the literature by conducting empirical research into the factors that influence university students' continuous intention to use e-learning. The existing theoretical understanding of the topic is also inadequate. This study was originally guided by the following research question: What are the significant factors influencing university students' continuous intention to use e-learning?

II. Literature Review

According to Ali and Arshad [23], most of the studies on the acceptance or rejection of information technology paid attention to expanding the "Technology Acceptance Model" (TAM) by utilizing external factors. For example, when studying learners' intention to return to the electronic environment through wiki pages, researchers Li and Yu [24] included three additional variables to the TAM: self-efficacy, prior experience, and IT competence. Their findings found that attitudes are influenced by perceived ease of use (PEOU), while self-efficacy and IT competence are key determinants of perceived usefulness (PU). In yet another research, Chen, *et al.* [25] incorporated social and mobile perspective factors into the conventional TAM to investigate the factors affecting the user's intention to play mobile social gaming. Mobile social games, according to the findings of the study, need to focus on making their games enjoyable and accessible, while also encouraging users to share their fun.

Moreover, to predict and explain travelers' acceptance of variable message signs (VMS) in advanced traveler information systems (ATIS), Diop, Zhao and Duy [26] used an enhanced version of TAM. An additional focus of this research was on how road users' attitudes toward route diversion, familiarity with their surroundings, and quality of information influenced their acceptance of VMS in addition to traditional TAM constructs (PU, PEOU, and behavioral intention). Findings confirmed that travelers' attitudes toward route diversion affected PU and VMS intention to use. Information quality positively affected PU, PEOU, and attitude towards route diversion. Familiarity with the network positively affected the attitude toward route diversion, while it had a negative effect on the PU. PEOU significantly affected PU and intention to use VMS. For the prediction of mobile-based money acceptance and sustainability, Gbongli, Xu and Amedjonekou [27] enhanced the original TAM by combining self-efficacy, technology anxiety, and personal innovativeness. Findings showed that PEOU affects customers' perceptions of mobile-based money. On the other hand, PU and a person's capacity for original thought are significantly lower. A set of six constructs, including competence, relatedness, autonomy, PEOU, PU, and behavioral intention to use open-source software (OOS), was tested by Racero, Bueno and Gallego [28] using a combination of the SDT and the TAM. An increase in behavioral intention to use OSS can be achieved through the use of intrinsic motivations such as autonomy and relatedness.

TAM and IDT were used to examine the possible variables that influence students' behavioral intents to utilize the e-learning system as outlined by TAM and IDT (innovation diffusion theory) were used to examine and explore the possible elements that influence students' behavioral intents to utilize e-learning system as outlined by Al-Rahmi *et al.* [29]. According to the results, the six perceptions of innovation characteristics influence students' behavioral intentions. Relative advantages, trialability, observability, compatibility, enjoyment, and complexity influence the PEOU. In addition, the PU is substantially influenced by relative advantages, complexity, trialability, observability, enjoyment, and compatibility. Because of this, the empirical evidence strongly supports the integration of TAM and IDT.

Moreover, Lew, Lau and Leow [30] extended TAM with three variables, computer self-efficacy, enjoyment, and user perception, to study the usability factors predicting continuance intention to use cloud e-learning applications. Researchers found that computer self-efficacy and enjoyment are two of the most important factors in determining continuance intention, while PEOU, PU, and user perception were unimportant. As a result, students' willingness to continue utilizing cloud e-learning programs in their studies appears to be strongly influenced by their feelings of computer self-efficacy and enjoyment. When looking at the continued intention to use mobile learning (m-learning), Al-Emran, Arpaci and Salloum [31] developed an integrated model of TAM, the theory of planned behavior (TPB), and the expectation-confirmation model (ECM). PEOU, attitude, perceived behavioral control, and subjective norms were found to be significant predictors of the continued use of m-learning. The researchers found that neither PU nor pleasure had any influence on the participants' continued intention.

The neural network modeling utilized by Al-Shihi, Sharma and Sarrab [32], based on the TAM and the UTAUT, could predict m-learning usage accurately. Research shows that social and flexible learning, economic learning, efficiency, and compatibility influence students' inclination to adopt m-learning. An integrated framework was established by Dalvi-Esfahani, *et al.* [33] that included the TAM, TPB, and Technology-to-Performance Chain (TPC) to investigate students' continuous intent to use mobile web 2.0 learning. PEOU, PU, task-technological fit, information exchange, social interaction, subjective norms, attitude, mobility, and perceived behavioral control substantially impacted the continuous intentions. Using the Task-Technology Fit (TTF) and TAM models, Gan, Li and Liu [34] investigated the influences on students' decisions to use mobile devices for learning at the university level. Technology and task parameters were found to be important predictors of task-technology fit and attitudes. Finally, according to the literature, integrated TAM with SDT to examine E-learning platforms is unknown. This study contributes by predicting students' continuing intention to use the E-learning platform through TAM and SDT.

III. Theoretical Background and Hypotheses Development

A. Theory of Technology Acceptance Model (TAM)

The TAM theory by Davis [35] examines how a new system or technological features affect users' internal attitudes, beliefs, and intentions [36]. According to Legris, Ingham and Collerette [36], PEOU and PU explain users' technological acceptance of new systems and technologies. PEOU indicates that technology will be easy, and PU boosts performance [35]. PEOU/PU affects attitudes and behavior [37]. They connect potential technology use to external factors. However, TAM components and relationships cannot predict how diverse students will perform [38]. Some students use technology naturally. For others, the fear of technology prevents them from using it. Lai [39] has confirmed that PEOU and PU explained technology acceptance. Davis [35] and Lin, Fofanah and Liang [40] showed that these factors cause behavioral intentions. PU and PEOU define online education goals in terms of usability and easiness. They play significant roles in technology acceptance [41, 42]. The greater the PEOU, the greater the PU [43]. Davis [35] found that even if technology is not easy to use, people might decide to use it because it is useful and makes their work easier. External TAM variables assist researchers in predicting technology adoption. It also provides justifications for choosing appropriate technology, prompting researchers and experts to take counteractive action [35].

B. Self-Determination Theory (SDT)

SDT is a tool for growth, inspiration, and health. As factors that influence performance, relationships, and well-being, SDT centers on controlled and autonomous motivation. When it came to predicting things like mental health, performance, creativity in solving problems, and conceptual or deep learning, the quality rather than the quantity of an individual's motivation was more important [44]. Mental health, tenacity, and heuristic accuracy are all enhanced by autonomous motivation [45]. Also, according to SDT, people are dynamic beings with innate capacities for psychological development [46]. A thirst for adventure, new experiences, and educational opportunities is an innate trait of humans. It is also readily apparent in internalization, as pointed out by Ryan [47], which is defined as an individual's innate tendency to adopt and incorporate the values and norms of their society. That is why SDT lays out the groundwork for development, honesty, and health in terms of fundamental psychological needs. It acknowledges competency, independence, and interconnectedness [48].

The present study builds a model by combining TAM with SDT. The perspective of TAM is that both PU and PEOU influence the intent to use the e-learning platform continuously. It has been suggested in SDT that competence, relatedness, and autonomy have a substantial impact on PU and usability. Furthermore, autonomy is a factor in the planned study model's prediction of the E-learning platform users' continuous intention to use the system. Fig. 1 shows the proposed model for the study.

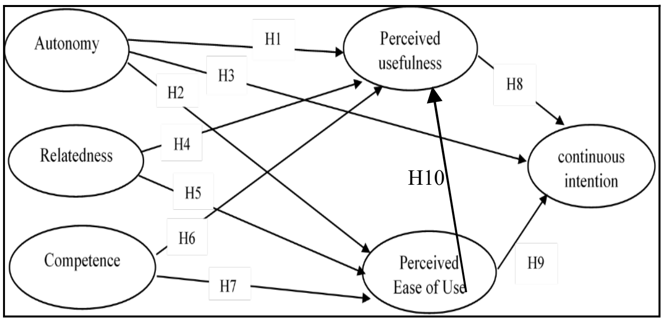

Fig. 1. The proposed research framework.

1) Autonomy

Self-regulation is the fundamental key of the autonomy construct, not peripheral interference. Being autonomous means not depending on other people but taking charge of one's own life. It implies that students should take initiative in their own education. It is the student's choice to learn [38, 49]. When Students take responsibility for their own education, they experience a sense of agency over their own learning and the outcomes they seek [50]. Autonomy is impacted by student satisfaction [38]. Increased happiness is achieved through autonomy-based motivation (Joo, Park, & Lim, 2018). Perceived autonomy, PU, and PEOU were found to be positively associated in various information and communication technology (ICT) contexts by Racero, Bueno and Gallego [28], Nikou and Economides [38], Rezvani, Khosravi and Dong [51], and Roca and Gagné [52]. Moreover, a substantial correlation between autonomy and technology acceptance was demonstrated by Cortez, *et al.* [53], Ali and Arshad [23], and Liaw, Hatala and Huang [54]. Based on the results, the following hypotheses were derived for this study:

H1: Autonomy positively improves PU.

H2: PEOU is positively impacted by autonomy.

H3: Autonomy influences CI in a positive way.

2) Relatedness

Being "related" means yearning for acceptance into a bigger fraternity. "Relatedness" in the classroom means that students are able to work together and communicate with one another [55]. According to SDT, students can gain a lot from interacting with one another and forming social relationships [50]. So, relatedness can make people feel more comfortable opening up and sharing information. Cortez, *et al.* [53] and Racero, Bueno and Gallego [28] discovered that relatedness significantly predicted PEOU and PU. Thus, the achieving assumptions have been put forth:

H4: Relatedness improves PU in a positive way.

H5: Relatedness influences the PEOU in a positive way.

3) Competence

When people feel competent, they are able to accomplish their goals and excel at what they set out to do. This leads to a sense of value achievement [56]. In earlier research on competence in education, the ideas of PU and PEOU have been connected [52, 57]. Students need to be very proficient with E-learning if they want to do well in our classes [58]. Therefore, the following is assumed:

H6: Competence positively improves PU.

H7: Competence improves the PEOU in a positive way.

4) TAM constructs: PU and PEOU

A person's level of confidence in a system's safety and ease of use is known as perceived ease of use (PEOU) [35]. Conversely, perceived usefulness (PU) is associated with the conviction that a particular system's implementation will enhance job performance [35]. According to various studies [26, 28, 29, 52], PEOU and PU play a significant role in deciding technology adoption. Therefore,

H8: Students' CI to use the E-learning platform is positively impacted by PU.

H9: PU improves students' CI to use the E-learning platform in a positive way.

H10: PEOU positively influences PU.

IV. Methods

A. Population and Sample

The present study follows the ethical principles of voluntary participation, informed consent, confidentiality, and anonymity, along with the human ethical approval (psu.pn.2-070/65) identified to collect data during the academic year 2023/2024. The participants of this study were university students in Thai southern border provinces (i.e., Pattani, Yala, and Narathiwat). University students who use E-learning platforms are included in the study's research unit (inclusion criteria). The initial version of the current research instrument was rigorously pre-tested by a group of three academics (in the field of education and information technology) and two E-learning experts. Based on this iterative process, some items were refined using rewording or upgrading, leading to the final set of measurement items. Also, the questionnaire items were tested in a pilot study to determine a scale's reliability by using the Cronbach alpha statistic. Results indicated that all items are reliable since their values are beyond a threshold of 0.70 [59]. The G*Power tool determined the minimum sample size [60]. The G*Power parameters include 0.15 for moderate effect size, 0.05 for error type (α), 0.80 for effect power, and five predictors. This convinced researchers that 92 cases were the minimum for a valid sample. Google Forms was used to create the survey. The subject participants were selected through a purposive sampling technique. The survey questions have compulsory answers to avert any missing data; 340 Thai university students completed the online survey. Structural equation modeling was used with SmartPLS 4.0 software to analyze the direct and indirect interactions between the research variables.

B. Instrument

A survey was conducted among Thai students to determine their ongoing intention to use the E-learning platform. In the first part of the survey, we ask participants to provide some basic personal information. In the second section, we measured the conceptual model, which includes constructs of PEOU, PU, autonomy, relatedness, competence, and continuous intention. A "7-point Likert scale" was used to measure these constructs. The items used to assess competence and autonomy were taken from the works of Nikou and Economides [38] and Lee, Lee and Hwang [61]. Lee, Lee and Hwang [61] and Sørebø, *et al.* [62] were used to develop the items measuring relatedness. The items used to measure constructs of PU and PEOU were taken from two sources: Venkatesh, *et al.* [63] and Nikou and Economides [38]. We used items from Bhattacherjee [64] for continuous intention.

C. Data Analysis

This study evaluated the suggested research model by consuming SmartPLS 4.0 software and Partial Least Squares (PLS) analysis [65]. Anderson and Gerbing [66] divided analytical procedures into twofold parts: measurement model evaluation and hypothesized relationship testing (structural model evaluation). PLS-SEM has a large community of researchers who use it to analyze their research models [2, 53, 67–69]. This is the main PLS-SEM benefit. PLS-SEM tests causal-predictive model relationships to generate hypotheses [70]. Optimizing causal relationship estimates extends the variance of a target variable supported by predictive constructs [71]. Their model closes the explanation-prediction gap and has greater statistical power than factor-based SEM [21, 72]. Ordinary least squares regressions can analyze aggregate indicator scores [73]. Based on these factors, the PLS-SEM approach is the best method for this study.

D. Profile of Respondents

Most respondents in this survey are females (63.8 percent), while males are 36.2 percent. Their ages are between 19 and 23 years since the samples represent university students. When it comes to their usage of educational websites or YouTube in learning, 42.1 percent of respondents have used it, while 57.9 percent never used it. Also, 55.8 percent said they prefer continuing learning via the e-learning platform, while the remaining 44.2 percent said they did not.

E. Common Method Variance (CMV)

CMV should not be a serious issue in PLS-SEM analysis. There is disagreement about the relevancy of CMV in a PLS analysis [74, 75]. Also, the current model is considered free of CMV since the VIF values of the inner model are less than 3.3

(see Table 5) [76]. However, reducing the effects of common method variance caused by the similarity in data collection methods can be done on various levels, starting from the study design and data collection. This study focuses on procedural and statistical remedies before and after collecting the data. Thus, a marker variable method was used to test the CMV issue by following the research of Rönkkö and Ylitalo [77]. It compares the PLS marker model results with the ones of the baseline model. There are slightly small R^2 changes (less than 10 %) in CI of 0.2 %, PU of 3.5%, and PEOU of 0.5 %. Hence, CMV is not a severe issue in this research model [78].

V. PLS-SEM Findings

A. Measurement Model Assessment

According to Hair Jr, *et al.* [79], testing the outer models is necessary when building the proposed model. The outer model is evaluated using average variance extracted (AVE), discriminate validity, composite reliability (CR), and factor loading. With the exception of the removed PU1 (0.494) and RLT4 (0.629), all outer loadings are greater than the suggested value of 0.708 by Hair, *et al.* [80], meaning that AVE and CR (see Table 1) have achieved their thresholds of AVE > 0.50 and CR > 0.70.

Table 1. Factor loading, CR, and AVE

Constructs	**Items**	**Loadings**	**CR**	**AVE**
Autonomy	AUT1	0.870	0.895	0.741
	AUT2	0.911		
	AUT3	0.797		
CI	CI1	0.784	0.883	0.716
	CI2	0.908		
	CI3	0.842		
Competence	COM1	0.751	0.832	0.624
	COM2	0.852		
	COM3	0.764		
PEOU	EOU1	0.830	0.891	0.731
	EOU2	0.878		
	EOU3	0.855		
PU	PU2	0.899	0.916	0.785
	PU3	0.899		
	PU4	0.847		
Relatedness	RLT1	0.767	0.871	0.694
	RLT2	0.794		
	RLT3	0.898		

B. Discriminant Validity

In order for a construct to be considered discriminately valid, its AVE must be greater than either the squared correlation of other constructs or their square root, as suggested by Fornell and Larcker [81]. Table 2 displays discriminant measures because the diagonal contains values that are greater than the corresponding row and column values. In addition, the HTMT was proposed by Henseler, Ringle and Sarstedt [82] as a tool for evaluating discriminant validity. Therefore, this research used the recently proposed method by Ramayah, *et al.* [83] to assess the discriminant validity. The findings can be found in Table 2. According to Gold, Malhotra and Segars [84], there is no issue with discriminant validity because the HTMT values are lower than the HTMT.90 value of 0.90.

C. Structural Model Assessment

Examining the internal model is the subsequent stage. Using estimates of multicollinearity, R^2, $PLS_{predict}$, the path coefficient, GoF, and model fit measures, this study examines the inner model [73].

Table 2. Discriminant Validity

Discriminant Validity (Fornell and Larcker)						
	Autonomy	CI	Competence	PEOU	PU	Relatedness
Autonomy	**0.861**					
CI	0.725	**0.790**				
Competence	0.693	0.615	**0.846**			
PEOU	0.495	0.478	0.416	**0.855**		
PU	0.531	0.398	0.515	0.541	**0.886**	
Relatedness	0.667	0.639	0.738	0.456	0.611	**0.833**
Discriminant Validity (HTMT)						
	Autonomy	Competence	CI	PEOU	PU	Relatedness
Autonomy						
Competence	0.836					
CI	0.847	0.804				
PEOU	0.581	0.631	0.488			
PU	0.621	0.503	0.623	0.626		
Relatedness	0.818	0.856	0.830	0.540	0.742	

Note: the square root of the AVE (bold values on the diagonal) and the correlations (off-diagonals) on the graph.

D. Multicollinearity Test (VIF)

In order to avoid skewed regression results caused by collinearity, the structural model must be checked before it can be evaluated [80]. The scores of the predictor constructs' latent variables in the partial regression are used to calculate variance inflation factors (VIFs). The presence of multicollinearity is indicative of redundant information provided by correlated predictors. VIF found its value. Variables are not highly correlated when the VIF value is small. If it is below 3.3, the VIF value is considered good [76]. In terms of the study model, every VIF value is below 3.3 (see Table 5). This meant that the research model did not have any multicollinearity issues.

E. Coefficient of Determination (R^2)

Table 3. Coefficient of determination

Endogenous variables	**R Square**
CI	0.511
PEOU	0.290
PU	0.485

When it comes to $R^{2,}$ the effect level ranges from zero to one. For endogenous variables, Cohen [85] deemed R2 values of 0.26,0.13, and 0.02 to be substantial, moderately strong, and weak, respectively. In this study, Table 3 shows a high level of predictive power. Together, competence, relatedness, and autonomy explain 29% of the variation in PEOU. They are also responsible for 48.5% of the variation in PU. Finally, PEOU and PU explain 51.1% of the variation in CI.

F. PLS Predictive Power

Table 4. Predictive power assessment using $PLS_{predict}$

Items	Q^2predict	PLS-SEM_RMSE	Linear model _RMSE
CI1	0.253	1.161	1.273
CI2	0.410	1.077	1.123
CI3	0.424	1.197	1.246
PEOU1	0.090	1.208	1.185
PEOU2	0.154	1.347	1.160
PEOU3	0.233	1.232	1.204
PU2	0.246	0.892	0.975
PU3	0.312	1.140	1.033
PU4	0.291	1.247	1.248

Taking the model's predictive power into account concerning the endogenous constructs (i.e., PU, PEOU, CI), ten folds and ten iterations of the PLSpredict method were employed [86]. First, we checked to see if Q2predict was greater than zero, indicating that the PLS path model outperformed the indicator means from the training data. We then compared the PLS-SEM estimations to a linear benchmark model's root mean squared error (RMSE) [80]. Table 4 presents the PLSpredict results. All indicators for endogenous constructs have Q2predict values that are positive (above zero). Furthermore, PLS-SEM had reduced RMSE values across the board compared to the linear model. Taken as a whole, these findings suggest that the PLS path model is quite predictive of the endogenous constructs of interest.

G. Path Coefficient

The suggested research model's path coefficients were investigated by estimating t-values using the bootstrap method with 5,000 resamples [87]. The values of the path coefficients range from -1 to +1. When the value is near 1, a strong positive relationship is achieved; when it is near -1, the relationship turns negative. That is why 0.05 ought to be the smallest significant level for the path coefficients. The one-tailed test has critical values of 1.645, 1.96, and 2.33 for a 10%, 5%, and 1% significance level, respectively [88]. H4, H6, and H9, out of ten hypotheses proposed for the study, were all completely unfounded (see Table 5).

In order to determine whether the PLS structural model, which looked at students' continued intention to use the E-learning platform, was valid, seven out of ten of its hypotheses were confirmed. Both autonomy and PU were found to have a positive impact on the variables that affect CI prediction, with a beta coefficient of 0.577 with a p-value less than 0.01 and a beta coefficient of 0.195 with a p-value less than 0.05, respectively. Regardless, with a beta coefficient of 0.026 and a p-value greater than 0.05, no statistically significant correlation was found between PEOU and CI. Both PEOU and PU were positively associated with autonomy (beta coefficient = 0.238, $p < 0.05$ and beta coefficient = 0.220, $p < 0.05$). Competence was found to have a significant relationship with PU (beta coefficient = -0.202, $p < 0.01$) according to the statistical analysis, while there was no significance to PEOU with a beta coefficient of 0.196 and a p-value greater than 0.05. Similar significant results were obtained for relatedness and PU, where a beta coefficient = 0.445 and a p-value less than 0.05, but no significant relationship was found between relatedness and PEOU (beta coefficient = 0.173, $p > 0.05$). Finally, with beta coefficient = 0.325 and $p < 0.05$, it was determined that PEOU and PU had a positive and substantial relationship. The effect size was determined using Cohen's effect size estimation [85]. Small, medium, and large effect sizes are denoted by values of 0.02, 0.15, and 0.35, correspondingly. Both relatedness and autonomy significantly impact CI and PU, as shown in Table 5. The impact of PEOU on PU is moderate, whereas the impact of the other factors is negligible. On the other hand, CI was unaffected by PEOU.

Table 5. Result of hypothesis test and path coefficient

No.	Relationship	Std. Beta	Std Error	t-value	P value	f2	Effect size	VIF	Decision
H1	Autonomy -> CI	0.577	0.115	5.033	0.000	0.45	large	1.52	supported
H2	Autonomy -> PEOU	0.238	0.143	1.661	0.048	0.03	small	2.47	supported
H3	Autonomy -> PU	0.220	0.117	1.875	0.030	0.04	small	2.55	supported
H4	Competence -> PEOU	0.196	0.154	1.273	0.101	0.02	small	2.32	not supported
H5	Competence -> PU	-0.20	0.108	1.864	0.031	0.03	small	2.38	supported
H6	PEOU -> CI	0.026	0.103	0.247	0.403	0.00	no effect	1.54	not supported
H7	PEOU -> PU	0.325	0.145	2.240	0.013	0.15	medium	1.41	supported
H8	PU -> CI	0.195	0.108	1.813	0.035	0.05	small	1.63	supported
H9	Relatedness -> PEOU	0.173	0.129	1.338	0.090	0.02	small	1.98	not supported
H10	Relatedness -> PU	0.445	0.127	3.512	0.000	0.19	large	2.02	supported

H. Research Model Fit and Goodness of Fit (GoF)

Our first step in evaluating the model's accuracy was to check its fit with two adjustment variables: the normed fit index (NFI) and the standardized root mean square residual (SRMR). A good fit model is defined as an SRMR value (derived by taking the observed correlation matrix and subtracting it from the model-implied correlation matrix) that is less than 0.08 [89]. To avoid model misspecification in PLS-SEM, Henseler, et al. [90] suggested the SRMR as a goodness-of-fit metric. The second metric for evaluating the fitness of a model is the normed fit index (NFI). This incremental fit metric compares the proposed model's chi-square value to a meaningful standard, providing a second measure of model fitness [83]. In most cases, an NFI value above 0.90 indicates a good fit [91]. Results from estimating the structural (estimated) model and fitting it to the measurement model were very similar because there were no free paths in the saturated (measurement) model. The data fit the model well (see Table 6), as indicated by the SRMR calculation of 0.075 (< 0.08) and the NFI of 0.927 (> 0.90).

Moreover, GoF indicates the model's general adjustment. Tenenhaus, *et al.* [92] proposed a GoF, the square root of the mean of R^2 multiplied by the mean of AVE. According to Wetzels, Odekerken-Schröder and Van Oppen [93], the value 0.360 is suitable. The GoF value for the proposed model is 0.563, indicating that the model had an adequate adjustment. Fig. 2 displays the analysis end result in the proposed research model.

Table 6. Testing model fit

Parameter	Saturated model	Estimated model
SRMR	0.064	0.070
NFI	0.915	0.910

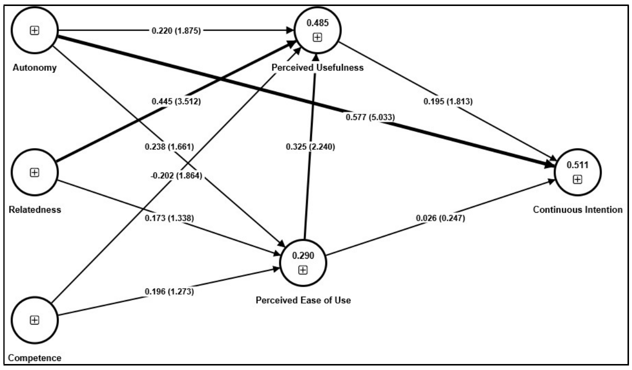

Fig. 2. The research model.

VI. Discussion

The key objective of this investigation was to identify the drivers that influence Thai university students' continuous intention to use E-learning platforms. Combining TAM and SDT, two separate theoretical frameworks, allowed us to complete this study. The findings from the survey's empirical component are detailed in the section devoted to discussion. The suggested model provided evidence in favor of seven of the ten additional hypotheses. For the most part, this research adds to the expanding body of work examining how technological advancements impact a person's education and training.

The effects of relatedness and autonomy on PU and PEOU are positive. That is why relatedness and autonomy are thought of as important predictors. This finding was in line with previous research by Liaw, Hatala and Huang [54], Ali and Arshad [23], and Racero, Bueno and Gallego [28]. This finding establishes that the E-learning platform becomes practical and user-friendly when it possesses the traits of independence and connection. In contrast, PU and PEOU are unaffected by competence. So, competency is a trivial indicator. Liaw and Huang [94] and Jeno, Grytnes and Vandvik [57] found that competence is an important factor in PU and PEOU, so this finding contradicts their findings. One possible explanation for this disparity is the fact that Thai culture is very different from other countries. When it comes to their education, students in Thailand, for instance, rely on adults such as teachers, parents, or private instructors. As a result, they may not have confidence in using E-learning platforms.

The intention to use E-learning platforms continuously is positively affected by autonomy and PU. Consequently, autonomy and PU are thought to be strong indicators. Feeling independent and making a difference increases students' motivation to keep using the E-learning platform. Liaw, Hatala and Huang [54], Ali and Arshad [23], Roca and Gagné [52], and Racero, Bueno and Gallego [28] have reached similar conclusions. The surprising result of this study, however, is that PEOU had no bearing on the participants' continued intent to use the E-learning platform. The results agree with those of Fan and Jiang [95]. Since this is the first occasion that the E-learning platform has been requested of them, the majority of students are unfamiliar with it and have no prior experience using it.

Moreover, the work detailed in this paper is responsible for a great deal of theoretical development. Improving upon previous research, this study develops a new hybrid model that incorporates TAM and SDT. In a country where few studies have addressed the topic, this model was utilized to forecast the ongoing intention to utilize the E-learning platform as a teaching tool in Thailand. Additionally, this study presents a number of important findings and implications regarding the ongoing intention of Thai students to utilize the E-learning platform. Autonomy and PU are the main findings. It was found that autonomy was more dependable than PU. Thirdly, this research presents a number of important conclusions about the elements that influence PU and PEOU. The two most important results are relatedness and autonomy. When compared to relatedness, autonomy is the factor that significantly affects PU. Autonomy is less influential on PEU than relatedness.

A set of recommendations for practical implications can be made based on these important findings. To begin, the E-learning platform must incorporate methods that facilitate relatedness elements like online forums, chats, IMS (instant messaging), and bulletin boards. The ongoing goal of the E-learning platform can be improved with these suggestions, which can make it more practical and easier to use. Second, introducing tools that let students determine their own learning speed and establish a sense of freedom and choice can promote autonomy, which is a vital aspect. Finally, PU is critical for growing the E-learning platform's CI to use. Enhancements that facilitate learning, save time, and make knowledge easier to access can strengthen it. For example, a comprehensive and helpful database is available for all courses, where students can rapidly obtain material.

VII. Conclusion, Limitations, and Future Directions

Due to the outbreak of COVID-19, the Thai government had to close schools and universities. However, universities have chosen the E-learning platform as a useful educational platform to ensure that students' learning will continue progressively during and after the pandemic. The reason is that most university students are reluctant to use E-learning platforms, especially after universities open onsite classes. Besides, they still prefer using E-learning platforms for internet browsing and gaming for educational purposes. Also, there was a dearth of information regarding students' CI in utilizing E-learning platforms in the classroom. Therefore, it was necessary to study the factors that impact the CI to use the E-learning platform among Thai university students. As a result, by developing and testing an empirical research model that combines both theories, this study adds to the existing body of knowledge. Using a questionnaire, we solicited responses from university students. The PLS-SEM method was employed to analyze the data. Two key factors that Thai students considered when deciding whether or not to keep using the E-learning platform were autonomy and PU. The difference is that PEOU had no bearing on the likelihood of continuous intention. In addition, the study found that competence is not a significant predictor of PU and PEOU, but relatedness and autonomy are.

However, some cautions should be noted regarding this work. Due to time limitations, this study is cross-sectional and measures intentions at a specific point in time. Individuals' perspectives evolve as they accumulate life experiences. Therefore, the longitudinal approach is the most effective [96, 97]. Using a purposive sampling technique (i.e., non-probability), the participants in the study were chosen. Therefore, it would be unfair to apply the findings of this study to every university in Thailand. As a result, future work could include different sampling techniques (i.e., probability) to generalize the results. This study has the potential to lay the groundwork for the E-learning system to be used in the classroom. There is still a lack of comprehensive comparison data, information from other nations, and details regarding the practical use. Researchers may want to look into this further in the future to shed light on E-learning's broader educational applications. Incorporating more theories of technology acceptance into future studies can help researchers better understand students' interests and the factors that impact their continuous intention to use new technologies. Cognitive ability, social interactions, and security concerns are additional important factors that may be considered in future research. Moreover, privacy issues with student data collection and algorithmic biases that might unfairly affect disadvantaged groups are just two examples of ethical considerations that need to be carefully considered and regulated in relation to the E-learning system implementation. Recognizing the limitations of E-learning is essential for responsible and effective integration in higher education, despite its potential to improve certain areas. Finally, qualitative methods should be used to better understand the attitudes and behaviors of younger learners in the context of education. More information may be gleaned via participant interviews or focus groups, for example.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Mohamed Soliman conducted the research by developing conceptualization, formal analysis, funding acquisition, project administration, supervision, visualization, writing – original draft, writing, review, and editing. Muhammadafeefee Assalihee developed the methodology, resources, validation, writing – review, and editing. Muhammad Roflee Weahama shared in preparing the methodology, set data curation, validation, writing – review, and editing. Reham Adel Ali set data curation, validation, writing – review, and editing; all authors had approved the final version.

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