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Unlocking AI-Powered Tools Adoption among University Students: A Fuzzy-Set Approach

[1]Mohamed Soliman, [2]Reham Adel Ali, [3]Imran Mahmud & [4]Tawat Noipom
[1&4]Department of Business Innovation, Prince of Songkla University, Thailand
[2]Faculty of Computer Science and IT, Ahram Canadian University, Egypt
[3]Department of Software Engineering, Daffodil International University, Bangladesh

[*1]mohamed.so@psu.ac.th
[2]reham.adel@acu.edu.eg
[3]imranmahmud@daffodilvarsity.edu.bd
[4]tawat.n@psu.ac.th
[*]Corresponding author

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ABSTRACT

This study examines, from a post-pandemic theoretical perspective, university students' continuous intention (CI) to utilise AI-powered tools for educational purposes. AI-powered tools are new and underutilised in higher education. The fact that students and teachers need knowledge to use these apps in the classroom compounds the issue. Despite this technology's recent academic introduction, nothing is known about its impacts. In order to investigate the variables that influence the continual intention to employ artificial intelligence, this study discusses the possibility of integrating the self-determination theory (SDT) and technology acceptance model (TAM) with the post-acceptance model (PAM). Three hundred forty university students were solicited to complete a questionnaire to collect data for the proposed model. A dual-stage approach uses both symmetrical assumptions from structural equation modelling with partial least squares (PLS-SEM) and asymmetrical configurations from fuzzy-set qualitative comparative analysis (fsQCA). In order to better comprehend the intricate interplay between the model's inputs and its desired output, this approach is devised. Consideration is given to the fact that various configurations of external constructs exert distinct influences on internal constructs. In Thailand, perceived usefulness (PU) and autonomy predict continued AI-powered tool use. Perceived ease of use (PEOU) did not affect continuing intention. Conclusions drawn from the configurational analysis show that no single factor adequately explains a high CI level. Rather, three distinct configurations were identified as improving CI using AI-powered tools. Overall, theoretical and practical ramifications are addressed.

Keywords: AI-powered tools, self-determination theory, technology acceptance model, fsQCA, Fuzzy-set.

INTRODUCTION

Higher education has been changed by artificial intelligence (AI) powered tools. Many in- and out-of-class actions constitute student behaviour (Ouyang et al., 2022). Professionalism requires punctuality, thoughtful class participation, meeting deadlines, acting ethically, and engaging with professors and peers. What learners do with these AI-powered tools is a huge concern. AI applications personalise learning and make information accessible, giving students control over their education (Crompton & Burke, 2023). Technologies such as adaptive learning platforms, virtual assistants, and intelligent tutoring are able to fulfil their requirements. This innovative device boosts learners' creativity, problem-solving, and critical thinking (Jaboob et al., 2024). Overusing AI-powered tools can reduce self-regulation and social interaction; thus, colleges and other institutions must handle this. To optimise AI-powered technologies in university settings, instructors must promote safe use and poise human-technology communication (Chen et al., 2023).

However, AI-powered tool implementation strategies and adoption best practices are understudied. Due to their novelty and limited use in higher education, AI applications are deducted (Michel-Villarreal et al., 2023). There is little data and research on how AI applications affect college students' learning (Jaboob et al., 2024). The fact that students and teachers need expertise to use these apps in the classroom compounds the issue. In commercial and industrial settings, generative AI research is still young (Javaid et al., 2022). Thai university faculty, staff, and students can use these apps to better prepare for future jobs. This research will highlight their rank in the university setting and boost them (Yeralan & Lee, 2023).

Furthermore, most learners are wary of AI tools (Yeralan & Lee, 2023). Additionally, the majority of them favour using online learning platforms for internet browsing and gaming for educational purposes (Alzaidi & Shehawy, 2022). The educational system still struggles with high-rote learning, low student interaction, and complete teacher dependence (Jurayev, 2023). Research on what encourages students to use AI-powered technologies and their benefits is needed. There are no methods to measure their ongoing commitment to the instructor's teaching and AI-powered tools. There is little study on university students' continuous AI use in developing nations like Thailand.

This study examines the elements influencing learners' continued usage of AI-powered tools to fill the gaps. This study will motivate students to use AI and improve policymakers' methods and resources. With the purpose of providing more detailed and nuanced insights into the complex causal relationships between the antecedent and selected key target output, partial least squares structural equation modelling (PLS-SEM), which makes symmetric assumptions, is paired with a fuzzy-set qualitative comparative analysis (fsQCA) method, which makes asymmetric configurations (Cifci et al., 2023). This study provides practitioners valuable insight and enhances our theoretical understanding of AI-powered teaching aids. Through self-determination theory (SDT), the technological acceptance model (TAM), and the post-acceptance model (PAM), this research advances understanding. It illuminates what motivates college students to use AI-powered products. Finally, this study addresses a literature gap by empirically investigating college students' intentions to use AI. Our theoretical grasp of the problem is equally inadequate. “What are the important factors and configurations of external variables that impact university students' CI to utilise AI-powered tools?” That was the primary research question that inspired this study.

LITERATURE REVIEW

Table 1 provides a comprehensive overview of previous studies that have explored the use of various learning technologies, the associated variables, and the theoretical frameworks underpinning these studies. By summarising this information, the table highlights trends, gaps, and patterns in the field, serving as a foundation for understanding the diverse applications of technology in learning environments. This contextualisation supports further analysis and comparison of how different technologies and theoretical approaches influence learning outcomes and user behaviour. It reveals that most studies develop learning tools and ignore university AI technology. Thus, AI-powered tool deployment methodologies and adoption best practices are understudied. The extent to which AI applications affect college students' learning is unknown. Integrating SDT, TAM, and PAM to study AI has not been documented. This study utilises SDT, TAM, and PAM to predict student AI use.

Table 1

Learning Technology-Based Previous Studies

Author	Technology used	Variables	Theory
Cortez et al. (2024)	Communicational AI	Autonomy, Relatedness, Competence, Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), Habit, Value, Hedonic motivation, Behavioral Intention (BI), Use	SDT, UTAUT2 (Unified Theory of Acceptance and Use of Technology)
Fan and Jiang (2024)	AI Drawing Tools	PU, PEOU, Switching cost, Confirmation, Satisfaction, SN, Risk, Playfulness, CI	Expectation confirmation model (ECM)
Foroughi et al. (2023)	Chat Generative Pre-Trained Transformer (ChatGPT)	PE, EE, FC, Social Influence (SI), Hedonic Motivation, Learning Value, Habit, Information accuracy, Innovativeness, BI	UTAUT2
Wang and Zhang (2023)	Generative AI for Art Designing	Performance Expectancy, Effort Expectancy, Optimism, Innovativeness, Hedonic Motivation, Price Value, Trait curiosity, BI	UTAUT2, Technology Readiness Index (TRI)

(continued)

Author	Technology used	Variables	Theory
Saxena et al. (2021)	E-learning	Assurance, Empathy, Reliability Responsiveness, Learning content Website Content, EL Quilty, Satisfaction	Cognitive theory of multimedia learning, Social cognitive theory, Information systems continuance model
Mailizar, Burg and Maulina (2021)	E-learning	System Quality (SQ), E-Learning Experience (XS), PU, PEOU, Attitude, BI	TAM
Yuan et al. (2021)	Mobile learning	Learning content quality, Interactivity, User Interface, Connectivity, PU, PEOU, Experience Response (ER)	TAM
Shahzad et al. (2021)	E-learning	SQ, Information quality (IQ), Service quality (SQ), Use, Satisfaction, EL Success	DeLone & McLean Theory
Sukendro et al. (2020)	E-learning	FC, PU, PEOU, Attitude, BI, Use	TAM
Lai (2020)	Mobile learning	EE, PE, SI, FC, BI, Use	UTAUT
Tawafak et al. (2020)	E-learning	Interactivity, Support Assessment Teacher Subject Knowledge, Academic Performance, PU PEOU, Technology Integration, Course Content, BI, Effectiveness, Satisfaction, CI	TAM
Tam et al. (2020)	Mobile learning	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, Habit, Confirmation, Satisfaction, CI	UTAUT 2, ECM
Al-Emran et al. (2020)	Mobile learning	PU, PEOU, Satisfaction, Expectation confirmation, Attitude, Perceived Behaviour Control, Subjective Norms, CI, Actual Use	TAM, ECM, Theory of planned behaviour (TPB)
Akour et al. (2021)	Mobile Learning	Attitude, Subjective norm, Perceived behavioural control, Perceived fear, PEOU, PU, BI	TAM, TPB
Racero et al. (2020)	Open-Source Software	Autonomy, Relatedness, Competence, PU, PEOU, BI	TAM, SDT

Self-Determination Theory (SDT)

SDT holds that humans are dynamic and naturally evolve psychologically (Sheeran et al., 2020). Humans naturally seek adventure, new experiences, and education. Internalisation also shows it, according to Ryan (2009). SDT creates the framework for development, honesty, and wellness by addressing basic psychological needs. It recognises competence, independence, and interdependence (Howard et al., 2020). SDT is particularly relevant to technology adoption because it focuses on intrinsic motivation factors (autonomy, competence, and relatedness) that are critical for ensuring people adopt, engage with, and continue using technologies. The theory provides a deep psychological understanding that can be applied to the design of tech products, improving their adoption rates (Ryan, 2009).

Technology Acceptance Model (TAM)

Davis (1989)'s information systems theory investigates how new systems or technologies alter users' attitudes, beliefs, and intentions. Perceived ease of use (PEOU) and perceived usefulness (PU) describe users' technological acceptance of new systems and technology, according to Legris et al., (2003). PEOU defines that technology will be easy, while PU boosts performance (Davis et al., 2023). PU and PEOU demonstrate that simple technology is valued. They cause behavioural intentions and provide explanations for preferring appropriate technologies, causing academics and professionals to act (Davis et al., 2023).

The Post-Acceptance Model (PAM)

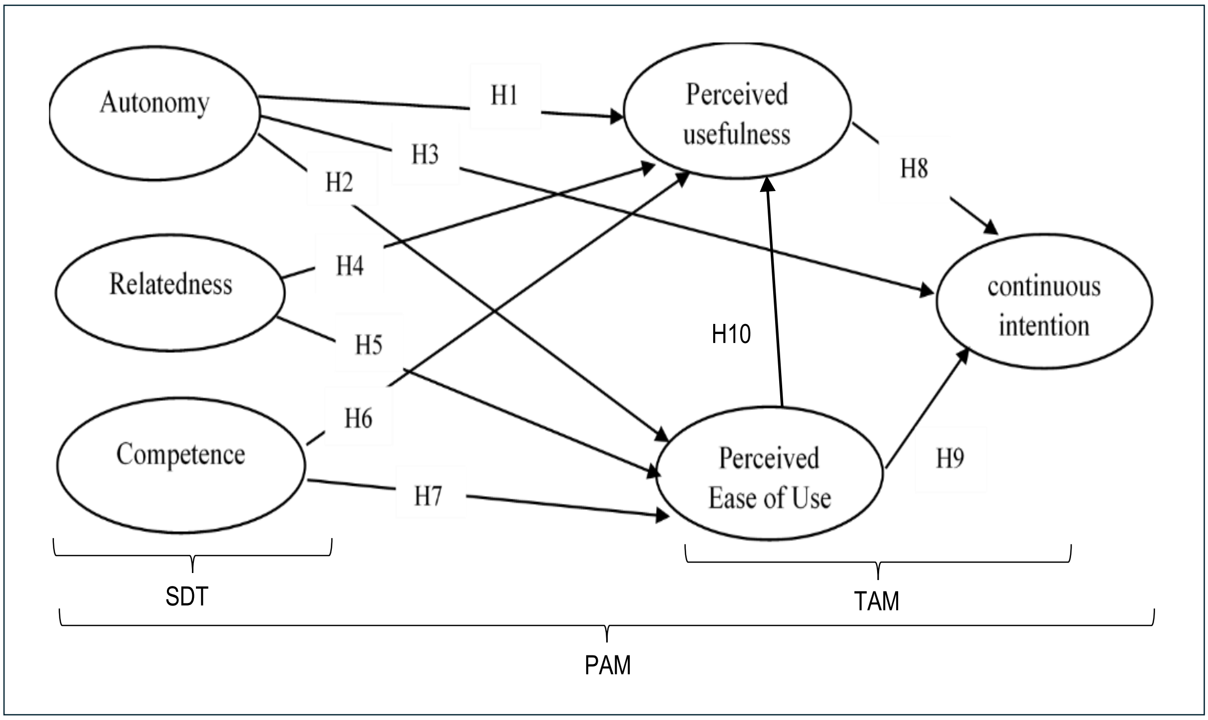
The post-acceptance model of an information system (IS) continuance seeks to explain IS users' intention to continue (or discontinue) IS use (Bhattacherjee, 2001). Because of its emphasis on actions taken after acceptance, it is a great theoretical framework for studying both new and ongoing usage patterns (Wang & Hsieh, 2006). The concept is based on the premise that consumers will generate an opinion about how much their pre-acceptance expectations are confirmed after an initial period of use and acceptance. Consequentially, consumers form views regarding the advantages (Mishra et al., 2023). Users' levels of satisfaction with the IS are impacted by their perceptions of its utility and the degree to which they feel it confirms their initial assumptions. Lastly, the users' happiness and PU play a role in explaining their willingness to keep using the IS (Larsen et al., 2009). Nevertheless, PAM disregards the pre-consumption assumption in favour of a confirmation-influenced variable that influences customer satisfaction through PU, which in turn affects customers' intentions to continue using that particular information system (Susanto et al., 2023).

Research Framework and Hypotheses Development

Figure 1 exhibits the study's proposed research framework. This study model is developed by combining SDT (i.e., competence, relatedness, and autonomy) and TAM (i.e., PU and PEOU) with PAM.

Figure 1

The Proposed Research Framework



SDT Constructs: Autonomy

In autonomy, self-regulation is the key, not external interference. Being independent means taking command of one's life. It means learners have to take charge of their learning. Students choose to study (Nikou & Economides, 2017). Students feel empowered to learn and achieve their goals (Adams & Khojasteh, 2018). Student satisfaction affects autonomy. Autonomy-based motivation boosts happiness (Joo et al., 2018). Racero et al. (2020), Nikou and Economides (2017), and Rezvani et al. (2017) demonstrated favourable associations between perceived autonomy, PU, and PEOU in ICT environments. Cortez et al. (2024) and Liaw et al. (2010) found a strong link between autonomy and technological acceptability. These findings led to these hypotheses:

H1: Autonomy boosts PU.
H2: Autonomy boosts PEOU.
H3: Autonomy improves CI.

SDT Constructs: Relatedness

Becoming "related" signifies wanting to join a larger fraternity. "Relatedness" in the classroom allows students to collaborate and interact (Sergis et al., 2018). Socialising and making friends can benefit pupils, according to SDT (Adams & Khojasteh, 2018). Individuals may experience a greater sense of ease when discussing knowledge due to the relatedness. According to Cortez et al. (2024) and Racero et al. (2020), relatedness predicted PEOU and PU. The following hypotheses were proposed:

H4: Relatedness boosts PU.

H5: Relatedness boosts PEOU.

SDT Constructs: Competence

Competence helps people achieve their goals and excel. A perception of value is achieved (Ryan & Deci, 2017). Previous research on education competence linked PU to PEOU (Jeno et al., 2017; Roca & Gagné, 2008). Students must master online learning to succeed in class (Niemiec & Ryan, 2009). Thus, the following hypotheses have been put forth:

H6: Competence boosts PU.
H7: Competence boosts PEOU.

TAM Constructs: PEOU and PU

An individual's level of confidence in the convenience and security of a system is measured by the PEOU. In contrast, Perceived Usefulness (PU) is the belief that a system would improve job performance (Davis, 1989). Following studies of Racero et al. (2020), Diop et al. (2019), and Al-Rahmi et al. (2021), PU and PEOU influence technological adoption. The following hypotheses were proposed:

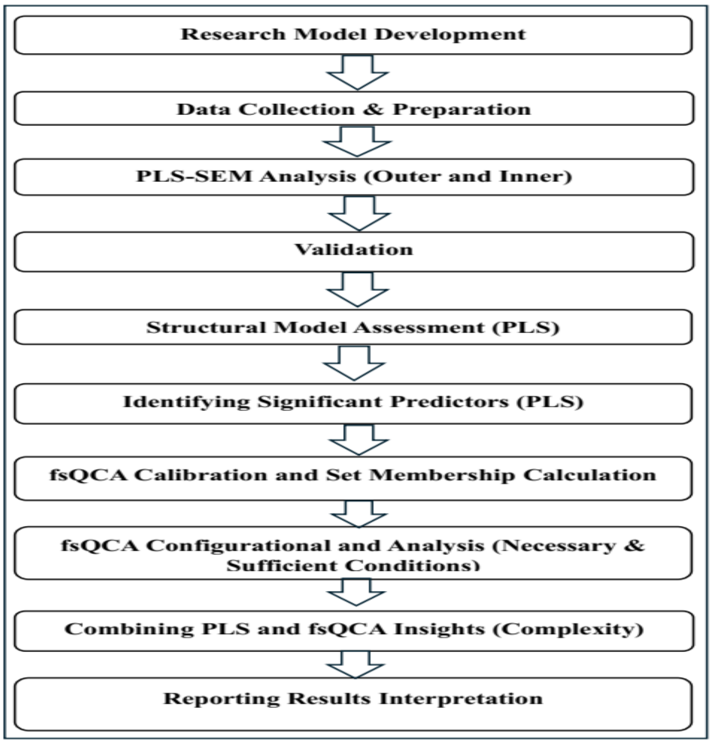
H8: PEOU improves students' AI CI.
H9: PU boosts students' CI to use AI well.
H10: PEOU boosts PU.

METHODOLOGY

Figure 2 depicts the study methodology providing a well-rounded approach by integrating both PLS-SEM, which is strong in identifying direct relationships, and fsQCA, which is ideal for exploring complex and non-linear combinations of factors. Each step contributes to a comprehensive understanding of the research question. By systematically following these steps, researchers can effectively combine PLS-SEM and fsQCA methodologies to explore linear and complex configurational relationships, providing a richer understanding of the studied phenomena.

Figure 2

The Research Process



Population and Sample

This study honours consensual, informed, discreet, and anonymous. This survey included university students from Pattani, Yala, and Narathiwat in southern Thailand. AI-using university students were involved in the research unit of analysis. The initial research instrument was carefully pre-tested by three education and IT academics and two online learning professionals. After this iterative process, certain things were reworded or upgraded to create the final measuring items. In pilot research, the Cronbach alpha statistic was used to examine questionnaire items for scale reliability. Tavakol and Dennick (2011) stated that all items were dependable since their values were above 0.70. According to Faul et al. (2009), G*Power established a minimal sample size. For the G*Power measures, the values for medium effect size are 0.15, error type (α) is 0.05, power is 0.80, and predictors are 5. Researchers concluded that 92 instances were necessary for a viable sample. The survey was done with Google Forms. The subjects were purposively sampled. The online survey was completed by 340 students, and all questions are mandatory to avoid missing data. The software of SmartPLS 4.0 analysed the direct and indirect research variables relations using structural equation modelling. IBM SPSS 26 analysed descriptive data. The fuzzy set approach was implemented in fsQCA 4.0.

Instrument

The initial portion of the survey is designed to gather demographic information from the participants. In section two, we measured the conceptual model's constructs, which include autonomy, PU, relatedness, PEOU, competence, and CI (see Table 2). We used the "7-point Likert scale" to quantify these variables. References for the competence and autonomy assessment items are from Nikou and Economides (2017) and Lee et al. (2015). Relatedness items were taken from the works of Lee et al. (2015) and Sørebø et al. (2009). We used items from Venkatesh et al. (2003) and Nikou and Economides (2017) to measure PU and PEOU. Bhattacherjee (2001) was consulted for the items of continuing intention. We selected three items adapted from Lin et al. (2015) as a marker variable that would be collected in the same survey but were not included in the model being tested: (1) "Once I have come to a conclusion, I am not likely to change my mind;" (2) "I do not change my mind easily;" and (3) "My views are very consistent over time."

Table 2

Measurement Items

x	Survey questions	Source
Autonomy	AUT1. I feel a sense of choice and freedom using AI-powered tools. AUTO2. AI-powered tools provide me with interesting options and choices. AUT3. I have more control while using AI-powered tools. AUT4.AI-powered tools give me more chances to control my tasks.	Nikou and Economides (2017) and Lee et al. (2015)
Relatedness	RLT1. I really like AI-powered tools users. RLT2. AI-powered tools give me more chances to interact with others. RLT3. I feel close to others while using AI-powered tools. RLT 4. I have more opportunities to be close to others through AI-powered tools.	Lee et al. (2015) and Sørebø et al. (2009)
Competence	COM1. I am better at AI-powered tools than other users. COM2. I have stronger capability than other users, thanks to AI-powered tools COM3. I am superior to others by using AI-powered tools. COM4. I have been able to learn an interesting new skill through AI-powered tools.	Nikou and Economides (2017) and Lee et al. (2015)
Perceived usefulness	PU1. Using AI-powered tools enhances my effectiveness. PU2. AI-powered tools are useful for my life/job. PU3. Using AI-powered tools increases my productivity. PU4. Using AI-powered tools helps me accomplish things more quickly.	Venkatesh et al. (2003) and Nikou and Economides (2017)
Perceived ease of use	PEOU1. My interaction with AI-powered tools and solutions is clear and stable. PEOU2. It is easy for me to become skilful at using AI-powered tools. PEOU3. I find AI-powered tools easy to use.	Venkatesh et al. (2003) and Nikou and Economides (2017)
Continuous intention	CI1. I intend to continue using AI-powered tools rather than discontinue their use. CI2. I intend to continue using AI-powered tools rather than other alternative means. CI3. If I could, I would like to continue using AI-powered tools	Bhattacherjee (2001)
Marker variable	Mk1. Once I have concluded, I am not likely to change my mind. Mk2. I do not change my mind easily. Mk3. My views are very consistent over time.	Lin et al. (2015)

Data Analysis

The proposed research model was assessed using SmartPLS 4.0 and PLS analysis (Ringle et al., 2022). Anderson and Gerbing (1988) split analytical techniques into measurement model assessment and postulated relationship testing as structural model evaluation. Many researchers utilise PLS-SEM to analyse their research models as a key advantage. PLS-SEM generates hypotheses from causal-predictive model linkages (Chin et al., 2020). Augmenting underlying relationship estimates enhances predictive concept-explained target construct (Liu et al., 2022). The gap between explanation and prediction has been narrowed, and their model possesses greater statistical power than factor-based structural equation modeling (Becker et al., 2023; Sarstedt et al., 2022). Hair and Alamer (2022) analyse aggregate indicator scores using ordinary least squares regressions. PLS is best for this study due to these considerations. To further integrate symmetric assumptions with asymmetric configurations, a fuzzy-set qualitative comparative analysis (fsQCA) method is applied on top of the PLS-SEM (Aw et al., 2022; Ragin, 2008). The fsQCA creates several routes by following the complex and asymmetrical relationships between causes and effects, as opposed to PLS-SEM's symmetric assumptions (Pappas & Woodside, 2021). Our goal in using this approach is to comprehend better the relationship between the antecedent and a few selected result variables. The effects of different output and input configurations are considered (Li et al., 2022; Rasoolimanesh et al., 2021).

Profile of the Respondents

This survey had 64.1% female and 35.9% male respondents. Since the sample is made up of university students, they are 19–23 years old. Only 42.1% of respondents have used instructional websites like YouTube for learning, while 57.9% have never done so. Also, 55.9% preferred AI-powered tools for continued learning, whereas 44.1% disliked using them.

Common Method Bias (CMB)

PLS-SEM analysis would not be affected by CMB. CMB relevance in PLS analysis is disputed (Ghasemy et al., 2020). Table 7 shows that the inner model's VIF values are less than 3.3, making the current model CMB-free (Kock, 2015). From study design to data collection, common method variation generated by data collection method similarity can be reduced. This study addresses procedural and statistical remedies before and after data collection. Following Rönkkö and Ylitalo (2011), the marker variable technique was utilised to check the CMB concern. PLS marker model results are compared to baseline model results. R^2 changes are less than 10% in CI of 0.23%, PU of 3.7%, and PEOU of 0.49%. CMB is not a major concern in this study paradigm (Mahmud et al., 2017).

RESULTS AND FINDINGS

Measurement Model Assessment

Building the proposed model requires evaluating the outer models, according to Hair and Alamer (2022). When evaluating the outer model, factor loading, discriminate validity, composite reliability (CR), and average variance extracted (AVE) are all taken into consideration. With the exclusion of the eliminated PU1 (0.496) and RLT4 (0.638), all outer loadings are greater than Hair et al. (2019)'s proposed value of 0.708, indicating that AVE and CR have met the requirements of > 0.50 and > 0.70 (see Table 3).

Table 3

Factor Loading, CR, and AVE

Constructs	Items	Loadings	CR	AVE
Autonomy	AUT.1	0.859	0.885	0.731
	AUT.2	0.900		
	AUT.3	0.786		
CI	CI.1	0.773	0.873	0.706
	CI.2	0.897		
	CI.3	0.831		
Competence	COM.1	0.740	0.822	0.614
	COM.2	0.841		
	COM.3	0.753		
PEOU	PEOU.1	0.819	0.881	0.721
	PEOU.2	0.867		
	PEOU.3	0.844		
PU	PU.2	0.888	0.906	0.775
	PU.3	0.888		
	PU.4	0.836		
Relatedness	RLT.1	0.756	0.861	0.684
	RLT.2	0.783		
	RLT.3	0.887		

Discriminant Validity

Henseler et al. (2015) proposed the HTMT for discriminant validity evaluation (Table 4). Given that the HTMT values are less than the HTMT.90 value of 0.90, Gold et al. (2001) state that discriminant validity is not a concern.

Table 4

Discriminant Validity

	Autonomy	Competence	CI	PEOU	PU	Relatedness
Autonomy						
Competence	0.825					
CI	0.836	0.793				
PEOU	0.570	0.620	0.477			
PU	0.610	0.492	0.612	0.615		
Relatedness	0.807	0.845	0.819	0.529	0.732	

Assessment of Structural Model

Multicollinearity Test (VIF)

Before assessing the inner model, check for collinearity to avoid biased regression findings (Hair et al., 2019). The partial regression scores of the latent variables on the predictor constructs yield a variance inflation factor (VIF). Multicollinearity indicates redundant information from associated predictors. The VIF found value. A small VIF means variables are not closely connected. VIF values below 3.3 are excellent (Kock, 2015). In the study model, all VIFs are below 3.3 (Table 7). It was concluded that the research model had no multicollinearity concerns.

Coefficient of Determination (R2)

The impact level for R^2 is zero to one. Cohen (1988) considered R^2 values of 0.26, 0.13, and 0.02 considerable, moderately strong, and weak for endogenous variables. Table 5 reveals high predictive accuracy for CI, PEOU, and PU in this investigation. Relatedness, competence, and autonomy describe 29 percent of PEOU variation. Also, they affect PU variation by 49 percent. Lastly, 51 percent of the variation in CI may be explained by PEOU and PU.

Table 5

Coefficient of Determination

Endogenous variables	R Square
CI	0.51
PEOU	0.29
PU	0.49

PLS Predictive Power

Using the model's predictive power for endogenous constructs (PEOU, PU, CI), ten folds and ten iterations of $PLS_{predict}$ were used (Sharma et al., 2022). We first examined if $Q^2_{predict}$ was above zero, suggesting that the PLS route model exceeded the training data indicator means. PLS-SEM estimates were compared to a linear benchmark model's RMSE (Hair et al., 2019). Table 6 shows $PLS_{predict}$ results. All endogenous construct indicators had positive $Q^2_{predict}$ values. Compared to the linear model, PLS-SEM had lower RMSE values overall. Overall, the PLS path model predicts the endogenous constructs of interest strongly because all item differences (PLS-LM) are smaller (Shmueli et al., 2019).

Table 6

Predictive Power Assessment using $PLS_{predict}$

Items	$Q^2_{predict}$	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

(continued)

Items	$Q^2_{predict}$	PLS-SEM_RMSE	Linear Model _RMSE
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

Predicting Path Coefficient

An estimation of the path coefficients for the proposed research model was carried out using bootstrap t-values with 5,000 resamples (Henseler et al., 2009). Path coefficients range from -1 to +1. A strong positive association is produced when the value is around 1; -1 is negative. Thus, the path coefficients' least significant level should be 0.05. At 10%, 5%, and 1% significant levels, critical values of 1.645, 1.96, and 2.33 are assigned to the one-tailed test (Ramayah et al., 2014). Out of the ten hypotheses evaluated in the study, Table 7 reveals that three hypotheses (i.e., H4, H6, and H9) were not supported by the data. The effect size was estimated using Cohen's method (Cohen, 1988). Effect sizes of 0.02, 0.15, and 0.35 are small, medium, and substantial. Table 7 shows that relatedness and autonomy greatly affect CI and PU. PEOU moderately affects PU, while other factors are negligible. PEOU did not influence CI.

Table 7

Result of Hypothesis Test and Path Coefficient

No.	Relationship	Std. Beta	Std Error	t-value	P value	f^2	Effect size	VIF	Supported
H1.	Autonomy -> CI	0.58	0.12	5.03	0.00	0.45	Larger	1.52	Yes
H2.	Autonomy -> PEOU	0.24	0.14	1.66	0.05	0.03	Low	2.47	Yes
H3.	Autonomy -> PU	0.22	0.12	1.88	0.03	0.04	Low	2.55	Yes
H4.	Competence -> PEOU	0.20	0.15	1.27	0.10	0.02	Low	2.32	No
H5.	Competence -> PU	-0.20	0.11	1.86	0.03	0.03	Low	2.38	Yes
H6.	PEOU -> CI	0.03	0.10	0.25	0.40	0.00	No	1.54	No
H7.	PEOU -> PU	0.33	0.15	2.24	0.01	0.15	Moderate	1.41	Yes
H8.	PU -> CI	0.20	0.11	1.81	0.04	0.05	Small	1.63	Yes
H9.	Relatedness -> PEOU	0.17	0.13	1.34	0.09	0.02	Low	1.98	No
H10.	Relatedness -> PU	0.45	0.13	3.51	0.00	0.19	Larger	2.02	Yes

Model Fit

The model's accuracy was initially assessed by fitting it to two adjustment variables: the normed fit index (NFI) and the standardised root mean square residual. SRMR values less than 0.08 (calculated by subtracting the observed correlation matrix from the model-implied correlation matrix) indicate a well-fit model (Hu & Bentler, 1998). In the PLS-SEM approach, Henseler et al. (2014) recommended the SRMR as a goodness-of-fit metric to avoid model misspecification. The normed fit index is the second model fitness metric. Ramayah et al. (2017) present a second model fitness metric that compares the proposed model's chi-square value to a meaningful standard. NFI values above 0.90 usually suggest a satisfactory match (Bentler & Bonett, 1980). The saturated (measurement) model had no free routes, therefore calculating the structural model and fitting it to it yielded comparable results. Table 8 shows that the data matched the model well, with an SRMR of 0.070 (< 0.08) and an NFI of 0.910 (> 0.90).

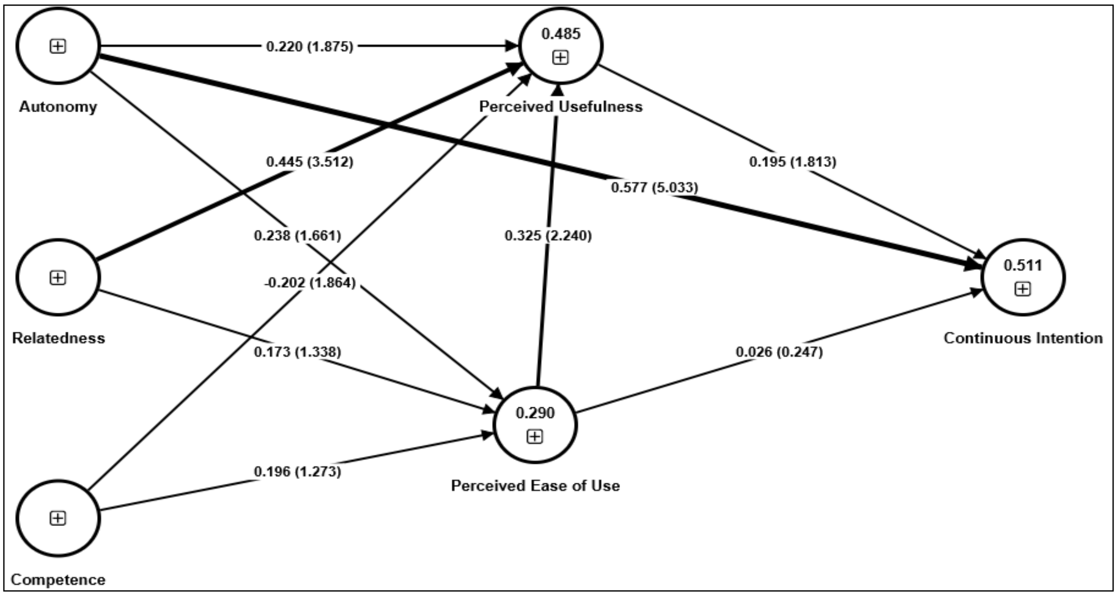
Table 8

Testing Model Fit

Parameter	Saturated model	Estimated model
SRMR	0.063	0.070
NFI	0.913	0.910

Figure 3

The Research Model



Findings of Asymmetric Analysis

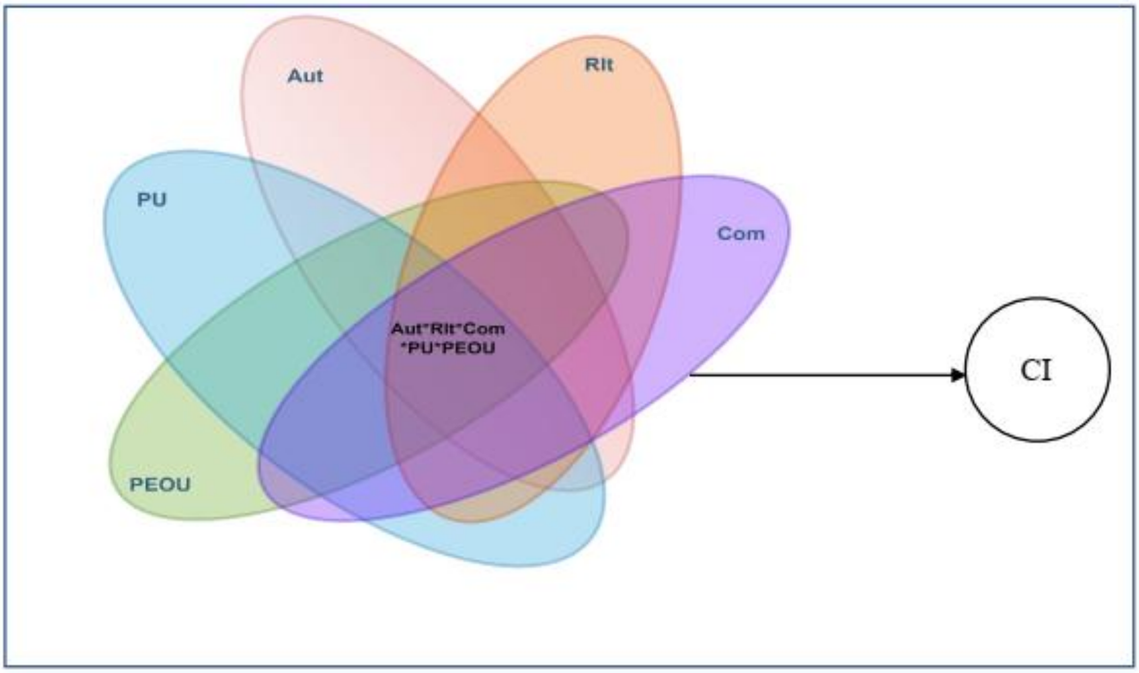
We used fuzzy-set qualitative comparative analysis (fsQCA), as shown in Figure 3, to offer a new viewpoint compared to PLS-SEM (Pappas & Woodside, 2021). PLS-SEM is based on symmetric assumptions and finds the net influence of competing variables in a model. When compared to the SEM approach, fsQCA produces more pathways since it follows the complex and uneven relationships between causes and effects. Because it works with both inductive and deductive reasoning, the fsQCA approach is flexible enough to be utilised for theory testing, creation, and elaboration (Park et al., 2020). Considering the intricate web of links between the independent variables and the dependent variable, we think fsQCA can shed light on the true causes of the result (Cifci et al., 2023).

Calibration

Following the methods laid out by Ragin and Fiss (2008), the first step of fsQCA, calibration, was executed. The membership score sets used by fsQCA are derived from ordinal or interval scales by the application of the set membership theory. Fuzzy set membership scores were produced by converting latent variable scores from a PLS-SEM model using the calibrating function available in the fsQCA 4.0 software (Rasoolimanesh et al., 2021). A score of 0 indicates complete non-membership of any fuzzy set, while a score of 1 indicates complete membership in any fuzzy set. Scores for fuzzy sets can be anywhere from 0 (not at all in the fuzzy set) to 1 (completely in the fuzzy set), with 0.50 serving as a cross-over point (intermediate set) (Ragin, 2008). We used a 7-point Likert scale with a full membership guarantee of 0.95, a cross-over point of 0.50, and a foundation for full non-membership of 0.25 (Ordanini et al., 2014; Pappas & Woodside, 2021).

Figure 4

The Research Model (Asymmetric Model)



Note: Aut: autonomy, Rlt: relatedness, Com: competence, PU: perceived usefulness, PEOU: perceived ease of use, CI: continuous intention.

Identifying the Configurations

Ragin (2008) proposed that sufficiency should take priority compared to necessity. However, when we looked at each possible causal factor independently, we concluded that the maximum consistency falls below the threshold value of 0.90, with a value of 0.83, as shown in Table 10. Consequently, we failed to identify any prerequisites. Next, the fuzzy set technique was used using the fsQCA 4.0 program. The outcome was a 2k-row truth table, and every row stands for a distinct combination of those variables, with k being the number of independent variables. The following step involves removing the rows of the truth table that did not meet the minimum frequency requirement of 2. If the sample size is 100, Fiss (2011) suggests using a threshold of 2, but if it is 150 or more, you should use a threshold of 3 or higher.

Parsimonious, complex, and intermediate are the three primary results of the fsQCA (Ragin, 2008). According to Rasoolimanesh et al. (2021), the intermediate solution was chosen due to its perceived superiority in terms of completeness and interpretability. A high CI was observed in three distinct configurations. A model's value and the fsQCA findings can be better understood by paying close attention to the two most important metrics: coverage and consistency. Similar to correlation, consistency evaluates the accuracy of a set of observed configurations in predicting an event, whereas coverage, similar to R^2 in regression, determines the set's practical significance (Ragin, 2008). We remove any settings with a consistency score below 0.90. Every single configuration and the final solution we kept showed very high levels of consistency (>0.75) and coverage (>0.20) (Rasoolimanesh et al., 2021). The three identified configurations were determined to give adequate explanations for the presented results, with an overall solution coverage of 0.726 (Table 9).

Table 9

Intermediate Solution Results (i.e., Combinations that Lead to High CI)

Path	Aut_	Com_	Rlt_	PU_	PEOU_	Raw Coverage	Unique coverage	Consistency
PU_*Rlt_*Aut_	●		●	●		0.668688	0.399839	0.965276
PU_*PEOU_*Rlt_*~Com_		○	●	●	●	0.210894	0.0234487	0.928096
~PEOU_*Rlt_*Com_*Aut_	●	●	●		○	0.242571	0.0343643	0.923077
Solution coverage: 0.726403								
Solution consistency: 0.9617334								

Note: Black circles (●) symbolise a condition presence, and circles with “x” (○) symbolise its negation. Blank spaces show that the condition may be either present or absent.

Necessity Conditions

Analysing whether a single condition is always present or absent when the outcome is present is known as necessary condition analysis (or absent). Ragin (2008) put out a 0.90 consistency for causal components that, by themselves, may account for the result (CI). The consistency ratings are between 0.223 and 0.830 (see Table 10). Conditions that meet or surpass the 0.65 consistency threshold are denoted by a superscript (a). According to the findings, consistency scores for four causal conditions are higher than 0.65. Although none of our conditions can fully explain CI alone, these causal conditions are typically necessary prerequisites.

Table 10

Necessity Conditions

Construct	Consistency	Coverage
Aut_	0.779665 [a]	0.780453
~Aut_	0.309077	0.159971
Com_	0.708308 [a]	0.660384
~Com_	0.373964	0.201218

(continued)

Construct	Consistency	Coverage
PU_	0.806348 [a]	0.798120
~PU_	0.254700	0.132604
PEOU_	0.592885	0.643485
~PEOU_	0.480089	0.238886
Rlt_	0.830403 [a]	0.843186
~Rlt_	0.223974	0.115081

Note: Symbol "~" indicates the absence of a condition—a Meets 0.65 consistency benchmark for usually necessary conditions.

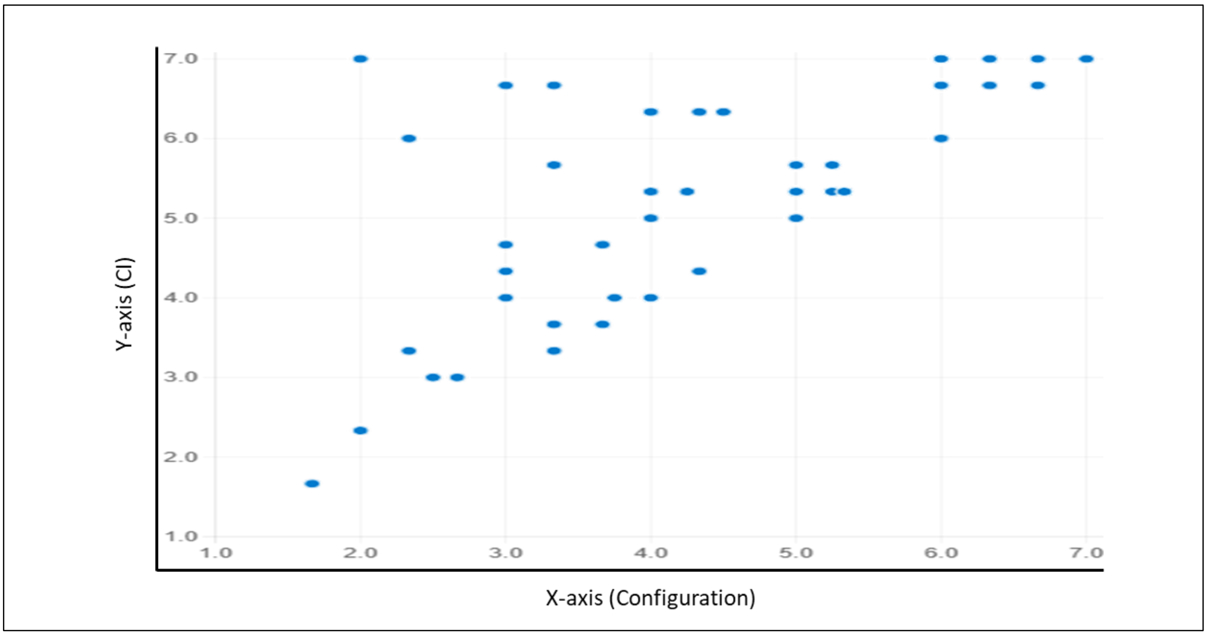
Predictive Validity

When a model can accurately anticipate results across multiple data sets, this is called predictive validity (Rasoolimanesh et al., 2021). According to Pappas and Woodside (2021), predictive validity is important since a good model fit does not guarantee accurate predictions. It sheds light on how well the model performs when asked to forecast the dependent variable across diverse samples. First, we use SPSS software to randomly divide the sample into two subsamples (a subsample and a holdout sample) to evaluate predictive validity. Subsample 1 was modelled with the help of the fsQCA analysis. Subsample 1's findings were compared to those of the whole sample. Subsample 1 results were consistent with the sample as a whole, showing a solution consistency of 0.971. A high score in CI, for instance, can be shown by a predictive validity test using a variety of algorithms (PU*PEOU*Rlt*Aut*Com) for Subsample 1 (consistency: 0.971) similar to the findings from fsQCA across the full sample (consistency: 0.961). Second, using the holdout sample and the XY plot of fsQCA 4.0, each solution, which includes various combinations of causal conditions that are present and those that are absent, was modeled as a single variable and plotted against the intended outcome (CI).

Each solution, which includes various combinations of present and absent causal circumstances, is plotted (using the XY plot of fsQCA 4.0) against the desired result (CI) using the holdout sample. As an illustration, the holdout sample (subsample 2) was used to test the prior configurational model (PU*PEOU*Rlt*Aut*Com). The asymmetric association in subsample 2 (consistency: 0.997) was almost identical. As illustrated in Figure 5, the results of Subsample 2 indicate that the model's predictive validity has been established for all configurations that are necessary to predict CI from Subsample 2. For the CI construct, the results of the fsQCA's predictive power analysis agree with those of $PLS_{predict}$, indicating that the predictive power is adequate for the proposed model.

Figure 5

The XY Plots for Predictive Validity to Predict CI on Subsample 2



DISCUSSION

This study sought to determine what motivates Thai university students to adopt AI-powered technologies. This study used SDT, TAM, and PAM, three theoretical frameworks. The discussion section details the survey's empirical findings. Seven of the 10 further hypotheses were supported by the model. This study mostly adds to the growing body of studies on how technology affects education and training. We offer three configurations as options to cope with causal complexity and accomplish CI using AI-powered tools; we explain how the fsQCA application may be better than linear-based PLS-SEM. The first proposed solution states that CI can be advanced in the presence or lack of competence or PEOU through the combined effects of relatedness, autonomy, and PU. In the same vein, solution 2 shows that relatedness, PU, and PEOU, in conjunction with autonomy (or its absence) during competence negation, can produce high CI.

Solution 3 significantly shows that high CI can still be reached with relatedness, competence, and autonomy, even while PEOU is not present. Besides, the predictive power obtained using fsQCA is consistent with that obtained using $PLS_{predict}$, indicating that the predictive power is a good fit. Finally, the three configurations of fsQCA that use a combination of content attributes provide credence to the "general tendency" results of PLS-SEM, which indicate a high CI of using AI-powered tools in the classroom. These new data suggest that we should not focus on finding the one variable that makes the most difference in CI outcomes but rather that several effective ways exist to achieve the same goal. The relative relevance of each attribute is situational; thus, there is no universally applicable criterion for determining which qualities merit special attention. Based on the findings, a "mix and match" approach is recommended for creating the best possible pattern combinations.

Predictors of Perceived Usefulness and Perceived Ease of Use

Relatedness and autonomy constructs boost PU and PEOU. Thus, relatedness and autonomy are crucial determinants. This finding supported prior studies by Cortez et al. (2024) and Racero et al. (2020). It shows that AI with independence and connection is practical and user-friendly. Competence does not impact PU or PEOU. Competency is a poor indicator. This deduction contradicts Liaw and Huang (2015) and Jeno et al. (2017), who found competence crucial in PU and PEOU. It may be because Thai culture differs from other countries (Imsa-ard, 2020). Thai learners depend on teachers, parents, and private tutors. Thus, they may distrust AI-powered tools.

Predictors of Continuous Intention to Use AI-Powered Tools

Autonomy and PU are substantial factors since they favourably affect the inclination to use AI-powered solutions continually. Students are motivated to use AI when they feel independent and impactful. Cortez et al. (2024), Liaw et al. (2010), and Racero et al. (2020) reached similar conclusions. However, PEOU did not affect participants' AI use, which was surprising. Results match Fan and Jiang (2024). Since AI is being requested for the first time, most students have never used it.

Threats of Validity

All the model constructs have accomplished the thresholds of average variance extracted (AVE) > 0.50 and composite reliability (CR) > 0.70 (see Table 3). Also, the discriminant validity of this study is not a concern (see Table 2). Autonomy has an AVE value of 0.741 and a CR value of 0.895. Likewise, the competence fulfils the AVE (0.624) and CR (0.832) thresholds. Relatedness has an AVE value of 0.694 and a CR value of 0.871. Both PEOU and PU constructs achieve AVE values of 0.731 and 0.785 within CR values of 0.891 and 0.916, respectively. CI fulfils the thresholds of AVE (0.716) and CR (0.883).

Research Implications

The theory has advanced greatly due to this paper's effort. This work creates a hybrid model using SDT, TAM, and PAM, improving on earlier research. This model predicted the CI to use AI as a teaching tool in Thailand, where few studies have been done. This study also sheds light on Thai students' AI usage intentions. The major findings are autonomy and PU. PU was less reliable than autonomous. Thirdly, this study draws numerous key findings about PU and PEOU factors. The most important outcomes are the constructs of relatedness and autonomy. Autonomy influences PU more than relatedness. PEOU is more affected by relatedness than autonomy. This study additionally improves on previous methods by using a PLS marker variable strategy to eliminate CMB in the PLS structural pathway. The results prove beyond a reasonable doubt that using the PLS marker variable to eradicate CMB problems is a viable option.

We further state that the study's contribution (i.e., CI) is enhanced by the fact that the hypothetical variables can be found in other configurations and asymmetric relations. However, there are different ways to look at the model estimates produced by PLS-SEM and fsQCA, both algorithms centre on prediction. The interplay of variables can be better understood with the help of these additional perspectives, which in turn allows for more profound managerial implications to be derived. One reason PLS-SEM is so promising is that it generates construct scores through nomological links. What is more, its estimations take the measurement error inherent to the indicators into explicit consideration (Sarstedt et al., 2022). The use of total scores of multi-item measures has been a hallmark of fsQCA and kindred approaches, including their seminal presentation methods (Aw et al., 2022). Therefore, this sets it apart. Also, fsQCA strengthens and expands the individual-level PLS-SEM results by finding all possible necessary combinations of antecedents that produce an outcome.

Most studies on AI-powered tools have looked at the "net effect" of individual variables, but that does not take into consideration how these elements may interact with one another. Traditional regression-based methods fail to clarify more complex relationships, which in turn disrupts students' CI. Specifically, we found three configurations that boost CI through a multidimensional causal form that includes relatedness, competence, autonomy, PU, and PEOU variables. Consequently, we show that there are many viable solutions to the problem at hand, rather than just one ideal one, and we add to the growing body of evidence about the CI model of AI-driven educational tools.

Moreover, the increased utility of combining the symmetric PLS-SEM method with the asymmetric fsQCA approach is illustrated by our example model. PLS-SEM analyses that are supplemented with fsQCA reveal novel insights into model relationships that would otherwise go unnoticed. Precisely, the fsQCA findings provide fresh perspectives on the model's underlying heterogeneity (Olya & Gavilyan, 2017) and detect nonlinearities (Olya & Altinay, 2016). To that end, this approach is a good fit alongside the more commonplace latent class analysis techniques based on PLS-SEM (Rasoolimanesh et al., 2021).

AI tools' effects on Thai HEIs have only been studied briefly. AI-powered tools could change the area for learners, educators, and institutes, but Thai universities should consider many things in advance before using them. AI-powered solutions are able to personalise studying by tailoring programs to each learner's capabilities and limitations, offering timely responses, and identifying issues (Chen et al., 2023; Jaboob, Hazaimeh, & Al-Ansi, 2024). AI can schedule classes and grade papers, freeing up teachers' time. These advancements pose student data security and privacy ethical concerns. Institutes need to manage these challenges thoroughly for transparency and data security (Mazurowski, 2020). To apply AI in education, faculty must master new skills. University AI implementation is difficult, but the rewards outweigh it. AI can make learning fun and prepare youngsters for the unpredictable employment market.

The widespread deployment of AI-powered technologies in universities will have huge pedagogical effects. First, AI can tailor course content to each student's needs, improving tailored instruction. Individualised recommendations, adaptive learning components, and rapid response can help students understand difficult subjects. By automating administrative duties like grading and arranging course materials with AI, teachers may spend more time helping students. Teachers must consider the ethical and social ramifications of AI in the classroom to ensure fairness, transparency, and student privacy. They must also maximise AI's potential while emphasising human interaction and critical thinking in innovation and creativity. By using AI-powered technologies, universities can improve teaching and student success.

Moreover, the rise of AI-powered classroom tools and approaches has far-reaching social and financial effects. AI might save schools money through computerising labor-intensive tasks like grade scoring and course management. AI-powered instructional software and platforms offer new revenue streams (Garad et al., 2021). However, the potential of automation replacing educators worries others. If the occupations are outdated or they demand considerable retraining to operate with AI-powered systems, educators may suffer. When it comes to culture, the employment of AI in the classroom prompts us to reflect on the extent to which we rely on technology and how it influences our ability to communicate and think critically. New technology in education must be carefully considered in light of pedagogical values. Data privacy and algorithmic bias, which can affect society for years, must be addressed when implementing AI into education.

In conclusion, developers and service providers of AI-powered tools can use fsQCA results to create causal recipes that mix antecedents (such as PU, PEOU, relatedness, autonomy, and competence) to achieve the best possible CI results (Hossain et al., 2021). In addition, by combining fsQCA with PLS-SEM, researchers may assess the predictive power of their models from both symmetric and asymmetric perspectives in a more thorough manner. Our study gives researchers the appropriate tools to examine their models from two distinct but complementary viewpoints by providing explicit guidance on how to employ PLS-SEM and fsQCA together.

CONCLUSION

This study examined Thai university students' CI to use AI-powered teaching technologies. There is little study on students' CI for AI in the classroom. Little research has addressed the learners' continued intent in using the PLS-SEM assessment with SDT, TAM, and PAM. Thus, students' ongoing intention to use AI-powered tools in the classroom was unknown. The elements that affect Thai university students' continuing intention to utilise AI-powered technologies need to be studied. Thus, by building and evaluating an empirical model that includes all three hypotheses, our study advances knowledge. A questionnaire was sent to college students. The data was analysed using PLS-SEM. Thai students weighed autonomy and PU when selecting to use AI-powered technologies. PEOU did not affect continuous intention. Competence did not predict PEOU and PU, but autonomy and relatedness did.

Furthermore, results were enhanced, and new insights were added by applying the dual analytic approach, which consists of PLS-SEM and fsQCA. To gain a better understanding of the aspects that contributed to the outcome, we used the powers of both techniques to assess the symmetric (PLS-SEM) assumptions and the asymmetric (fsQCA) configurations. This approach considers the several situations where an external construct can impact an internal one (Aw et al., 2022; Zhang & Zhang, 2019). Any multi-methods approach seeks to provide a more in-depth estimation of the intricate causal connections that exist between the antecedent and a few important target outcomes (Rasoolimanesh et al., 2021). The PLS-SEM causal links and fsQCA's prediction power strengthened the findings to address the study questions. The predictive power obtained using fsQCA is consistent with that obtained using $PLS_{predict}$, indicating that the predictive power is appropriate for the proposed CI model of AI-powered tools. The results collected with the fsQCA approach also exhibit a consistent pattern of equifinality. A high level of CI cannot be explained by any one of the criteria on their own, according to the configuration analysis. Instead, the research pointed to three distinct setups that resulted in a better CI.

Cross-sectional studies examine intentions at a certain period, which is a limitation. Life experiences shape people's views. Thus, the longitudinal method works well. The study participants were selected via non-probability purposive sampling. It would be inappropriate to extend this study's findings to all Thai universities. Thus, future research may use probability sampling to generalise results. This discovery could pave the way for AI-powered teaching tools. There is a paucity of comparison data, international statistics, and practical use facts. Future researchers may investigate this to illuminate AI's educational uses. Including more technology acceptance theories in future studies can assist academics in understanding students' interests and what influences their continued use of new technologies. Future studies may also examine cognitive abilities, social connections, and security concerns. In AI deployment, ethical issues, including data privacy and algorithmic biases that unethically harm disadvantaged groups must be properly studied and regulated. For responsible and efficient higher education integration, AI's limitations must be addressed despite its promise to improve certain areas.

Moreover, while we employ standardised concept scores in our example, unstandardised scores, such as those used in some PLS-SEM-based impact-performance map analyses (IPMA), may have a significant bearing on the results (Ringle & Sarstedt, 2016). Models, including mediators and moderators, can be rigorously tested using PLS-SEM (Sarstedt et al., 2022). However, moderator models can be tested with fsQCA by looking at different permutations of predictor variables or by dividing the sample into subsets (Rasoolimanesh et al., 2021). Hence, it is valuable to investigate ways to incorporate mediator connections in future studies. We also concentrate on a particular result (i.e., CI). Likewise, while employing other techniques, such as the machine learning approach (Ch'ng, 2024) and adaptive neuro-fuzzy inference system (ANFIS) model (Zaidouni et al., 2024), we can get a significant bearing on the results. The current study model is proposed to be expanded with additional outcomes in future investigations, such as task performance, effectiveness, or experience. Lastly, qualitative methodologies should be employed to study younger learners' educational attitudes and behaviours. Focus groups and participant interviews can reveal more information.

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