Submitted: 11/10/2025 - Accepted: 13/11/2025 - Published: 29/12/2025

Determinants of Generative AI Adoption in Higher Education: A Social Science Perspective on Thai Faculty Behavioral Intentions

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DOI: 10.26417/ bamx9m98

Abstract

The elements influencing Thai university faculty members' behavioral intents to employ generative artificial intelligence in their academic work are investigated in this study. The unique features of GAI adoption were captured using an expanded UTAUT framework that included felt satisfaction and perceived risk. A bilingual questionnaire was utilized to gather information from faculty members at several Thai universities, and the suggested associations were assessed using structural equation modeling. The findings indicate that while perceived risk has a negative impact, performance expectancy, effort expectancy, perceived enjoyment, and social influence all strongly predict faculty members' inclinations to adopt GAI. Through effort expectancy, facilitating situations have an indirect impact on intention. These results show that in order to encourage responsible and successful GAI adoption, colleges must improve training opportunities, bolster institutional support, and address ethical and practical issues. The study offers empirical insights into the factors that influence GAI adoption in the setting of higher education.

Keywords: Generative AI; UTAUT; Thai University Faculty; SEM; Education

Introduction

In recent years, Generative Artificial Intelligence (GAI)—a class of artificial intelligence technologies capable of autonomously generating diverse forms of content, including text, images, audio, code, and video (Bommasani, Hudson, Adeli, Altman, Arora, von Arx & Liang, 2021)—has rapidly gained attention among scholars and educators worldwide. Generative Artificial Intelligence (GAI) has become highly used to integrate into educational contexts worldwide, yet adoption among faculty tends to progress more slowly than among students. In Thailand, universities have

begun promoting GAI to enhance teaching, learning, and research, faculty adoption remains inconsistence due to concerns related to usability and ethical risks. To address this gap, this research applies an extended UTAUT model incorporating enjoyment and perceived risk to examine the determinants of Thai university faculty members behavioural intention to use GAI.

Various theoretical frameworks have been established to explain technology acceptance. Among them, the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh, Morris, Davis and Davis (2003), has received significant attention from scholars due to its strong explanatory power in accounting for an acceptance to use new technologies. According to the UTAUT model (Venkatesh, Morris, Davis, & Davis, 2003), individual usage behavior is primarily determined by behavioral intention. The model specifies four factors that influence behavioral intention (BI) including effort expectancy (EE), performance expectancy (PE), Facilitating Conditions (FC) and social influence (SI) (Venkatesh, Thong, & Xu, 2012). Khechine (2016) conducted multiple empirical tests on these original variables and found that UTAUT had a stronger predictive capability in forecasting users' technology usage intentions, with an accuracy rate exceeding 69%, significantly higher than that of other models (Khechine, 2016). However, researchers have emphasized the importance of appropriately integrating and adapting the core variables of the UTAUT model to enhance its explanatory power in different contexts (Alrawashdeh, Elbes, Almomani, ElQirem, & Tamimi, 2020). As such, the model should be modified to align with the specific research context and subject matter. Empirical evidence of Mayr, Stahmann, Nebel and Janiesch (2023) supports that revised versions of the UTAUT model demonstrate greater applicability and improved explanatory power across various studies. Therefore, to strengthen the ability of the UTAUT model in accounting for GAI adoption among faculty in Thai universities, the present study expands the original model by integrating two additional variables, which are perceived risk (PR) and perceived enjoyment (PENJ), to explain behavioral intention (BI) to use GAI. In addition, this study proposes that the effects of facilitating conditions (FC) and perceived enjoyment (PENJ) on BI may not only direct. It may mediate by effort expectancy (EE). Furthermore, the influences of social influence (SI), effort expectancy (EE), and perceived enjoyment (PENJ) on BI may also be mediated by performance expectancy (PE).

Research Framework and Hypotheses Behavioral Intention

Direct Effects

Performance Expectancy (PE) defines as the extent to which a person perceived that the use of innovative technology can contribute to an improvement in job performance (Venkatesh et al., 2012). In this study, PE refers to the level at which Thai university faculty members believe that GAI can improve their job performance, including aspects such as professional development, promotion opportunities, and potential salary increases. When university faculty perceive that GAI can enhance

work efficiency or contributes to career advancement, they are more likely to adopt GAI in their academic practices. This assumption is supported by prior empirical evidence. For instance, Cojean and Martin (2022), in a study of 406 prospective teachers enrolled in master's programs in France, found that PE was significantly and positively associated with technology acceptance. Therefore, the following hypothesis is proposed:

According to UTAUT framework (Venkatesh et al., 2003; 2012), behavioral intention to use technology is shaped primarily by performing expectancy, effort expectancy, social influence and facilitating conditions. To account for the characteristics of GAI use in higher education, this research integrates perceived risk, which captures concerns related to accuracy, privacy, and ethical implications. Prior research across educational settings consistently demonstrates that PE, EE, SI, FC and PENJ positively predict behavioral intentions, while perceived risk tends to suppress usage intentions. Based on these insights, hypotheses H1-H6 are formulated.

Building on UTAUT extensions, prior literature indicates that FC and PENJ can indirectly influence behavioral intention through effort expectancy, while SI, EE, and PENJ may also shape intention through performance expectancy. Accordingly, this tests five indirect hypothesis H7-H11 related to these mediating pathways.

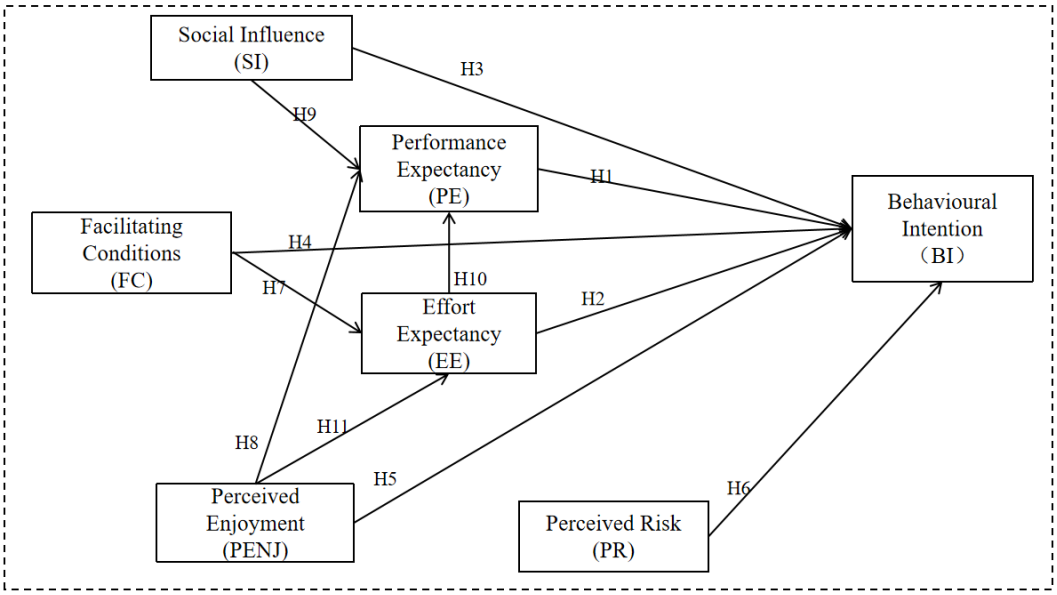

Figure 1. Research Model of Thai University Teachers' BI to use generative AI.

Methodology

To test the conceptual model, data were collected through a questionnaire survey administered to Thai university faculty members. Then, Structural Equation Modelling (SEM) was employed to analyze the survey data. The following section

provides insights into sampling procedure, questionnaire development, pretest of the questionnaire, data collection and the analysis of the model.

Sample Size and Sampling Method

According to Ministry of Higher Education, Science, Research and innovation (2023), Thailand has 154 universities, comprising 83 public universities and 71 private universities. To enhance the generalizability of the findings, faculty members from a variety of disciplines across these institutions were included in the research sample. Since the present study aims to test the research model using structural equation modelling method, a minimum samples size of 500 is required to test the model (Selem, 2025).

To ensure that the respondents are universities lecturers, the present study employed the "snowball sampling" method. First, an initial group of faculty members from various universities were invited to participate in the survey, then, the questionnaires were sent to an initial group of faculty members through email. Then, these initial respondents were subsequently asked to refer or forward the survey invitation to other eligible colleagues within their professional circles who met the inclusion criteria. This referral process was repeated in successive waves until the number of respondents met the minimum sample size requirement.

Questionnaire Development

The questionnaire was developed based on items adopted from previous studies. The questionnaire consisted of two sections: *(1)* a survey of respondents' personal characteristics, i.e. gender, tenure, discipline, and proficiency in information technology, and *(2)* the measurement of the seven variables in the constructed model. To minimize potential misunderstandings and ensure a consistent interpretation of terminology related to GAI, a brief explanatory note was included at the beginning of the questionnaire.

Since the respondents are Thai faculty members, questionnaire was provided in both Thai and English to assure the understanding of all respondents. The questionnaire was translated into Thai by the researcher and back translate by the expert in the field. The inconsistency between English and Thai questions are correct and improve. Then, to ensure the validity, the questionnaire in both Thai and English was sent to three experts. Experts were asked to rate each item in the questionnaire, ranging from "-1" (an item does not measure the mentioned variable), "0" (an expert is not sure whether an item is a measure of the mentioned variable), to "1" (an item is a measure of the mentioned variable). A score of each item from the three expert was average and the items that received the score less than "0" was improved. Additional feedback from experts was used to improve the questionnaire to ensure clarity and comprehensibility after translation.

Measurement of Variables

The measurement of each variable was primarily based on UTAUT model developed by Venkatesh et al. (2003, 2012), which served as the theoretical foundation for five core constructs: PE, EE, SI, FC, and BI. These constructs were operationalized through validated scales adapted from previous studies to match the specific context of Thai higher education. In addition to the UTAUT constructs, PENJ was adapted from Huang (2006) and Hoffman (2009), Ahmad, Al-Nawaiseh and Al-Nawaiseh (2023), and Lewis, Williams, Frayeh and Marcus (2016), while PR, which based on Bauer's (1967) foundational theory of PR, was measured by the items adapted from Obenza, Salvahan, Rios, Solo, Alburo, Gabila (2024) and Namahoot, Jantasri (2023). To collect data, faculty members were asked to rate on each question, while 1 indicating "strongly disagree" to 5 indicating "strongly agree". Table 1 presents the measurement of each variable in the model.

Variable	Item	Item Configuration	References
PE	PE1	Generative AI tools are very useful for me	Venkatesh et al., 2003 Saleem et al., 2016
	PE2	Generative AI tools can increase the chances of improving performance-based pay or professional titles	Saleem et al., 2016
	PE3	Generative AI tools can help me utilize fragmented time	Saleem et al., 2016
	PE4	Generative AI tools can enhance my comprehensive research capabilities	Zhang, X., & Wareewanich, T. , 2024
	PE5	Generative AI is conducive to promoting professional development of teachers	Zhang, X., & Wareewanich, T. , 2024
EE	EE1	I believe that generative AI tools are very easy to use	Venkatesh et al., 2003 Oyewole., 2018
	EE2	I think it does not require too much effort to learn how to use generative AI tools	Venkatesh et al., 2003 Oyewole., 2018
	EE3	I find the operation of generative AI tools to be simple	Oyewole., 2018
	EE4	I can quickly adapt to the use of generative AI tools	Zhang, X., & Wareewanich, T., 2024
	EE5	I think I can quickly integrate generative AI tools into my daily work.	Zhang, X., & Wareewanich, T., 2024
SI	SI1	If the people around me are using generative AI tools, I would also try to use them	Venkatesh et al., 2003
	SI2	If a colleague or someone nearby recommends the use of generative AI tools, I would be willing to use them	Contractor, N. S., & DeChurch, L. A., 2014

	SI3	Most people in my circle are using generative AI tools, which is a trend	Contractor, N. S., & DeChurch, L. A., 2014
	SI4	I only like to implement a business if the result is very safe.	Zhang, X., & Wareewanich, T., 2024
	SI5	Encouragement from relevant educational authorities to use generative AI tools would prompt me to use them	Zhang, X., & Wareewanich, T., 2024
FC	FC1	I have accessible platforms and resources for using generative AI tools around me	Venkatesh et al.,2003 Yang, K., & Forney, J. C., 2013
	FC2	I possess the basic conditions needed to use generative AI tools	Yang, K., & Forney, J. C., 2013
	FC3	The school provides me with the necessary equipment resources to use generative AI tools	Yang, K., & Forney, J. C., 2013
	FC4	When choosing and learning to use a specific generative AI tool, I receive specialized guidance and training	Zhang, X., & Wareewanich, T., 2024
	FC5	If I encounter problems while using generative AI tools at work, I can find help in a timely manner	Zhang, X., & Wareewanich, T., 2024
PENJ	PP1	I find generative artificial intelligence to be interesting	Ahmad et al., 2023
	PP2	When working with generative AI tools, I feel that time passes quickly	Ahmad et al., 2023
	PP3	Using generative AI tools makes my work more enjoyable	Lewis, B. A.,et al., 2016
	PP4	Using generative AI tools stimulates my curiosity	Lewis, B. A.,et al., 2016
	PP5	Generative AI tools lead me to explore new knowledge	Lewis, B. A.,et al., 2016
PR	PR1	Using generative AI tools, I am concerned about personal information leakage.	Obenza et al., 2024
	PR2	I believe that generative AI could lead to issues with academic integrity	Obenza et al., 2024
	PR3	I think the technology of generative AI is not mature enough	Obenza et al., 2024
	PR4	I do not trust generative AI tools very much	Namahoot et al., 2023
	PR5	I believe that generative AI tools could be misused in academic settings	Namahoot et al., 2023
BI	BI1	I believe I will continue to use generative AI tools in my future work	Revythi, A., & Tselios, N., 2019

BI2	My attitude towards using generative AI tools is positive	Revythi, A., & Tselios, N., 2019
BI3	I hope to have more opportunities to interact with generative AI tools	Zhang, X., & Wareewanich, T., 2024
BI4	I look forward to the widespread adoption of generative AI tools in society	Zhang, X., & Wareewanich, T., 2024
BI5	I am willing to recommend generative AI tools to colleagues or friends	Zhang, X., & Wareewanich, T., 2024

Table 1: Measurement Dimensions

Pretest: Analysis of Reliability of the Questionnaire

The pretest questionnaires were distributed electronically via email to university lecturers, spanning two weeks. After eliminating questionnaires that were incomplete, a total of 50 questionnaires were collected. Then, test of the reliability of the questionnaire was conducted. Reliability primarily reflects the accuracy, consistency, and stability of the data collected from the sample. It represents the degree of variability in measurement results that is attributable to random error during the measurement process (Bartko, & Carpenter, 1976). Indicators for measuring internal reliability typically include the Theta(θ) coefficient, Omega(Ω) coefficient, Cronbach's Alpha reliability coefficient, and the Corrected Item-Total Correlation. Among these, Cronbach's Alpha is commonly used methods for evaluating reliability (Hajjar, 2018).

Standard procedures were used to assess reliability and validity. Table 2 shows All constructs achieved Cronbach's Alpha values above 0.80, indicating strong internal consistency. KMO and bartlett's test confirmed the suitability of the data for factor analysis, and EFA supported the intended factor structure with all items loading above 0.40.

Variable	Number of Items	Cronbach α
PE	5	0.850
EE	5	0.852
SI	4	0.827
FC	5	0.896
PENJ	5	0.841
PR	5	0.829
BI	5	0.849

Table 2: Analysis of Predictive Questionnaire Reliability: Cronbach's Alpha Values

Ethical Statement

This study involved voluntary participation from faculty members who were fully informed about the purpose and procedures of the research. Informed consent was

obtained from all participants prior to data collection. Participants' confidentiality and anonymity were strictly maintained, and the study was conducted in accordance with standard ethical guidelines for social science research.

Collection of Data

Following the pretest, data were collected using the snowball sampling method, which facilitated the recruitment of university lecturers and ensured that all respondents belonged to the intended target group. First, fifty-five sets of questionnaires were sent to an initial group of faculty members from various universities through email. Then, these faculty members were then asked to refer or forward the survey invitation to ten other eligible colleagues. Finally, 506 questionnaires were collected. However, six questionnaires were excluded due to invalid responses, including incomplete content, uniform answers, inconsistent responses, or extreme values. Consequently, 500 valid questionnaires were retained, yielding a final valid response rate of 98.8%, which met the predetermined sample size requirements for the study.

Results

Descriptive Statistical Analysis

Through the questionnaire survey process described above, 500 valid questionnaires were analyzed. A descriptive statistical analysis of the questionnaire data was conducted using SPSS 23.0 data processing software. The specific statistical data are shown in the table below. The characteristics of Thai higher education faculties covered in the questionnaire mainly included gender, tenure, proficiency in information technology, disciplines, and education level. Table 4 presents the descriptive statistical results of the sample.

Characteristic Information	Options	Total Frequency	Frequency	Percentage
Gender	Male	500	271	54.20%
	Female	500	229	45.80%
Tenure	Less than 2 years	500	103	20.60%
	2-5 years	500	191	38.20%
	6-15 years	500	149	29.80%
	More than 15 years	500	57	11.40%
Proficiency in Information Technology	Never use	500	103	20.60%
	Beginner	500	191	38.20%
	Competent	500	149	29.80%
	Proficient	500	57	11.40%
Disciplines	STEM	500	178	35.60%
	Social Sciences	500	110	22.00%
	Applied Disciplines	500	99	19.80%
	Humanities	500	62	12.40%
	Arts	500	51	10.20%

Education Level	Bachelor's	500	120	24%
	Master's	500	208	41.60%
	Doctorate	500	151	30.20%
	Other	500	21	4.20%

Table 4: Descriptive Statistics of Respondents

Reliability and Validity Testing of the Measurement Model

Table 5 indicated that the Cronbach's α coefficients of the measurement item in the questionnaire were all above the threshold of 0.7. The overall reliability of the formal research questionnaire also achieved a value of 0.850. As shown in Table 5, the measurement model (formal questionnaire) exhibited high reliability. Furthermore, when conducting item analysis for each measurement dimension, it was found that the corrected item-total correlation values for PE, EE, SI, FC, PENJ, PR, and BI ranged from 0.474 to 0.715. The correlation coefficients presented by the overall questionnaire and measurement dimensions exceed the recommended threshold of 0.3 (Hajjar, 2018). This indicated that the research questionnaire demonstrated high reliability.

Core Variables	Items	Corrected Item-Total Correlation	Cronbach α	Credibility Level	Pre-test Cronbach α
PE	PE1	0.474	0.855	Reliable	0.850
	PE2	0.502			
	PE3	0.503			
EE	EE1	0.488	0.882	Reliable	0.852
	EE2	0.507			
	EE3	0.474			
	EE4	0.506			
SI	SI1	0.539	0.849	Reliable	0.827
	SI2	0.483			
	SI3	0.469			
FC	FC1	0.515	0.899	Reliable	0.896
	FC2	0.551			
	FC3	0.601			
	FC4	0.592			
	FC5	0.524			
PENJ	PENJ1	0.561	0.900	Highly Reliable	0.841
	PENJ2	0.518			
	PENJ3	0.531			
	PENJ4	0.511			
	PENJ5	0.567			
PR	PR1	0.649	0.909	Highly Reliable	0.829
	PR2	0.663			
	PR3	0.703			

	PR4	0.715			
	PR5	0.699			
BI	BI1	0.528	0.885	Reliable	0.849
	BI2	0.544			
	BI3	0.566			
	BI4	0.560			
Overall Reliability of the Questionnaire:			0.850	Reliable	0.846

Table 5: Cronbach's α values of each variable

Table 6 showed that the KMO value of the questionnaire was 0.926 exceeding the threshold of 0.6 (Napitupulu, 2017). Bartlett's chi-square value was 8939.474 with a degree of freedom (df) of 406, and the significance (Sig.) value was less than 0.05, indicating that the data were appropriate for conducting Exploratory Factor Analysis (EFA).

		Formal questionnaire	Pre-test questionnaire
KMO sampling adequacy measure		0.926	0.679
Bratlett's test of sphericity	Approximate chi-square distribution	8939.474	1039.565
	Df	406	465
	Sig.	0.000	0.000

Table 6: KMO and Bartlett's Test Results of the Formal Questionnaire

Exploratory Factor Analysis (EFA)

Since the present study integrated measurement items from several prior studies, EFA was performed to examine the factor structure and assess construct validity. EFA is particularly appropriate in this context, as it enables researchers to identify latent dimensions, confirm whether items load onto the intended constructs, and eliminate items with weak or cross-loadings (Williams, Onsman, & Brown, 2010). In evaluating the results, common factor variance (communality) was used to assess the degree at which each item shared variance with other items. A higher extracted communality value indicates stronger commonality and greater importance of the measurement item, with values above 0.4 generally considered acceptable (Stapleton, 1997). As shown in Table 7, the majority of items had extraction values above 0.7, while a few items were slightly below 0.7 but still greater than 0.4. These results suggested that the measurement items demonstrated good commonality, supporting their usefulness for the formal survey.

Core variables	Measurement indicators	Common factor variance	Core variables	Measurement indicators	Common factor variance
PE	PE1	0.779	PENJ	PENJ1	0.71
	PE2	0.751		PENJ2	0.748
	PE3	0.795		PENJ3	0.699
EE	EE1	0.749		PENJ4	0.718

	EE2	0.74		PENJ5	0.724
	EE3	0.751		PR1	0.698
	EE4	0.723		PR2	0.75
	SI1	0.767	PR	PR3	0.742
SI	SI2	0.77		PR4	0.753
	SI3	0.781		PR5	0.744
	FC1	0.738		BI1	0.755
	FC2	0.7	BI	BI2	0.758
FC	FC3	0.731		BI3	0.724
	FC4	0.721		BI4	0.749
	FC5	0.706			

Table 7: Common Factor Variance

Results from Hypothesis Testing and Structural Equation Modelling

Following EFA, data were analyzed using the SEM with AMOS 22.0. SEM offers advantages over traditional statistical methods, as it allowed for the simultaneous analysis of multiple relationships and enables the evaluation of model fit across different specifications, thereby identifying the optimal explanatory model and enhancing both validity and interpretive strength (Owolabi, Ayandele, & Olaoye, 2020). The results of the overall model fit are presented in Table 8.

Fit index	SEM fitting result	Recommended Threshold	SEM fit or not
Absolute fit index			
CMIN/DF	1.448	＜3	Fit
RMR	0.062	＜0.08	Fit
RMSEA	0.030	＜0.08	Fit
GFI	0.935	＞0.90	Fit
AGFI	0.921	＞0.90	Fit
Value-added fit index			
NFI	0.943	＞0.90	Fit
RFI	0.936	＞0.90	Fit
IFI	0.982	＞0.90	Fit
TLI	0.979	＞0.90	Fit
CFI	0.981	＞0.90	Fit

Table 8: Overall Model Fit Testing Results

As shown in Table 8, all fit indices satisfied the recommended thresholds (e.g., CMIN/DF = 1.448, RMR = 0.062, RMSEA = 0.030, GFI = 0.935, AGFI = 0.921, NFI = 0.943, IFI = 0.982, TLI = 0.979, and CFI = 0.981), indicating that the SEM model demonstrated a good overall fit with the sample data. The initial model proposed in this study was empirically supported, and no further modifications were required.

Table 9 shows the results from hypothesis testing and the estimation of path coefficients and significance analysis for the SEM model. The results indicated that all

structural paths in the SEM model were statistically significant. PE (β = 0.177, P < .001), EE (β = 0.108, P < .05), SI (β = 0.238, P < .001), FC (β = 0.111, P < .05), and PENJ (β = 0.164, P < .01) were found to be positively and significantly influenced BI to use GAI, while PR (β = -0.106, P < .05) was found to negatively and significantly influenced BI to use GAI. In addition, FC (β = 0.377, P < .001) and PENJ (β = 0.26, P < .001) were positively and significantly influence EE. Finally, SI (β = 0.22, P < .001), EE (β = 0.247, P < .001), and PENJ (β = 0.294, P < .001) were positively and significantly influenced PE.

Hypothesis	Independent Variable → Dependent Variable	B	S.E.	C.R.	P	Significance
H1	PE →BI	0.177	0.052	3.336	***	Yes
H2	EE→BI	0.108	0.05	2.095	0.036	Yes
H3	SI→BI	0.238	0.056	4.381	***	Yes
H4	FC→BI	0.111	0.057	1.982	0.047	Yes
H5	PENJ→BI	0.164	0.06	3.008	0.003	Yes
H6	PR→BI	-0.106	0.05	-2.162	0.031	Yes
H7	FC→EE	0.377	0.057	6.628	***	Yes
H8	PENJ→EE	0.26	0.06	4.323	***	Yes
H9	SI→PE	0.22	0.055	3.997	***	Yes
H10	EE→PE	0.247	0.05	4.961	***	Yes
H11	PENJ→PE	0.294	0.061	4.85	***	Yes

Note: *** indicates p < 0.001

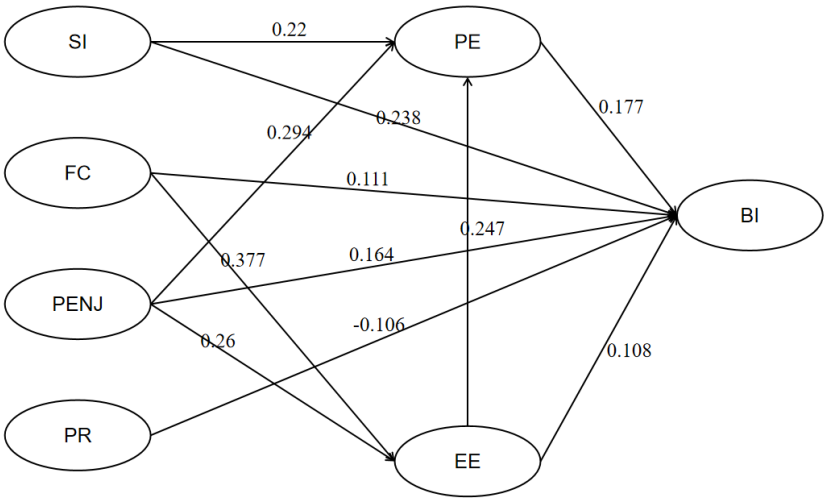

Figure 2. Path Coefficient Diagram for SEM

Variables	Indirect	Variables	Direct	Variables	Total
		PE→BI	0.177*** (0.000)	PE→BI	0.177*** (0.000)
		PR→BI	-0.106* (0.031)	PR→BI	-0.106* (0.031)
EE→PE→BI	0.045** (0.001)	EE→BI	0.108* (0.036)	EE→BI EE→PE→BI	0.153** (0.001)
SI→PE→BI	0.037** (0.008)	SI→BI	0.238*** (0.000)	SI→BI SI→PE→BI	0.275** (0.001)
FC→EE→BI FC→EE→PE→BI	0.055*** (0.000)	FC→BI	0.111* (0.047)	FC→BI FC→EE→BI FC→EE→PE→BI	0.166** (0.000)
PENJ→PE→BI PENJ→EE→BI PENJ→EE→PE→BI	0.082*** (0.000)	PENJ→BI	0.164** (0.003)	PENJ→BI PENJ→PE→BI PENJ→EE→BI PENJ→EE→PE→BI	0.246** (0.001)

Table 10: Degree of Influence of Various Factors on Behavioral Intention in SEM
Note: * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$

Table 10 shows the level of influences of factors influencing BI to use GAI, it was evident that the factors exerting the greatest effect on the BI of Thai faculties was SI ($\beta = 0.275$, $p < 0.001$). This finding indicates that faculty members in Thailand are more likely to decide whether to use generative artificial intelligence (GAI) based primarily on SI. When influential colleagues or individuals in their professional environment adopt GAI, faculty members are more likely to follow them and adopt GAI. In addition, SI was found to affect BI to use GAI indirectly through PE. When Thai faculty members observe that influential colleagues adopt GAI and achieve positive performance outcomes, they are more likely to develop favorable expectations about its usefulness, which in turn increases their intention to use GAI.

The second most influential factor on BI to use GAI was PENJ ($\beta = 0.246$, $p < 0.01$). A positive enjoyment experience when using GAI significantly and directly encouraged Thai faculty members to explore new knowledge, thereby fostering greater engagement and increasing their intention to use the technology. In addition, perceive enjoyment was found to affect BI to use GAI indirectly through effort expectance and PE. When Thai faculty members perceive the use of GAI as enjoyable, they tend to view it as requiring less effort and as more likely to generate positive outcomes, which in turn increases their likelihood of adopting GAI.

The third most influential factor on the BI to use GAI was PE ($\beta = 0.177$, $p < 0.001$). The findings indicated that when Thai faculty believed that generative artificial intelligence could effectively improve their teaching quality, increase work efficiency, or lead to better learning outcomes, they were more likely to show a positive BI toward its use.

The fourth factor influencing the BI to use GAI was FC ($\beta = 0.166$, $p < 0.001$). The results showed that when faculty received sufficient resources and technical support in the process of using generative artificial intelligence, they were more willing to adopt GAI. For example, training opportunities, hardware facilities, technical assistance, and institutional encouragement provided by universities played an important role. In addition, the study revealed that FC not only directly influenced faculty's use of GAI but also indirectly affected their BI through PE and EE. Therefore, when faculty perceived a well-established support system, they felt that learning and using GAI was easier and developed greater confidence in its expected outcomes, which further enhanced their BI.

The fifth factor influencing the BI to use GAI was EE ($\beta = 0.153$, $p < 0.01$). The study found that when Thai faculty perceived GAI as easy to use and requiring lower learning costs, they were more likely to use it. Furthermore, EE was also found to indirectly influenced BI through PE. Thus, when faculty believed that using GAI did not require significant additional effort, they were more likely to recognize its potential value and effectiveness, thereby increasing their actual BI to adopt it.

The least influential factor on the BI to use GAI was PR ($\beta = -0.106$, $p < 0.001$). Although PR had the smallest impact compared with other factors, it remained statistically significant. The findings suggested that Thai faculty still had concerns when considering the adoption of GAI, including potential issues such as data privacy breaches, inaccuracy of generated content, overreliance on technology, and ethical challenges. These concerns weakened their BI to some extent. Policymakers and university administrators needed to address faculty's concerns by improving privacy protection mechanisms, ethical guidelines, and reliable technical support, thereby reducing PR and facilitating the broader adoption of this technology.

Implications

Drawing on the results, this research proposes several recommendations to enhance the adoption of GAI within Thai higher education institutions.

The findings highlights the central role of social influence and perceived enjoyment in shaping GAI adoption among Thai faculty. Institutions should promote visible role models, peer communities, and collaborative practices to normalize GAI use. Enhancing usability and performance expectancy. At the policy level, universities must ensure adequate facilitating conditions through technical infrastructure, staff support and targeted professional development. Finally, reducing perceived risk through clear ethical guidelines and transparent data privacy policies is essential to alleviating concerns and encourage responsible adoption.

Compared with international research on faculty technology adoption, the findings of this study reveal both convergences and distinctive contextual factors. Similar to studies conducted in East Asian, Middle Eastern, and Western higher education systems, performance expectancy, effort expectancy, and perceived enjoyment

consistently emerge as strong predictors of behavioral intention. This suggests that faculty across diverse countries tend to adopt generative AI when the tools are useful, easy to use, and intrinsically engaging. However, the magnitude of social influence observed among Thai faculty appears stronger than what is typically reported in studies from the United States or Europe, where individual autonomy and decentralized decision-making play a greater role. This difference highlights the importance of considering cultural context when interpreting AI adoption trends.

References

[1] Ahmad, F.B., Al-Nawaiseh, S.J., & Al-Nawaiseh, A.J. (2023). Receptivity level of faculty members in universities using digital learning tools: A UTAUT perspective. International Journal of Emerging Technologies in Learning, 18(13), 209–219.
[2] Alrawashdeh, T. A., Elbes, M. W., Almomani, A., ElQirem, F., & Tamimi, A. (2020). User acceptance model of open-source software. Journal of Ambient Intelligence and Humanized Computing, 11, 3315–3327.
[3] Bokhari, S. A. A., & Myeong, S. (2023). Artificial intelligence adoption behavior applying extended UTAUT. Engineering Proceedings, 56(1), 289.
[4] Chao, C. M. (2019). Determinants of the behavioral intention to use mobile learning. Frontiers in Psychology, 10, 1052.
[5] Collins, D. (2003). Pretesting survey instruments: An overview of cognitive methods. Quality of Life Research, 12, 229–238.
[6] Cronbach, L. J. (1951). Coefficient alpha and the internal structure of tests. Psychometrika, 16(3), 297–334.
[7] Davis, F. D. (1986). A technology acceptance model for empirically testing new systems. MIT.
[8] Hoffman, D. L., & Novak, T. P. (2009). Flow online. Journal of Interactive Marketing, 23(1), 23–34.
[9] Lewis, B. A., Williams, D. M., Frayeh, A., & Marcus, B. H. (2016). Self-efficacy vs. perceived enjoyment. Psychology & Health, 31(4), 456–469.
[10] Lin, H. C., Ho, C. F., & Yang, H. (2022). Adoption of AI-enabled language e-learning. International Journal of Mobile Learning and Organisation, 16(1), 74–94.
[11] Obenza, B., et al. (2024). University Students' Perception and Use of ChatGPT. International Journal of Human Computing Studies, 5(12), 5–18.
[12] Park, J., Amendah, E., Lee, Y., & Hyun, H. (2019). M-payment service: Perceived risk and trust. Human Factors and Ergonomics in Manufacturing, 29(1), 31–43.
[13] Saleem, N. E., Al-Saqri, M. N., & Ahmad, S. E. (2016). Acceptance of Moodle by faculty. International Journal of Knowledge Content Development & Technology, 6(2), 5–27.
[14] Selem, K. M., et al. (2025). ChatGPT-related risk patterns and creative thinking. Journal of Hospitality & Tourism Education, 37(3), 1–16.

[15] Straub, D. W. (1989). Validating instruments in MIS research. MIS Quarterly, 13(2), 147–169.
[16] Venkatesh, V., & Davis, F. D. (2000). TAM2. Management Science, 46(2), 186–204.
[17] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). UTAUT. MIS Quarterly, 27(3), 425–478.
[18] Venkatesh, V., Thong, J. Y., & Xu, X. (2012). UTAUT2. MIS Quarterly, 157–178.
[19] Williams, B., Onsman, A., & Brown, T. (2010). Exploratory factor analysis. Australasian Journal of Paramedicine, 8(3), 1–13.
[20] Zhang, X., & Wareewanich, T. (2024). Teachers' willingness to use generative AI using UTAUT. International Journal of Interactive Mobile Technologies, 18(6), 126–142.