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Acceptance of Generative AI in Vocational Teaching and Learning Management

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Abstract

The rapid advancement of Generative Artificial Intelligence (GenAI) has created new opportunities for teaching and learning across educational sectors. However, limited empirical evidence explains both vocational teachers' intentions to adopt GenAI and their actual classroom use. This study examined the acceptance and use of GenAI among private vocational teachers in Thailand through the Unified Theory of Acceptance and Use of Technology (UTAUT), with particular attention to the intention-behavior gap.

A quantitative cross-sectional survey design was employed. Data were collected from 400 private vocational teachers across Thailand using a structured questionnaire. The research model comprised Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), and Use Behavior (UB). PE, EE, SI, FC, and BI were measured reflectively, whereas UB was specified formatively using self-reported indicators of usage frequency, duration, task breadth, and tool breadth. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to evaluate the measurement and structural models.

Partial Least Squares Structural Equation Modeling (PLS-SEM) showed that reflective constructs have acceptable internal consistency and convergent validity, but discriminant validity is problematic, especially for PE and BI (HTMT = 1.000), and UB indicator weights were non-significant. PE ($\beta = 0.560$, $p < .001$), FC ($\beta = 0.336$, $p < .001$), and EE ($\beta = 0.088$, $p = .004$) significantly predicted BI while SI did not. BI and FC were not significant predictors of UB. The model can explain 91.4% of BI but only 17.8% of UB. These findings highlight an intention-behavior gap and the need for infrastructure, pedagogical guidance, AI literacy, ethical protocols, and ongoing implementation support.

Keywords: Generative Artificial Intelligence, vocational education, UTAUT, intention-behavior gap, use behavior, PLS-SEM

1. Introduction

The rapid advancement of Generative Artificial Intelligence (GenAI) has transformed educational practices worldwide. Recent developments in large language models and generative systems have enabled educators to create instructional materials, generate assessments, provide personalized feedback, support content development, and facilitate adaptive learning experiences. Consequently, GenAI is increasingly recognized as a transformative educational technology capable of enhancing teaching effectiveness, learner engagement, and educational innovation (Giannakos et al., 2024; Law, 2024).

The integration of GenAI into educational settings has accelerated following the widespread adoption of tools such as ChatGPT, Gemini, Claude, and other AI-powered applications. These technologies offer significant opportunities to improve instructional design, automate routine tasks, support differentiated instruction, and promote collaborative learning. Studies have shown that both teachers and students perceive substantial benefits from GenAI, including increased productivity, enhanced learning support, improved writing assistance, and expanded access to educational resources (Barrett & Pack, 2023; Chan & Hu, 2023; Law, 2024). Furthermore, GenAI has been viewed as a valuable educational partner that can support teachers in planning lessons, developing learning activities, and addressing classroom challenges (Barbieri & Nguyen, 2025; Memon & Kwan, 2025).

Despite these promising opportunities, the adoption of GenAI in education remains uneven across institutions and educational sectors. Concerns related to trust, ethical implications, academic integrity, technological readiness, professional competence, and organizational support continue to influence educators' willingness to adopt AI technologies (Giannakos et al., 2024; Zhai, 2024). Previous research has demonstrated that teachers' acceptance of GenAI is shaped not only by technological characteristics but also by individual, organizational, and contextual factors (Al-Abdullatif, 2024; Hazzan-Bishara et al., 2025).

The vocational education sector represents a particularly important context for investigating GenAI adoption. Vocational education aims to develop practical competencies, occupational skills, problem-solving abilities, and workforce readiness. In this context, GenAI has considerable potential to support competency-based instruction, workplace simulations, technical training, content creation, and personalized learning pathways. Emerging studies have highlighted the relevance of GenAI in vocational and technical education, particularly for preparing future educators and enhancing industry-oriented teaching practices (Gumelar et al., 2025; Krismiyati et al., 2026). As vocational institutions increasingly seek to modernize teaching and learning processes, understanding teachers' acceptance of GenAI becomes essential for successful implementation.

To explain technology adoption behaviors, researchers have extensively employed technology acceptance theories such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Recent studies examining GenAI adoption among educators have confirmed the applicability of these theoretical frameworks in explaining teachers' behavioral intentions and usage behaviors (Kong et al., 2024; Yang & Appleget, 2024; Zheng et al., 2024). In particular, UTAUT has emerged as one of the most frequently applied models because it integrates multiple determinants of technology acceptance, including Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions (Venkatesh et al., 2003).

Recent investigations have increasingly extended UTAUT to understand educators' acceptance of Generative AI. For example, Al-Abdullatif (2024) found that AI literacy, intelligent technological pedagogical content knowledge (TPACK), and perceived trust significantly influenced teachers' intentions to use GenAI in higher education. Similarly, Ayyoub et al. (2025) demonstrated that extended UTAUT constructs effectively explained users' acceptance of Generative AI technologies. Studies conducted in language education, engineering education, teacher education, and higher education contexts have consistently reported that perceived usefulness, ease of use, institutional support, and social influences play important roles in shaping educators' adoption intentions (Gokturk-Saglam, 2026; Honig et al., 2025; Panday-Shukla, 2025; Zaim et al., 2024).

Although a growing body of research has examined GenAI adoption in higher education, teacher education, engineering education, and language learning, evidence from vocational education remains limited. Most studies have focused on university students, preservice teachers, or higher education instructors, and many have treated behavioral intention as the final outcome. Consequently, less is known about whether vocational teachers' positive intentions are translated into actual use in practice-oriented, competency-based learning environments (Gumelar et al., 2025; Krismiyati et al., 2026).

This gap is important because vocational teachers prepare learners for workplaces in which AI-supported production, communication, problem solving, and decision making are becoming increasingly prevalent. Their use of GenAI must also be aligned with occupational standards, authentic tasks, assessment integrity, and industry expectations. Understanding both acceptance and implementation can therefore inform policy, professional development, and institutional support for responsible AI integration.

Accordingly, this study investigates GenAI acceptance and use among private vocational teachers in Thailand by applying UTAUT. Beyond transferring an established model to another educational setting, the study examines a boundary condition of the theory: whether favorable acceptance of a rapidly evolving and not yet fully institutionalized technology is translated into routine teaching behavior. The intention-behavior gap is therefore positioned as the study's principal theoretical contribution, while the vocational context provides its distinctive practical contribution.

2. Theoretical Frameworks

2.1 Generative AI for Supporting Innovative Learning in Vocational Education

Generative Artificial Intelligence (Generative AI) refers to a category of artificial intelligence systems capable of producing human-like content, including text, images, code, audio, and other digital artifacts based on user prompts. Recent advances in large language models (LLMs), such as ChatGPT, Gemini, and Claude, have significantly expanded the educational applications of Generative AI by supporting content generation,

instructional planning, assessment development, feedback provision, and personalized learning experiences (Kasneci et al., 2023; Tlili et al., 2023).

In educational settings, Generative AI has emerged as a transformative technology that enhances teaching efficiency and learning effectiveness. Teachers can utilize AI tools to develop lesson plans, generate instructional materials, create assessment items, provide formative feedback, and support differentiated instruction. Meanwhile, learners can employ Generative AI as a learning companion for problem-solving, content exploration, and self-directed learning (Baidoo-Anu & Ansah, 2023).

Within vocational education, the integration of Generative AI is particularly relevant because vocational institutions emphasize practical skills, industry-oriented competencies, and workplace readiness. Generative AI can assist vocational teachers in designing authentic learning activities, developing competency-based instructional resources, simulating workplace scenarios, and supporting individualized learning pathways. These capabilities align with the objectives of vocational education, which seek to bridge the gap between classroom learning and professional practice (OECD, 2021).

Despite its potential benefits, the successful implementation of Generative AI depends largely on teachers' acceptance and willingness to use the technology. Educational innovations often fail when users perceive limited usefulness, complexity, or insufficient organizational support. Therefore, understanding the factors influencing vocational teachers' acceptance of Generative AI is critical for promoting its effective adoption and sustainable integration into teaching and learning processes.

Consequently, this study investigates the acceptance of Generative AI among private vocational teachers by applying a technology acceptance framework to identify the determinants of behavioral intention and actual usage behavior.

2.2 Technology Acceptance Research

Technology acceptance research seeks to explain why individuals adopt or reject new technologies. Among the numerous theoretical models proposed in this field, the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003) has become one of the most influential and widely validated frameworks.

The UTAUT model integrates key constructs from eight prominent technology acceptance theories, including the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). The model identifies four primary determinants of technology acceptance: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). These factors influence users' Behavioral Intention (BI) and actual Use Behavior (UB) toward technology adoption (Venkatesh et al., 2003).

Performance Expectancy refers to the degree to which individuals believe that using a technology will improve their job performance. Effort Expectancy reflects the perceived ease associated with technology use. Social Influence represents the extent to which significant others encourage technology adoption, while Facilitating Conditions describe the availability of organizational and technical resources supporting technology use.

Numerous studies have confirmed the usefulness of UTAUT in educational technology contexts, including e-learning, mobile learning, learning management systems, artificial intelligence applications, and GenAI technologies (Ayyoub et al., 2025; Kong et al., 2024; Nikolic et al., 2024). Nevertheless, UTAUT was developed largely around more established information systems. In GenAI contexts, rapidly changing tools, uncertain policies, ethical concerns, and unsettled pedagogical practices may interrupt the expected progression from intention to use.

Accordingly, this study adopts a UTAUT-based framework comprising PE, EE, SI, FC, BI, and UB. The framework is used not only to explain teachers' intentions but also to test whether BI and FC are sufficient to explain actual classroom use of GenAI. A weak BI-UB relationship would indicate that conventional acceptance determinants require contextual extension for emerging AI technologies.

Table 1. Integrated Research Constructs and Definitions

Construct	Definition	Source
Performance Expectancy (PE)	The degree to which a teacher believes that using Generative AI will improve teaching performance and educational outcomes.	Venkatesh et al. (2003)
Effort Expectancy (EE)	The degree of ease associated with learning and using Generative AI.	Venkatesh et al. (2003)
Social Influence (SI)	The extent to which important individuals or organizations encourage the use of Generative AI.	Venkatesh et al. (2003)
Facilitating Conditions (FC)	The degree to which organizational and technical infrastructures support the use of Generative AI.	Venkatesh et al. (2003)
Behavioral Intention (BI)	The intention of teachers to continue using Generative AI in teaching and learning activities.	Venkatesh et al. (2003)
Use Behavior (UB)	The actual extent of Generative AI utilization in teaching practices.	Venkatesh et al. (2003)

2.3 Research Model and Hypotheses

Based on UTAUT, PE, EE, SI, and FC are proposed as determinants of BI toward GenAI adoption, while BI and FC are expected to influence UB. In addition to testing the traditional relationships, the model directly examines whether acceptance is translated into implementation. A non-significant BI-UB path would identify an intention-behavior gap and suggest that factors beyond conventional UTAUT constructs are required to explain actual GenAI use.

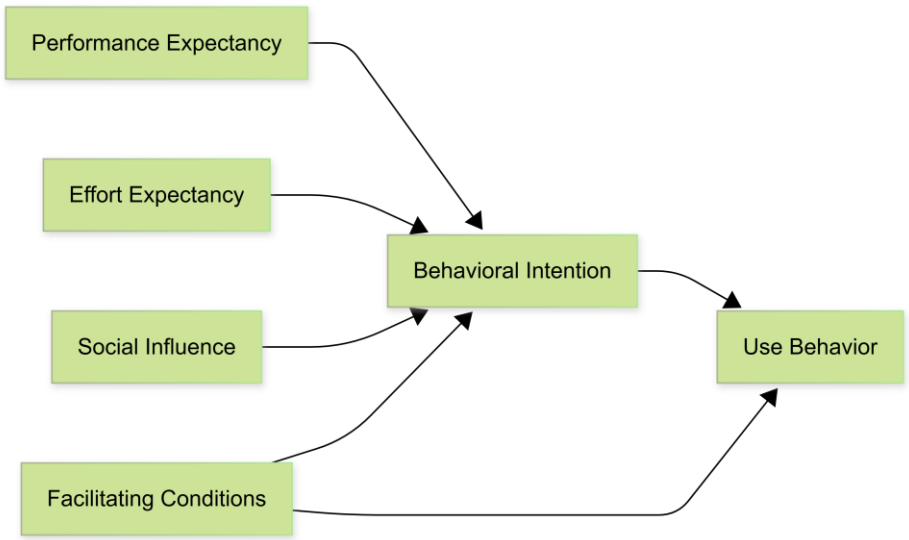

Figure 1. Proposed conceptual model.

This study adopts the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003) as the theoretical foundation for explaining vocational teachers' acceptance and use of Generative Artificial Intelligence (GenAI) in teaching and learning management. UTAUT proposes that users' intentions and actual technology usage are influenced by four key determinants: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.

Performance Expectancy refers to teachers' beliefs that using Generative AI can enhance instructional effectiveness, improve teaching performance, and contribute to better learning outcomes. Previous studies have consistently identified Performance Expectancy as one of the strongest predictors of technology acceptance and AI adoption in educational contexts (Al-Abdullatif, 2024; Kong et al., 2024). Therefore, teachers who perceive greater instructional benefits from GenAI are expected to demonstrate stronger intentions to use the technology.

Effort Expectancy represents the perceived ease of learning and using Generative AI tools. Technologies that are easier to understand and operate generally encourage higher levels of acceptance and continued use. Prior

research on educational AI adoption has reported positive relationships between perceived ease of use and behavioral intention (Yang & Appleget, 2024; Zheng et al., 2024). Accordingly, teachers who perceive GenAI as easy to use are expected to exhibit stronger intentions to adopt it.

Social Influence refers to the extent to which teachers perceive that colleagues, administrators, and significant others encourage the use of Generative AI. According to UTAUT, social expectations and organizational norms can influence individuals' intentions to adopt new technologies (Venkatesh et al., 2003). Therefore, positive social support is expected to strengthen teachers' behavioral intentions toward GenAI adoption.

Facilitating Conditions describe the availability of organizational resources, technical infrastructure, institutional policies, and support services that enable technology use. Previous studies have emphasized the importance of institutional support in promoting AI adoption among educators (Hazzan-Bishara et al., 2025; Honig et al., 2025). Consequently, teachers who perceive stronger facilitating conditions are expected to report higher behavioral intentions and greater actual use of GenAI.

Behavioral Intention represents teachers' willingness and planned commitment to use Generative AI in teaching activities. According to UTAUT, Behavioral Intention serves as the most immediate predictor of actual technology use. Therefore, teachers with stronger intentions to use GenAI are expected to demonstrate higher levels of actual utilization in their teaching practices.

Based on the theoretical foundations and empirical evidence discussed above, the research model proposes that Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions influence Behavioral Intention, while Behavioral Intention and Facilitating Conditions influence actual Use Behavior. The proposed conceptual model is presented in Figure 1.

Table 2. Hypotheses

Hypothesis	Structural Relationship
H1	Performance Expectancy positively influences Behavioral Intention to use Generative AI.
H2	Effort Expectancy positively influences Behavioral Intention to use Generative AI.
H3	Social Influence positively influences Behavioral Intention to use Generative AI.
H4	Facilitating Conditions positively influence Behavioral Intention to use Generative AI.
H5	Behavioral Intention positively influences Use Behavior of Generative AI.
H6	Facilitating Conditions positively influence Use Behavior of Generative AI

3. Methodology

3.1 Research Design

This study employed a quantitative research approach using a cross-sectional survey design to investigate the acceptance of Generative Artificial Intelligence (GenAI) in vocational teaching and learning management among private vocational teachers in Thailand. The study was grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003), which explains individuals' behavioral intentions and actual technology use through four key antecedents: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.

The proposed research model examined the relationships among five latent constructs and one outcome construct. Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) were specified as exogenous variables influencing Behavioral Intention (BI), while Behavioral Intention and Facilitating Conditions were hypothesized to affect actual Use Behavior (UB).

Data were collected through an online questionnaire administered to private vocational teachers across Thailand. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to evaluate both the measurement model and structural model. PLS-SEM was selected because it is particularly suitable for prediction-oriented studies, newly developed research models, and complex relationships involving both reflective and formative constructs (Hair et al., 2022).

3.2 Participants

The target population consisted of teachers employed in private vocational education institutions throughout Thailand. These institutions provide vocational and technical education in various fields, including business administration, information technology, engineering, hospitality, tourism, and health sciences.

A total of 400 private vocational teachers participated in the study. The sample size exceeded the minimum

requirements recommended for PLS-SEM analysis and provided adequate statistical power for hypothesis testing (Hair et al., 2022).

Participants were selected using a multi-stage sampling procedure. First, private vocational colleges from different geographical regions of Thailand were identified. Subsequently, teachers who had experience using or were familiar with Generative AI applications in teaching and learning activities were invited to participate voluntarily.

Table 3. Demographic Information of Respondents (N = 400)

Demographic Variable	Category	Frequency	Percentage
Gender	Male	172	43
	Female	228	57
Age	Below 30 years	76	19
	30-39 years	141	35.3
	40-49 years	116	29
	50 years and above	67	16.7
Educational Qualification	Bachelor's Degree	92	23
	Master's Degree	247	61.8
	Doctoral Degree	61	15.2
Teaching Experience	Less than 5 years	83	20.8
	5-10 years	121	30.2
	11-15 years	97	24.3
	More than 15 years	99	24.7
Experience Using GenAI	Less than 1 year	156	39
	1-2 years	167	41.8
	More than 2 years	77	19.2

3.3 Instrumentation

Data were collected using a structured questionnaire developed based on the UTAUT framework and recent literature on Generative AI adoption in education. The questionnaire consisted of two sections. The first section gathered demographic information, while the second section measured the research constructs.

Five constructs (PE, EE, SI, FC, and BI) were measured reflectively using a seven-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). UB was measured using four self-reported formative indicators. The formative specification was selected because usage frequency, duration, breadth of teaching tasks, and breadth of tools are distinct and non-interchangeable components that jointly define the extent of use. A teacher may, for example, use one tool frequently for a short duration or use several tools across many tasks; a change in one component does not necessarily cause a corresponding change in the others, and removing an indicator would alter the construct’s domain.

Prior to data collection, the questionnaire was reviewed by three experts in educational technology, artificial intelligence, and quantitative research to ensure content validity. A pilot study was conducted with vocational teachers who were not included in the final sample to assess item clarity and reliability.

Table 4. Items of Questionnaire

Construct	Code	Item
Performance Expectancy	PE1	Using GenAI will improve my teaching performance.
	PE2	GenAI helps me achieve better teaching outcomes.
	PE3	Overall, GenAI is beneficial for student learning outcomes.
Effort Expectancy	EE1	I find GenAI easy to use.
	EE2	Learning to use GenAI is easy for me.
	EE3	I can quickly become skillful at using GenAI.
Social Influence	SI1	People important to me think that I should use GenAI.
	SI2	My institution and colleagues support my use of GenAI.
	SI3	Leadership encourages teachers to use GenAI.
Facilitating Conditions	FC1	I have the necessary resources to use GenAI.
	FC2	I receive technical support when using GenAI.
	FC3	Institutional policies facilitate the use of GenAI in teaching.
Behavioral Intention	BI1	I intend to use GenAI regularly in my teaching.
	BI2	I will increase my use of GenAI in the next term.
	BI3	I will recommend GenAI to fellow teachers.
Use Behavior (Formative)	UB1	Self-reported frequency of GenAI use per week.
	UB2	Self-reported average duration per GenAI session.
	UB3	Number of teaching tasks supported by GenAI.
	UB4	Number of GenAI tools regularly used.

3.4 Data Analysis

Data analysis was conducted using SmartPLS 4. Initially, descriptive statistics were calculated to summarize respondents' demographic characteristics and item distributions, including means, standard deviations, skewness, and kurtosis values.

The measurement model was then evaluated. Reflective constructs were assessed using indicator loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), the Fornell-Larcker criterion, and the Heterotrait-Monotrait ratio (HTMT). HTMT values below .90 were treated as evidence of discriminant validity. For the formative UB construct, indicator collinearity, outer weights, weight significance, and the conceptual relevance of each indicator were considered. Non-significant formative weights were not treated as sufficient grounds for deletion when an indicator represented a distinct part of the construct domain, but such results were recognized as evidence of measurement instability.

After establishing measurement quality, the structural model was assessed through bootstrapping with 5,000 resamples. Path coefficients (β), t-values, p-values, confidence intervals, coefficient of determination (R^2), effect sizes (f^2), predictive relevance (Q^2), and PLSpredict were analyzed to evaluate the proposed hypotheses and predictive capability of the model.

The significance level for all statistical tests was set at .05.

4. Results

4.1 Descriptive Statistics

Descriptive statistics were calculated for the 15 reflective Likert-scale items shown in Table 5. The four UB indicators were expressed in different behavioral units and were therefore evaluated separately as formative indicators rather than summarized on the same Likert metric.

The item means ranged from 4.943 to 5.735 on the seven-point scale, and all values were above the scale midpoint. The highest mean was recorded for EE3 (M = 5.735), indicating that respondents generally believed they could become skillful in using GenAI. The lowest mean was recorded for FC1 (M = 4.943), suggesting that access to necessary resources was evaluated less favorably than the other measured conditions. These results indicate generally positive perceptions, while also showing comparatively weaker perceptions of some facilitating conditions.

Standard deviations ranged from 0.672 to 1.161. The smallest dispersion occurred for SI3 (SD = 0.672), whereas PE3 showed the greatest variability (SD = 1.161). Thus, although respondents tended to report favorable views, the degree of agreement varied across instructional-benefit and resource-related items. The descriptive statistics

were used to characterize the sample and were not treated as evidence of construct validity.

Table 5. Descriptive Statistics of Reflective Measurement Items

Construct	Item	Mean	SD
Performance Expectancy	PE1	5.33	0.908
	PE2	5.475	0.873
	PE3	5.278	1.161
Effort Expectancy	EE1	5.585	0.688
	EE2	5.477	0.965
	EE3	5.735	0.903
Social Influence	SI1	5.6	0.693
	SI2	5.458	0.765
	SI3	5.72	0.672
Facilitating Conditions	FC1	4.943	1.065
	FC2	5.167	0.889
	FC3	5.333	0.872
Behavioral Intention	BI1	5.545	0.806
	BI2	5.39	0.981
	BI3	5.475	0.896

4.2 Evaluation of Indicator Loadings and Weights

The measurement model was initially assessed by examining the indicator loadings of the reflective constructs and the indicator weights of the formative construct. Following the recommendations of Hair et al. (2022), reflective indicators were evaluated using outer loadings, whereas the formative construct was assessed using outer weights and their statistical significance.

For the reflective constructs, all indicators demonstrated satisfactory outer loadings ranging from 0.735 to 0.973, exceeding the recommended threshold of 0.70. Specifically, the loadings for Performance Expectancy ranged from 0.895 to 0.918, Effort Expectancy from 0.735 to 0.973, Social Influence from 0.908 to 0.967, Facilitating Conditions from 0.906 to 0.969, and Behavioral Intention from 0.968 to 0.972. These results indicate strong indicator reliability and support the retention of all reflective measurement items.

UB was operationalized formatively through four indicators representing frequency of use, duration of use, task breadth, and tool breadth. The outer weights were 0.851, -0.238, -0.195, and -0.543, respectively, and none was statistically significant ($p > .05$). The indicators were retained because each represents a conceptually distinct component of actual GenAI use; however, their non-significant and mixed-sign weights mean that the empirical contribution of each component to the composite was not established.

The formative specification was retained on conceptual grounds rather than on weight significance. Re-specifying UB as reflective would imply that the indicators are interchangeable manifestations of a single underlying trait and should covary, assumptions that are inconsistent with the indicator content. Nevertheless, the non-significant weights indicate that the current UB operationalization is unstable. Consequently, all UB-related results are treated as exploratory. Future validation should compare this formative specification with a standardized composite index and objective usage evidence, such as system logs or platform analytics.

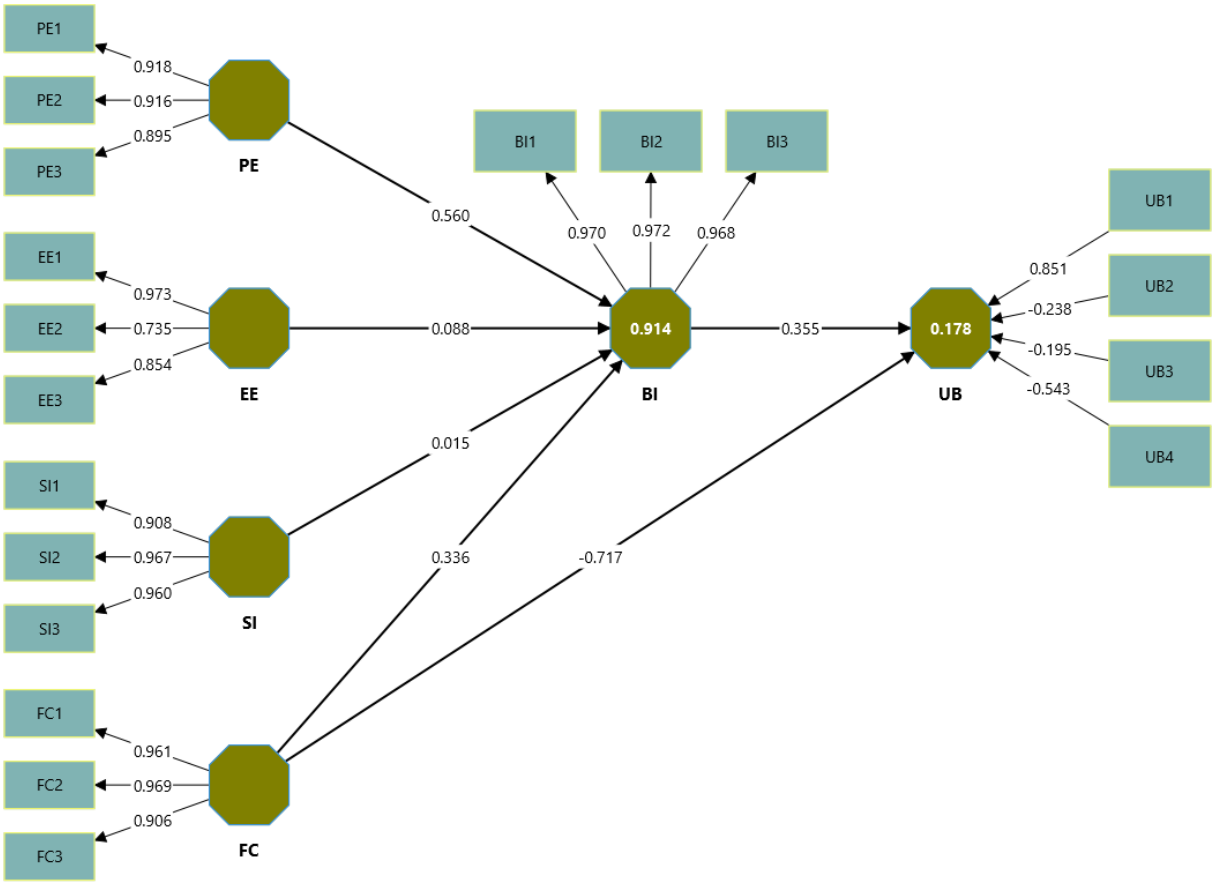

Figure 2. Final measurement and structural model with standardized loadings, outer weights, path coefficients, and R^2 values

4.3 Evaluation of the Measurement Model

Internal consistency reliability and convergent validity were assessed using Cronbach's alpha, CR, and AVE. As shown in Table 6, all reflective constructs exceeded the commonly recommended thresholds of .70 for reliability and .50 for AVE. These results support internal consistency and convergent validity, but they do not by themselves establish discriminant validity.

Table 6. Construct Validity and Reliability

Construct	Cronbach's α	CR	AVE
Behavioral Intention (BI)	0.969	0.979	0.941
Effort Expectancy (EE)	0.825	0.893	0.739
Facilitating Conditions (FC)	0.941	0.962	0.895
Performance Expectancy (PE)	0.896	0.935	0.827
Social Influence (SI)	0.94	0.962	0.894

The Fornell-Larcker criterion identified a discriminant-validity concern involving PE and BI. Although the square root of AVE for BI (0.970) exceeded its correlations with the other constructs, the square root of AVE for PE (0.910) was lower than the PE-BI correlation (0.935). Thus, PE was not sufficiently distinct from BI under this criterion.

Table 7. Discriminant Validity: Fornell-Larcker Criterion

Construct	BI	EE	FC	PE	SI
BI	**0.97**				
EE	0.811	**0.86**			
FC	0.909	0.818	**0.946**		
PE	0.935	0.777	0.87	**0.91**	
SI	0.885	0.816	0.869	0.902	**0.945**

The high PE-BI correlation suggests that respondents may have evaluated expected instructional benefits and their intention to use GenAI as closely connected judgments. This overlap is theoretically understandable in an early-adoption context, but it remains a measurement problem because the two constructs are intended to represent different concepts.

Table 8. Discriminant Validity - Heterotrait-Monotrait Ratio (HTMT)

Construct Pair	**HTMT**
EE ↔ BI	0.868
FC ↔ EE	0.885
PE ↔ EE	0.884
SI ↔ EE	0.918
FC ↔ BI	0.949
PE ↔ BI	1
SI ↔ BI	0.922
PE ↔ FC	0.94
SI ↔ FC	0.919
SI ↔ PE	0.979

HTMT provided stronger evidence of the problem. While EE-BI (0.868), FC-EE (0.885), and PE-EE (0.884) were below .90, FC-BI (0.949), PE-BI (1.000), SI-BI (0.922), PE-FC (0.940), SI-FC (0.919), and SI-PE (0.979) exceeded the recommended threshold. The PE-BI value of 1.000 is particularly problematic and indicates that these constructs were not empirically distinguishable in the present sample.

Therefore, discriminant validity was not established for all construct pairs. PE, FC, SI, and BI were retained because they are theoretically distinct UTAUT constructs and their item content addresses different domains; however, retaining them does not eliminate the empirical overlap. The PE-BI path coefficient may be inflated or unstable because of shared variance, and all structural results involving highly correlated constructs should be interpreted cautiously. Future studies should revise item wording, conduct cognitive pretesting, and collect new data before claiming clear separation among these constructs.

Table 9. Model Fit

	Saturated model	**Estimated model**
SRMR	0.096	0.097
d_ULS	1.746	1.786
d_G	3.399	3.396
Chi-square	13346.127	13353.243
NFI	0.591	0.591

Global fit indices also indicated limitations. The estimated model produced an SRMR of 0.097, which exceeds the commonly used .08 benchmark and approaches the more liberal .10 boundary, while the NFI value of 0.591 was low. These values do not support a claim of strong global model fit.

PLS-SEM places greater emphasis on explanation and prediction than covariance-based SEM; nevertheless, predictive emphasis does not override measurement or fit problems. The path coefficients, R^2, f^2, and Q^2predict values were therefore examined together with the discriminant-validity concerns, UB measurement instability, and imperfect fit indices.

The model was retained as a theory-driven exploratory test of GenAI acceptance in vocational education. Its results can identify patterns requiring further investigation, but they should not be interpreted as definitive

confirmation of the complete UTAUT structure in this context.

4.4 Evaluation of the Structural Model (Hypotheses Testing)

Bootstrapping with 5,000 resamples was performed to assess the proposed hypotheses. Table 10 presents the path coefficients, t-values, p-values, and hypothesis decisions.

Table 10. Hypothesis Testing

Hypothesis	Path	β	t	p	Result
H1	PE → BI	0.56	7.011	< .001	Supported
H2	EE → BI	0.088	2.857	0.004	Supported
H3	SI → BI	0.015	0.232	0.817	Not Supported
H4	FC → BI	0.336	6.117	< .001	Supported
H5	BI → UB	0.355	0.92	0.358	Not Supported
H6	FC → UB	-0.717	1.012	0.312	Not Supported

The results indicate that Performance Expectancy exerted the strongest positive effect on Behavioral Intention ($\beta = 0.560$, $p < .001$), followed by Facilitating Conditions ($\beta = 0.336$, $p < .001$) and Effort Expectancy ($\beta = 0.088$, $p = .004$). Social Influence did not significantly influence Behavioral Intention.

In contrast, neither BI nor FC significantly predicted UB. The negative FC → UB coefficient was theoretically unexpected but statistically non-significant. Given the high correlations among several predictors and the unstable formative weights for UB, the negative sign may reflect suppression or measurement instability rather than a substantive inverse effect. Accordingly, no causal interpretation is assigned to this coefficient.

Table 11. Coefficient of Determination (R^2)

	R-square	**R-square adjusted**
BI	0.914	0.914
UB	0.178	0.176

The model explained 91.4% of the variance in BI (adjusted $R^2 = 0.914$), indicating substantial explanatory power for intention. It explained 17.8% of the variance in UB (adjusted $R^2 = 0.176$), indicating limited explanatory power for actual use.

Table 12. Effect Size (f^2)

	f-square
BI -> UB	0.027
EE -> BI	0.026
FC -> BI	0.238
FC -> UB	0.109
PE -> BI	0.570
SI -> BI	0.000

The largest effect was observed for Performance Expectancy on Behavioral Intention ($f^2 = 0.570$), indicating that perceived usefulness was the most influential determinant of teachers' intention to adopt Generative AI.

Table 13. Predictive Relevance (Q^2predict)

Indicator	**Q^2predict**
BI1	0.874
BI2	0.845
BI3	0.846
UB1	0.103
UB2	-0.001
UB3	-0.012
UB4	0.047

The positive Q^2predict values for BI1-BI3 indicate predictive relevance for behavioral intention. By contrast, UB2 and UB3 had slightly negative values, and the remaining UB indicators had only small positive values.

These results reinforce the conclusion that the model predicts intention substantially better than actual usage behavior.

5. Discussion

5.1 Determinants of Behavioral Intention

The model explained a large proportion of variance in BI, but its structural estimates must be considered alongside incomplete discriminant validity and imperfect global fit. Within these limitations, PE showed the strongest positive association with BI, followed by FC and EE, whereas SI was non-significant.

The PE finding suggests that vocational teachers evaluate GenAI primarily through its perceived contribution to instructional performance. In this context, usefulness may involve preparing competency-based materials, explaining technical procedures, generating differentiated examples, providing feedback, and supporting authentic workplace tasks. This pattern is consistent with UTAUT and recent educational GenAI research (Al-Abdullatif, 2024; Kong et al., 2024; Venkatesh et al., 2003). However, because PE and BI were not empirically distinct (HTMT = 1.000), the magnitude of the PE → BI coefficient may partly reflect measurement overlap. It should therefore be treated as a strong association requiring replication rather than definitive evidence of causal dominance.

FC had a meaningful positive relationship with BI, indicating that resources, technical support, and institutional policies shape teachers' willingness to adopt GenAI. EE was also significant, although its effect size was small. Together, these findings imply that ease of use matters, but teachers place greater weight on instructional value and the organizational conditions that make experimentation feasible (Hazzan-Bishara et al., 2025; Honig et al., 2025; Yang & Appleget, 2024).

SI did not significantly influence BI. In private vocational education, GenAI adoption may be relatively individualized and task-specific, particularly while institutional norms remain unsettled. Teachers may rely more on direct experience, occupational relevance, and classroom needs than on encouragement from colleagues or administrators. Social endorsement may also be symbolic rather than operational: institutions can encourage innovation without providing clear policies, approved tools, or pedagogical guidance. Once perceived usefulness and facilitating conditions are considered, normative pressure may therefore add little explanatory value (Hazzan-Bishara et al., 2025; Nikolic et al., 2024).

5.2 The Intention-Behavior Gap as a Boundary Condition of UTAUT

The central finding is the mismatch between the model's strong explanation of BI ($R^2 = 0.914$) and its weak explanation of UB ($R^2 = 0.178$). Neither BI nor FC significantly predicted UB. Rather than being a routine replication of UTAUT intention paths, this intention-behavior gap constitutes the study's main theoretical contribution. It suggests that UTAUT can capture favorable evaluations and planned use of GenAI while remaining insufficient to explain enacted classroom behavior for a rapidly evolving and weakly institutionalized technology.

Several mechanisms may interrupt the translation of intention into practice. Teachers may intend to use GenAI but remain uncertain about output accuracy, data privacy, copyright, academic integrity, assessment validity, curriculum alignment, and the relevance of generated content to occupational standards. They may also lack the pedagogical and prompting competence required to transform AI outputs into safe, authentic, and assessable vocational learning tasks. Under these conditions, intention must be accompanied by implementation competence, ethical assurance, policy clarity, and sustained opportunities for experimentation (Al-Abdullatif, 2024; Ayyoub et al., 2025; Zhai, 2024).

The negative FC → UB coefficient should not be interpreted as evidence that support reduces use because it was non-significant. In the presence of highly correlated predictors and an unstable formative UB measure, the negative direction may reflect a suppression effect or sampling and measurement instability. It is also conceivable that formal institutional support encourages more cautious and regulated use rather than more frequent use, but this explanation remains speculative and requires direct testing.

The formative measurement of UB further complicates interpretation. Frequency, duration, task breadth, and tool breadth may represent different usage profiles rather than a single stable behavioral pattern, and none of the outer weights was significant. Therefore, the weak prediction of UB may reflect both a substantive intention-behavior gap and limitations in how actual use was operationalized. Future research should compare alternative composite scoring, validate the measure across samples, and incorporate objective usage logs.

5.3 Theoretical and Practical Implications

Theoretically, the findings indicate that emerging AI adoption requires a more context-sensitive extension of UTAUT. Constructs such as AI literacy, pedagogical readiness, trust, perceived risk, ethical self-efficacy, policy clarity, organizational culture, and implementation competence may explain why favorable intentions do or do not become routine practice. Demographic and experience-based differences should also be examined after establishing measurement invariance.

Practically, vocational institutions should not equate positive intention with successful implementation. Effective support should include approved and context-appropriate tools, hands-on professional development, examples aligned with vocational competencies, privacy and copyright protocols, assessment guidance, technical consultation, communities of practice, and protected time for experimentation. Monitoring should focus on meaningful pedagogical uses rather than merely the frequency of tool access.

The results nevertheless require caution. The PE-BI discriminant-validity failure, SRMR of 0.097, NFI of 0.591, self-reported cross-sectional data, and unstable UB weights limit the strength of causal and theoretical claims. The study provides evidence of a useful pattern—high acceptance accompanied by limited explanation of actual use—but it does not establish that the traditional UTAUT mechanism is universally invalid for GenAI.

6. Limitations of the Study and Future Research

Several limitations should be considered when interpreting the findings.

First, the cross-sectional design captures perceptions and self-reported behavior at one point in time. The direction of relationships is theoretically proposed but cannot be established causally. Longitudinal or repeated-measures designs are needed to determine whether intentions and use change as teachers gain experience and institutional policies mature.

Second, the sample consisted exclusively of private vocational teachers in Thailand. The findings may not generalize to public vocational institutions, other educational sectors, or countries with different AI policies, infrastructure, and professional cultures. Cross-sector and cross-country replication is required.

Third, the measurement and model-fit results impose important limitations. Discriminant validity was not established for several construct pairs, especially PE and BI; SRMR and NFI indicated imperfect global fit; and all formative UB weights were non-significant. These issues may affect the stability and interpretation of the structural coefficients. Future instrument development should revise overlapping items, conduct cognitive interviews and pilot testing, compare alternative UB specifications, and validate the revised model with an independent sample.

Fourth, the study was designed to test aggregate relationships among the UTAUT constructs, and no a priori hypotheses were specified for demographic moderation. Post hoc comparisons across gender, age, teaching experience, and GenAI experience were therefore not conducted. Such analyses would require evidence of measurement invariance and appropriate control of multiple testing before group differences could be interpreted. Consequently, the aggregate findings should not be assumed to apply uniformly across demographic groups. Future studies should establish measurement invariance, for example through MICOM, before applying PLS multi-group analysis or appropriate mean-comparison procedures.

Finally, UB was measured through self-reported frequency, duration, task breadth, and tool breadth. Such measures may be affected by recall and social-desirability bias and may not capture the pedagogical quality of use. Future research should combine survey data with platform logs, classroom artifacts, observations, and qualitative evidence while continually reassessing the model as GenAI technologies and regulations evolve.

7. Conclusion

This study examined GenAI acceptance and use among private vocational teachers in Thailand through UTAUT. PE, FC, and EE were positively associated with BI, while SI was not significant.

The most important result was not simply the strong explanation of intention, but the failure of BI and FC to explain actual use. The model accounted for 91.4% of BI but only 17.8% of UB, indicating a substantial intention-behavior gap in the adoption of an emerging educational technology.

This pattern suggests that conventional acceptance constructs are more effective for explaining favorable evaluations than for explaining implementation. However, the conclusion is provisional because PE and BI were not empirically distinct, model fit was imperfect, and the UB measure was unstable. Revised measurement and independent replication are therefore necessary.

For vocational institutions, the findings indicate that infrastructure and positive attitudes are necessary but insufficient. Sustainable GenAI integration requires pedagogical competence, ethical and policy guidance, context-relevant use cases, technical support, and opportunities for teachers to convert intention into responsible classroom practice.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During manuscript revision, the authors used an AI-assisted language tool to improve clarity, organization, and grammar. No new data were generated and no new statistical analyses were performed by the tool. The authors reviewed and verified all revisions and take full responsibility for the accuracy, integrity, and originality of the manuscript.

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Author contributions

Nuttawoot Thoopthong, the doctoral researcher and first author, was responsible for the conceptualization, literature review, research design, instrument development, data collection, data analysis, and preparation of the original manuscript. Potsirin Limpinan, the principal advisor, supervised the research, contributed to the research design and methodology, and critically reviewed and revised the manuscript. Thada Jantakoon, the co-advisor, provided methodological and academic guidance and reviewed and revised the manuscript. All authors read and approved the final manuscript.

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Data sharing statement

No additional data are available.

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