Acceptance of Generative AI for Supporting Innovative Learning in Vocational Education

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Abstract

The rapid advancement of Generative Artificial Intelligence (Generative AI) has created new opportunities for enhancing teaching and learning, particularly in vocational education, where innovation and workforce readiness are essential. Despite the growing adoption of AI technologies, empirical evidence regarding the factors influencing vocational instructors' acceptance of Generative AI remains limited, especially in developing-country contexts. This study aims to examine the determinants of Generative AI acceptance for supporting innovative learning among private vocational education instructors in Thailand by integrating the Information Systems Success Model, the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Trust in Technology perspective.

A quantitative cross-sectional survey design was employed. Data were collected from 544 private vocational education instructors using stratified random sampling and a structured questionnaire measured on a seven-point Likert scale. The proposed research model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results revealed that 15 of the 18 proposed hypotheses were supported. System/service quality and information quality significantly enhanced performance expectancy and effort expectancy, while social influence and trust emerged as the strongest predictors of behavioral intention. Behavioral intention, in turn, exerted the strongest direct effect on innovative pedagogy behavior. The model explained 62.2% of the variance in behavioral intention and 51.7% of the variance in innovative pedagogy behavior, demonstrating substantial explanatory and predictive capability. In addition, the PLSpredict assessment indicated satisfactory out-of-sample predictive performance.

The findings extend existing technology acceptance research by integrating multiple theoretical perspectives and positioning innovative pedagogy behavior as the ultimate outcome of AI adoption. The study also provides practical guidance for policymakers, educational administrators, and technology developers by emphasizing the importance of high-quality AI systems, institutional support, trust-building mechanisms, and professional development programs to promote the effective and responsible integration of Generative AI in vocational education.

Keywords: Generative Artificial Intelligence, technology acceptance model, UTAUT, PLS-SEM, vocational education, innovative pedagogy behavior

1. Introduction

The rapid advancement and widespread adoption of Generative Artificial Intelligence (Generative AI), particularly large language models such as ChatGPT, Google Gemini, and Microsoft Copilot, have fundamentally transformed the educational landscape worldwide. Since the public release of ChatGPT, Generative AI technologies have attracted unprecedented attention because of their capability to generate text, images, programming code, instructional materials, and personalized learning support. Their rapid diffusion has encouraged educational institutions to reconsider traditional pedagogical approaches and explore innovative methods for teaching and learning (Alotaibi, 2026; Kong et al., 2024; Weis et al., 2026). Recent studies have demonstrated that Generative AI can support lesson planning, learning material development, assessment, feedback generation, and personalized instruction, thereby creating new opportunities for educational innovation and digital transformation (Lee et al., 2025; Yakubu et al., 2025).

Within this broader educational transformation, vocational education and training (TVET) represents a particularly important context for the application of Generative AI. Unlike general education, vocational education focuses on practical competencies, workplace readiness, and industry-oriented skills that require continuous adaptation to technological change. Vocational instructors are expected to prepare learners for Industry 4.0 and digitally transformed workplaces where artificial intelligence and automation increasingly influence professional practice (Baharin, 2025; Cui et al., 2025). Consequently, integrating Generative AI into vocational education has the potential to support authentic learning activities, competency-based instruction, personalized guidance, and innovative pedagogical strategies that align with labor market demands (Gumelar et al., 2025). In Southeast Asian countries, including Thailand, vocational education systems are undergoing significant modernization to enhance educational quality and workforce competitiveness, making the adoption of emerging digital technologies particularly relevant (Primartadi et al., 2026).

Despite these opportunities, the successful implementation of Generative AI depends largely on educators' willingness to adopt and effectively integrate the technology into their instructional practices (Şimşek et al., 2025). Existing research has shown that teachers' acceptance of educational technology significantly influences actual classroom implementation and pedagogical innovation. Although a growing body of literature has examined technology acceptance in educational settings, much of the previous research has focused on higher education faculty and K–12 teachers, while empirical evidence concerning vocational education instructors remains relatively limited (Hidayat et al., 2025). This limitation is particularly evident in developing countries, where institutional conditions, technological infrastructure, and cultural contexts may differ substantially from those found in developed nations (Cui et al., 2025).

Technology acceptance research has traditionally relied on well-established theoretical frameworks such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). TAM emphasizes that users' acceptance of technology is primarily influenced by perceived usefulness and perceived ease of use (Davis, 1989), whereas UTAUT extends this perspective by incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). These models have consistently demonstrated strong explanatory power across various educational technology contexts (Yakubu et al., 2025; Wijaya et al., 2025). However, the emergence of Generative AI introduces additional concerns related to system reliability, information quality, transparency, and trust, which may not be fully explained by traditional acceptance models alone.

The Information Systems Success Model proposed by DeLone and McLean (2003) suggests that system quality and information quality are critical determinants of users' perceptions and technology utilization. In the context of Generative AI, these dimensions become increasingly important because instructors must evaluate the reliability, accessibility, accuracy, and educational appropriateness of AI-generated outputs (Hidayat et al., 2025). Furthermore, trust has emerged as an essential factor influencing the acceptance of AI technologies. Users may recognize the potential benefits of Generative AI while simultaneously expressing concerns regarding hallucinations, misinformation, ethical issues, bias, and academic integrity. Consequently, trust in AI systems has become a significant predictor of users' intention to adopt and continuously use AI-supported technologies (Park, 2026; Weis et al., 2026; Masrek et al., 2025).

Although previous studies have examined individual aspects of technology acceptance, several important research gaps remain. First, empirical studies specifically focusing on vocational education instructors are still limited compared with those conducted in higher education settings (Hidayat et al., 2025). Second, most existing studies have applied single theoretical frameworks, such as TAM or UTAUT, without integrating complementary perspectives that capture technical, informational, social, and psychological dimensions of AI acceptance (Alotaibi, 2026). Third, limited evidence is available from developing countries in Southeast Asia, where educational institutions face unique technological and organizational challenges (Cui et al., 2025). Finally, many previous studies have focused primarily on behavioral intention while paying relatively little attention to how technology acceptance translates into innovative pedagogical practices (Cabero-Almenara et al., 2024).

To address these gaps, this study develops and empirically validates an integrated research framework that combines the Information Systems Success Model, the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Trust in Technology perspective. The proposed model incorporates eight key constructs: system/service quality, information quality, performance expectancy, effort expectancy, social influence, trust, behavioral intention, and innovative pedagogy behavior. By integrating these complementary theoretical perspectives, the study seeks to provide a more comprehensive explanation of vocational instructors' acceptance of Generative AI and its application in innovative teaching practices.

This study employs a quantitative cross-sectional survey design involving 544 private vocational education instructors in Thailand selected through stratified random sampling. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to evaluate both the measurement model and the structural relationships among the proposed constructs. Thailand provides an appropriate research context because the country is actively promoting digital transformation and educational innovation while strengthening vocational education to support the emerging digital economy (Primartadi et al., 2026).

The objectives of this study are fourfold. First, to examine the effects of system/service quality and information quality on performance expectancy, effort expectancy, and trust. Second, to investigate the influence of performance expectancy, effort expectancy, social influence, and trust on behavioral intention to use Generative AI. Third, to examine the effects of behavioral intention, trust, and effort expectancy on innovative pedagogy behavior. Fourth, to evaluate the predictive capability of the integrated research model in explaining vocational instructors' acceptance and innovative application of Generative AI.

This study contributes to literature in several important ways. Theoretically, it extends existing technology acceptance research by integrating four complementary theoretical perspectives into a unified framework for explaining Generative AI adoption in vocational education. Methodologically, it applies PLS-SEM and predictive assessment techniques to evaluate both explanatory and predictive performance. Practically, the findings provide evidence-based guidance for policymakers, vocational education administrators, and educational technology developers seeking to promote responsible and effective AI integration. More importantly, by positioning innovative pedagogy behavior as the ultimate outcome of technology acceptance, this study emphasizes that the value of Generative AI lies not only in its adoption but also in its capacity to transform teaching and learning practices.

The remainder of this paper is organized as follows. The next section presents the theoretical foundations and research hypotheses. The methodology section describes research design, participants, instrumentation, and data analysis procedures. The results section reports the findings of the measurement and structural model assessments. Finally, the discussion, implications, limitations, and conclusion summarize the major contributions of the study and provide recommendations for future research and practice.

2. Theoretical Frameworks

2.1 Generative AI for Supporting Innovative Learning in Vocational Education

Generative Artificial Intelligence (Generative AI) refers to intelligent systems capable of producing new content, including text, images, programming code, instructional materials, simulations, and personalized feedback. Unlike conventional information systems that primarily retrieve existing information, Generative AI enables users to interactively generate context-specific learning resources and instructional support (Dwivedi et al., 2023; Kasneci et al., 2023). In educational settings, Generative AI has increasingly been recognized as a transformative technology that can facilitate lesson planning, content creation, assessment design, formative feedback, and adaptive learning experiences.

The educational potential of Generative AI is particularly significant in vocational education and training (TVET), where learning emphasizes practical competence, authentic problem solving, and workplace readiness. Vocational instructors are expected to prepare learners for digitally transformed industries characterized by automation, artificial intelligence, and Industry 4.0 technologies. In this context, Generative AI can support the development of competency-based learning materials, scenario-based activities, individualized instruction, and innovative assessment strategies that better reflect real-world professional environments (Zawacki-Richter et al., 2019).

However, the successful integration of Generative AI depends not only on its technological capability but also on users' acceptance of the technology. Even highly advanced AI systems may fail to create educational value if instructors do not perceive them as useful, easy to use, trustworthy, and socially supported. Therefore, understanding the factors influencing the acceptance of Generative AI is essential for explaining how this technology can promote innovative pedagogy behavior in vocational education.

2.2 Technology Acceptance Research

Technology acceptance research seeks to explain why individuals decide to adopt, use, and continue using new technologies. Among the most influential theoretical frameworks, the Technology Acceptance Model (TAM) proposes that users' behavioral intention is primarily determined by their perceptions of usefulness and ease of use

(Davis, 1989). Later, the Unified Theory of Acceptance and Use of Technology (UTAUT) extended this perspective by incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions as important determinants of technology adoption (Venkatesh et al., 2003). These theories have been widely validated in educational technology research and have demonstrated strong predictive capability across various learning contexts.

Although TAM and UTAUT effectively explain users' cognitive and social perceptions, the unique characteristics of Generative AI require additional theoretical perspectives. AI systems generate dynamic outputs that may vary in quality, reliability, transparency, and trustworthiness. Consequently, users often evaluate not only the usefulness of the technology but also the quality of the system itself and the credibility of the information it produces.

The Information Systems Success Model addresses this issue by proposing that system quality and information quality are fundamental antecedents of successful technology utilization (DeLone & McLean, 2003). In the context of Generative AI, system/service quality reflects the reliability, accessibility, responsiveness, and functional suitability of AI applications, whereas information quality represents the accuracy, relevance, completeness, and educational usefulness of AI-generated outputs.

Trust provides another important dimension for understanding AI acceptance. Because Generative AI may produce inaccurate, biased, or unverifiable information, users must determine whether the technology is sufficiently dependable and appropriate for educational purposes. Previous studies integrating trust with TAM have demonstrated that trust significantly influences users' intention to adopt digital technologies under conditions of uncertainty (Gefen et al., 2003).

Accordingly, this study integrates the Information Systems Success Model, TAM, UTAUT, and the Trust perspective to provide a comprehensive explanation of Generative AI acceptance in vocational education. The integrated framework assumes that system/service quality and information quality shape users' cognitive evaluations, performance expectancy and effort expectancy influence behavioral perceptions, social influence captures organizational and professional support, trust reflects users' confidence in AI systems, and behavioral intention ultimately leads to innovative pedagogy behavior.

Table 1. Integrated Research Constructs and Definitions

Variable	Code	Definition in This Study
System/Service Quality	SQ	The degree to which Generative AI tools are reliable, accessible, responsive, and functionally suitable for supporting vocational teaching and learning.
Information Quality	IQ	The degree to which Generative AI provides relevant, accurate, clear, useful, and up-to-date information for instructional and learning purposes.
Performance Expectancy	PE	The extent to which users believe that Generative AI can improve teaching effectiveness, learning performance, productivity, and educational task completion.
Effort Expectancy	EE	The extent to which users perceive Generative AI as easy to learn, easy to use, and easy to integrate into teaching or learning activities.
Social Influence	SI	The extent to which users perceive that important people, peers, teachers, colleagues, or institutions support the use of Generative AI.
Trust	TR	The extent to which users believe that Generative AI is dependable, useful, and reliable for educational purposes.
Behavioral Intention	BI	The degree to which users intend to use, continue using, and recommend Generative AI for vocational teaching and learning.
Innovative Pedagogy Behavior	IPB	The extent to which users apply Generative AI to design, create, and implement innovative teaching and learning practices.

2.3 Research Model and Hypotheses

The proposed research model was developed by integrating complementary theoretical perspectives to explain the acceptance of Generative AI for supporting innovative learning in vocational education. The Information Systems Success Model provides the technical foundation by explaining how system/service quality and information quality influence users' perceptions. TAM and UTAUT explain how performance expectancy, effort expectancy, and social influence shape behavioral intention, whereas the Trust perspective captures users' confidence in AI-generated outputs and educational applications.

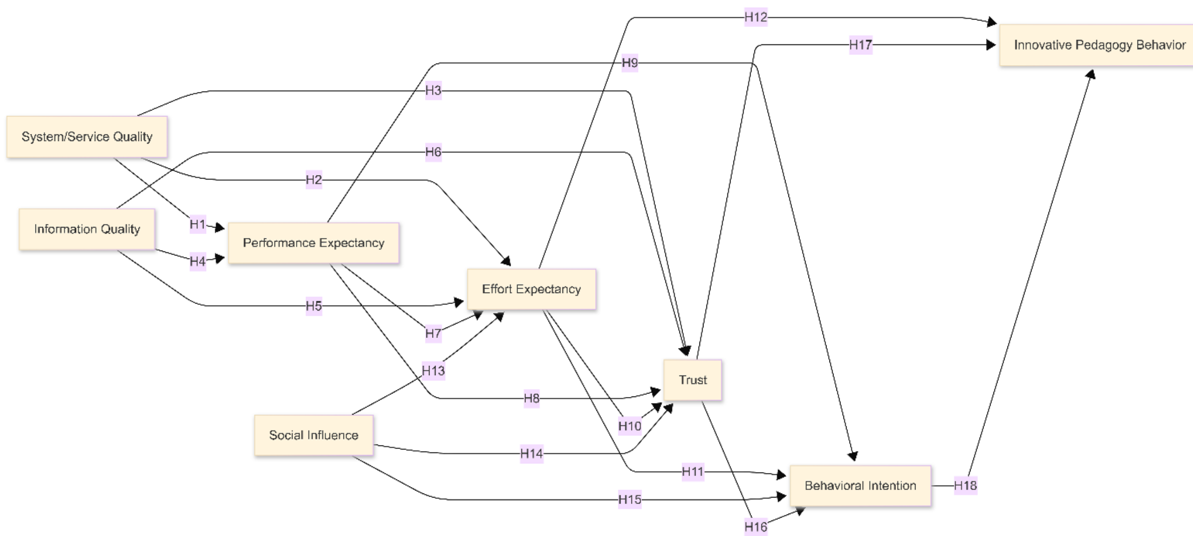

Figure 1. Proposed Research Model

The integrated model assumes that high-quality AI systems and information resources improve users' expectations regarding performance and ease of use. Social influence and trust strengthen behavioral intention, while behavioral intention represents the most immediate determinant of actual innovative pedagogy behavior. The model therefore extends traditional technology acceptance research by positioning innovative pedagogy behavior as the final educational outcome of Generative AI adoption.

Table 2. Hypotheses

Hypothesis	Structural Relationship	Expected Effect
H1	System/Service Quality → Performance Expectancy	Positive
H2	System/Service Quality → Effort Expectancy	Positive
H3	System/Service Quality → Trust	Positive
H4	Information Quality → Performance Expectancy	Positive
H5	Information Quality → Effort Expectancy	Positive
H6	Information Quality → Trust	Positive
H7	Performance Expectancy → Effort Expectancy	Positive
H8	Performance Expectancy → Trust	Positive
H9	Performance Expectancy → Behavioral Intention	Positive
H10	Effort Expectancy → Trust	Positive
H11	Effort Expectancy → Behavioral Intention	Positive
H12	Effort Expectancy → Innovative Pedagogy Behavior	Positive
H13	Social Influence → Effort Expectancy	Positive
H14	Social Influence → Trust	Positive
H15	Social Influence → Behavioral Intention	Positive
H16	Trust → Behavioral Intention	Positive
H17	Trust → Innovative Pedagogy Behavior	Positive
H18	Behavioral Intention → Innovative Pedagogy Behavior	Positive

3. Methodology

3.1 Research Design

This study employed a quantitative research design to investigate the acceptance of Generative Artificial Intelligence (Generative AI) for supporting innovative learning in vocational education. The proposed research model was developed by integrating the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Information Systems Success Model, and the Trust in Technology perspective. The model examined the relationships among system/service quality, information quality, performance expectancy, effort expectancy, social influence, trust, behavioral intention, and innovative pedagogy behavior.

A cross-sectional survey research design was adopted because it is appropriate for examining perceptions and behavioral intentions toward emerging educational technologies. Data were collected through a structured questionnaire using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to validate the measurement model and examine the hypothesized structural relationships. PLS-SEM was selected because it is suitable for prediction-oriented research involving multiple latent constructs and complex causal relationships.

3.2 Participants

The target population consisted of vocational education instructors working in private vocational institutions in Thailand. This population was selected because vocational instructors play a critical role in preparing learners for digitally transformed workplaces and are increasingly expected to integrate emerging technologies, including Generative AI, into instructional design, classroom activities, assessment, and professional development.

A stratified random sampling technique was employed to ensure adequate representation across different demographic characteristics. A total of 544 valid responses were obtained and included in the analysis. The sample size exceeded the minimum requirement for PLS-SEM and provided sufficient statistical power for testing the proposed structural model.

Participation in the study was voluntary, and all respondents were informed that the collected data would be used exclusively for academic research purposes.

Table 3. Demographic Information of Respondents

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	237	43.6
	Female	304	55.9
	Non-binary/Other	3	0.6
	Total	544	100.0
Age	Below 30 years	175	32.2
	31–40 years	162	29.8
	41–50 years	134	24.6
	51 years and above	73	13.4
	Total	544	100.0
Teaching Experience	Less than 5 years	92	16.9
	5–10 years	191	35.1
	11–20 years	175	32.2
	More than 20 years	86	15.8
	Total	544	100.0
Subject Area	Commerce / Business Administration	331	60.8
	Industrial / Vocational Technology	213	39.2
	Total	544	100.0

The respondents consisted of 544 vocational education instructors from private vocational institutions in Thailand. Female instructors represented the majority of the sample (55.9%), while male instructors accounted for 43.6%, and

0.6% identified as non-binary or other genders. Regarding age, the largest group was instructors below 30 years of age (32.2%), followed by those aged 31–40 years (29.8%), 41–50 years (24.6%), and 51 years and above (13.4%).

In terms of teaching experience, most respondents had between 5 and 10 years of teaching experience (35.1%), followed by 11–20 years (32.2%), less than 5 years (16.9%), and more than 20 years (15.8%). Regarding subject area, the majority were affiliated with Commerce and Business Administration programs (60.8%), whereas 39.2% specialized in Industrial and Vocational Technology. These demographic characteristics indicate that the sample included vocational instructors with diverse backgrounds and professional experience, thereby strengthening the representativeness of the study.

3.3 Instrumentation

Data were collected using a structured questionnaire developed from established theories and previous empirical studies. The instrument consisted of eight reflective constructs measured using a seven-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree).

The questionnaire was adapted from the Information Systems Success Model, the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, and trust-related technology adoption research.

Table 4. Items of Questionnaire

Construct	Code	Number of Items	Measurement Type
System/Service Quality	SQ	3	Reflective
Information Quality	IQ	3	Reflective
Performance Expectancy	PE	3	Reflective
Effort Expectancy	EE	3	Reflective
Social Influence	SI	3	Reflective
Trust	TR	3	Reflective
Behavioral Intention	BI	3	Reflective
Innovative Pedagogy Behavior	IPB	3	Reflective
Total		**24**	

Table 5. Questionnaire Items

Construct	Item Code	Questionnaire Item
System/Service Quality	SQ1	Generative AI systems are stable and readily available for educational use.
	SQ2	User support services for Generative AI are of high quality.
	SQ3	The interface of Generative AI is convenient and easy to use.
Information Quality	IQ1	The outputs generated by Generative AI are accurate and appropriate.
	IQ2	The outputs generated by Generative AI are current and relevant.
	IQ3	The outputs generated by Generative AI are sufficiently complete for educational use.
Performance Expectancy	PE1	Generative AI enhances learning outcomes in the classroom.
	PE2	Generative AI improves the efficiency of learning activities.
	PE3	Generative AI supports learner-centered education.
Effort Expectancy	EE1	Generative AI is easy to use.
	EE2	Learning how to use Generative AI is not difficult.
	EE3	Generative AI reduces unnecessary workload.
Social Influence	SI1	Institutional norms support the use of Generative AI.
	SI2	Colleagues encourage the use of Generative AI.
	SI3	Administrators support the integration of Generative AI.

Table 5. Questionnaire Items(continued)

Construct	Item Code	Questionnaire Item
Trust	TR1	I trust the outputs generated by Generative AI for teaching and learning.
	TR2	I believe that Generative AI is sufficiently transparent for classroom use.
	TR3	I believe that Generative AI is appropriate for the vocational education context.
Behavioral Intention	BI1	I intend to use Generative AI for innovative learning management.
	BI2	I plan to expand the use of Generative AI in my classroom.
	BI3	I will encourage others to use Generative AI for innovative learning.
Innovative Pedagogy Behavior	IPB1	I initiate new teaching methods by using Generative AI.
	IPB2	I experiment with AI-driven learning activities.
	IPB3	I share innovative teaching practices with others.

3.4 Data Analysis

The collected data were analyzed using SmartPLS 4. The analysis followed the two-step approach recommended for PLS-SEM.

First, the measurement model was evaluated through indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Factor loadings greater than 0.70, Cronbach's alpha values above 0.70, Composite Reliability (CR) values above 0.70, and Average Variance Extracted (AVE) values above 0.50 were considered acceptable. Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT).

Second, the structural model was evaluated by examining variance inflation factors (VIF), path coefficients, coefficients of determination (R^2), effect sizes (f^2), predictive relevance (Q^2), and the significance of path relationships using the bootstrapping procedure with 5,000 resamples. Model fit was additionally assessed using the standardized root mean square residual (SRMR). A significance level of .05 was adopted for all hypothesis testing.

4. Results

4.1 Descriptive Statistics

Descriptive statistics were calculated to examine the respondents' perceptions regarding the use of Generative Artificial Intelligence (Generative AI) for supporting innovative learning in vocational education. Table 6 presents the meaning, standard deviation, minimum value, maximum value, skewness, and kurtosis of the twenty-four measurement items.

Overall, the respondents exhibited positive attitudes toward the adoption of Generative AI. The mean scores ranged from 5.697 to 6.068 on a seven-point Likert scale, indicating a high level of agreement with the statements measuring system quality, information quality, performance expectancy, effort expectancy, social influence, trust, behavioral intention, and innovative pedagogy behavior. The highest mean score was observed for IPB1 (M = 6.068), suggesting that respondents strongly agreed that Generative AI could support experimentation with innovative teaching practices. Conversely, the lowest mean score was found for SQ1 (M = 5.697), although it remained substantially above the scale midpoint.

The standard deviations ranged from 1.033 to 1.351, indicating moderate variability in the responses. Furthermore, the skewness values were negative across all items, suggesting that respondents generally tended to provide favorable evaluations of Generative AI. The kurtosis values were within acceptable ranges, indicating no severe deviations from normality. Therefore, the descriptive statistics support the suitability of the dataset for subsequent PLS-SEM analysis.

Table 6. Descriptive Statistics

Name	Mean	Median	Observed min	Observed max	Standard deviation	Excess kurtosis	Skewness
SQ1	5.697	6	1	7	1.351	2.261	-1.406
SQ2	5.862	6	1	7	1.312	2.992	-1.648
SQ3	5.972	6	1	7	1.219	3.485	-1.65
IQ1	5.903	6	1	7	1.205	3.173	-1.538
IQ2	6.044	6	1	7	1.033	2.233	-1.26
IQ3	5.925	6	1	7	1.196	2.903	-1.51
PE1	5.95	6	1	7	1.171	2.891	-1.509
PE2	5.947	6	1	7	1.182	3.416	-1.586
PE3	5.98	6	1	7	1.138	2.512	-1.445
EE1	6.055	6	1	7	1.123	2.477	-1.451
EE2	6.046	6	1	7	1.111	3.258	-1.533
EE3	6.004	6	1	7	1.126	3.071	-1.517
SI1	5.936	6	1	7	1.154	1.452	-1.219
SI2	5.895	6	1	7	1.201	1.735	-1.284
SI3	5.961	6	1	7	1.155	3.715	-1.603
TR1	5.954	6	1	7	1.11	2.057	-1.293
TR2	5.969	6	1	7	1.222	3.392	-1.673
TR3	5.925	6	1	7	1.225	2.802	-1.518
BI1	5.943	6	1	7	1.208	3.544	-1.674
BI2	5.95	6	1	7	1.155	2.48	-1.403
BI3	6.031	6	1	7	1.213	2.181	-1.498
IPB1	6.068	6	1	7	1.141	4.457	-1.793
IPB2	6.011	6	1	7	1.074	2.255	-1.306
IPB3	5.991	6	1	7	1.114	3.357	-1.518

4.2 Factor Analysis

The outer measurement model was evaluated using standardized indicator loadings. The standardized factor loadings indicated that all indicators adequately represented their underlying constructs.

The measurement items associated with System/Service Quality, Information Quality, Performance Expectancy, Effort Expectancy, Social Influence, Trust, Behavioral Intention, and Innovative Pedagogy Behavior demonstrated satisfactory loadings. According to the recommended guidelines for PLS-SEM, factor loadings above 0.70 indicate acceptable indicator reliability. The loading values obtained in this study confirmed that the observed variables contributed meaningfully to their corresponding constructs.

The results therefore provide empirical support for retaining all measurement items in the subsequent assessment of the measurement model.

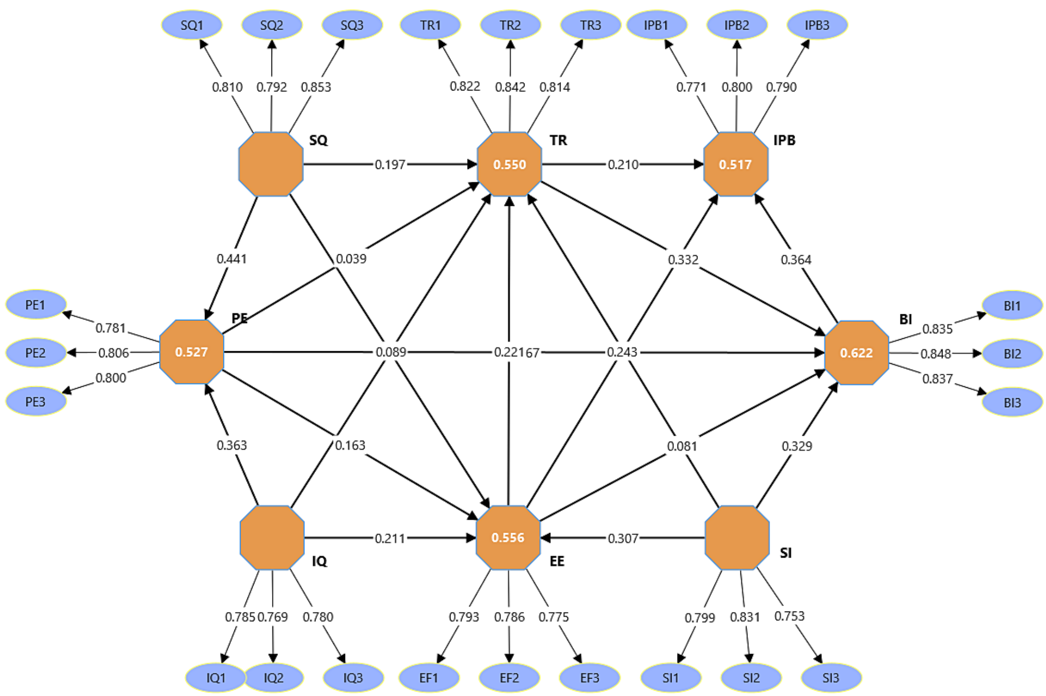

Figure 2. Factor Analysis Results

4.3 Evaluation of the Measurement Model

The measurement model was evaluated by examining internal consistency reliability, convergent validity, discriminant validity, and overall model fit.

Table 7. Construct Validity and Reliability

Construct	Cronbach's Alpha	Composite Reliability	AVE
BI	0.791	0.878	0.705
EE	0.689	0.828	0.616
IPB	0.693	0.83	0.62
IQ	0.675	0.822	0.605
PE	0.711	0.838	0.633
SI	0.708	0.837	0.632
SQ	0.754	0.859	0.67
TR	0.767	0.866	0.682

The results indicate that the Cronbach's alpha values ranged from 0.675 to 0.791, while Composite Reliability values ranged from 0.822 to 0.878. Although the Cronbach's alpha values for EE, IPB, and IQ were slightly below the conventional threshold of 0.70, their Composite Reliability values exceeded 0.80, indicating satisfactory internal consistency reliability.

Furthermore, the Average Variance Extracted (AVE) values ranged from 0.605 to 0.705, all exceeding the recommended threshold of 0.50. Therefore, the measurement model demonstrated adequate convergent validity.

Table 8. Discriminant Validity: Fornell–Larcker Criterion

Construct	BI	EE	IPB	IQ	PE	SI	SQ	TR
BI	**0.84**							
EE	0.616	**0.785**						
IPB	0.661	0.601	**0.787**					
IQ	0.633	0.624	0.64	**0.778**				
PE	0.622	0.622	0.609	0.639	**0.796**			
SI	0.717	0.67	0.647	0.63	0.653	**0.795**		
SQ	0.651	0.63	0.634	0.625	0.668	0.664	**0.819**	
TR	0.701	0.636	0.62	0.573	0.571	0.675	0.627	**0.826**

The square roots of the AVE for all constructs were greater than their corresponding inter-construct correlations. Consequently, the Fornell-Larcker criterion was satisfied, indicating that each construct was empirically distinct from the others and that adequate discriminant validity had been achieved.

The model fit assessment demonstrated that the proposed model achieved an acceptable level of fit. The estimated SRMR value was 0.070, which is below the recommended threshold of 0.08, indicating satisfactory model adequacy. Additional fit measures, including d_ULS, d_G, and NFI, were examined as complementary criteria for prediction-oriented PLS-SEM evaluation. Collectively, these results support the suitability of the proposed research model for structural analysis and hypothesis testing.

Table 9. Model Fit

Fit index	**Saturated model**	**Estimated model**
SRMR	0.061	0.070
d_ULS	1.116	1.487
d_G	0.501	0.537
Chi-square	1558.999	1601.560
NFI	0.746	0.739

4.4 Evaluation of the Structural Model (Hypotheses Testing)

Table 10. Hypothesis Testing

Hypothesis	Path	β	t-value	p-value	Decision
H1	SQ → PE	0.441	8.636	<0.001	Supported
H2	SQ → EE	0.185	3.103	0.002	Supported
H3	SQ → TR	0.197	2.501	0.012	Supported
H4	IQ → PE	0.363	7.272	<0.001	Supported
H5	IQ → EE	0.211	3.386	0.001	Supported
H6	IQ → TR	0.089	1.565	0.118	Not Supported
H7	PE → EE	0.163	2.501	0.012	Supported
H8	PE → TR	0.039	0.601	0.548	Not Supported
H9	PE → BI	0.167	2.883	0.004	Supported
H10	EE → TR	0.221	3.375	0.001	Supported
H11	EE → BI	0.081	1.387	0.165	Not Supported
H12	EE → IPB	0.243	3.403	0.001	Supported
H13	SI → EE	0.307	5.143	<0.001	Supported
H14	SI → TR	0.315	4.287	<0.001	Supported
H15	SI → BI	0.329	5.747	<0.001	Supported
H16	TR → BI	0.332	5.05	<0.001	Supported
H17	TR → IPB	0.21	2.901	0.004	Supported
H18	BI → IPB	0.364	5.516	<0.001	Supported

The structural model was evaluated using the bootstrapping procedure with 5,000 resamples. Table 10 summarizes the path coefficients, t-values, p-values, and hypothesis testing results.

The results reveal that 15 out of 18 hypotheses were supported, whereas three hypotheses (IQ → TR, PE → TR, and EE → BI) were not statistically significant. Among the antecedents of behavioral intention, trust (β = 0.332) and social influence (β = 0.329) exhibited stronger effects than performance expectancy (β = 0.167). Furthermore, behavioral intention exerted the strongest direct influence on innovative pedagogy behavior (β = 0.364), followed by effort expectancy (β = 0.243) and trust (β = 0.210).

Table 11. Coefficient of Determination (R^2)

Endogenous Construct	R^2	Interpretation
Performance Expectancy	0.527	Moderate
Trust	0.55	Moderate
Effort Expectancy	0.556	Moderate
Behavioral Intention	0.622	Moderate
Innovative Pedagogy Behavior	0.517	Moderate

The R^2 values indicate that the proposed model explains 62.2% of the variance in Behavioral Intention and 51.7% of the variance in Innovative Pedagogy Behavior, demonstrating substantial predictive capability for explaining vocational instructors' acceptance and innovative use of Generative AI.

Table 12. PLSpredict Assessment Results

	Q^2predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
BI1	0.395	0.940	0.669	0.959	0.667
BI2	0.391	0.903	0.681	0.913	0.681
BI3	0.434	0.914	0.671	0.932	0.685
EF1	0.362	0.899	0.685	0.916	0.688
EF2	0.272	0.950	0.701	0.962	0.715
EF3	0.335	0.920	0.676	0.921	0.677
IPB1	0.327	0.938	0.688	0.941	0.672
IPB2	0.294	0.904	0.695	0.922	0.688
IPB3	0.312	0.925	0.703	0.932	0.699
PE1	0.339	0.954	0.695	0.958	0.700
PE2	0.317	0.978	0.725	0.975	0.724
PE3	0.324	0.938	0.688	0.917	0.675
TR1	0.343	0.901	0.666	0.904	0.679
TR2	0.355	0.983	0.705	1.008	0.721
TR3	0.342	0.995	0.736	1.024	0.749

The PLSpredict analysis demonstrated positive Q^2 predict values for all indicators, indicating that the proposed model possesses predictive relevance. Moreover, most PLS-SEM prediction errors were lower than those of the benchmark linear model, suggesting that the model has satisfactory out-of-sample predictive performance. These findings further confirm the robustness and practical applicability of the proposed acceptance model for explaining the adoption of Generative AI in vocational education.

5. Discussion

This study investigated the factors influencing the acceptance of Generative Artificial Intelligence (Generative AI) for supporting innovative learning among private vocational education instructors in Thailand by integrating the

Information Systems Success Model, the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Trust in Technology perspective. The findings demonstrate that the proposed integrated framework provides substantial explanatory and predictive capability, explaining 62.2% of the variance in Behavioral Intention and 51.7% of the variance in Innovative Pedagogy Behavior. Overall, 15 of the 18 proposed hypotheses were supported, indicating that the acceptance of Generative AI in vocational education is influenced by technical, cognitive, social, and psychological factors simultaneously.

5.1 System/Service Quality and Information Quality as Foundational Drivers

The findings reveal that System/Service Quality significantly influenced Performance Expectancy, Effort Expectancy, and Trust, with the strongest effect observed on Performance Expectancy. This result supports the Information Systems Success Model proposed by DeLone and McLean (2003), which argues that the quality of an information system fundamentally shapes users' perceptions and subsequent technology utilization. In the context of Generative AI, vocational instructors appear to evaluate the technology based on its reliability, accessibility, responsiveness, and functional suitability before considering its educational benefits.

Similarly, Information Quality significantly enhanced both Performance Expectancy and Effort Expectancy. When AI-generated outputs are perceived as accurate, relevant, and educationally useful, instructors are more likely to believe that Generative AI can improve instructional performance while reducing the effort required to complete teaching tasks. These findings are consistent with previous studies emphasizing the importance of content quality in educational AI applications (Kasneci et al., 2023; Hidayat et al., 2025).

However, Information Quality did not significantly influence Trust. This finding suggests that trust in Generative AI extends beyond the perceived quality of information. Instructors may acknowledge that AI-generated outputs are useful while remaining cautious about issues such as transparency, accountability, bias, ethical considerations, and misinformation. Therefore, trust appears to represent a broader psychological evaluation rather than a simple assessment of information accuracy. This interpretation is consistent with recent Generative AI research emphasizing that trust is a multidimensional construct influenced by technical, ethical, and organizational factors (Masrek et al., 2025; Park, 2026).

5.2 Performance Expectancy and Effort Expectancy in the AI Era

Performance Expectancy significantly influenced Effort Expectancy and Behavioral Intention, confirming the central assumptions of TAM and UTAUT that users are more likely to adopt technologies when they believe such technologies improve work performance (Davis, 1989; Venkatesh et al., 2003). Vocational instructors who perceive that Generative AI enhances teaching effectiveness and instructional productivity demonstrate stronger intentions to integrate AI into their educational practices.

Nevertheless, Performance Expectancy did not significantly influence Trust. This result indicates that perceived usefulness and trust represent different psychological mechanisms. Users may recognize the practical value of Generative AI while simultaneously questioning its reliability, ethical implications, or long-term educational consequences. In other words, usefulness does not necessarily create confidence in the technology.

Effort Expectancy significantly influenced Trust and Innovative Pedagogy Behavior but failed to directly predict Behavioral Intention. This finding differs from many traditional technology acceptance studies and may reflect the increasing maturity of contemporary AI tools. As Generative AI platforms become easier to access and use, ease of use may no longer serve as a primary motivational factor for adoption. Instead, ease of use appears to facilitate experimentation and innovative application while indirectly supporting acceptance through enhanced trust. Similar patterns have been observed in recent studies of Generative AI adoption in educational contexts (Cabero-Almenara et al., 2024; Lu et al., 2024).

5.3 Social Influence and Trust as the Strongest Predictors of Behavioral Intention

One of the most important findings of this study is that Social Influence and Trust emerged as the strongest predictors of Behavioral Intention. Their effects were stronger than those of Performance Expectancy, suggesting that Generative AI adoption is influenced not only by functional benefits but also by organizational and social environments.

The significant role of Social Influence supports the UTAUT framework, which proposes that individuals are more likely to adopt technology when they perceive encouragement from colleagues, administrators, professional communities, and institutions (Venkatesh et al., 2003). In vocational education, where collaborative practice and institutional coordination are common, positive organizational culture may substantially accelerate AI adoption.

Trust also demonstrated a strong positive effect on Behavioral Intention, reinforcing the argument that confidence in AI systems is essential for educational implementation. Generative AI introduces unique uncertainties associated with hallucinations, bias, academic integrity, and ethical responsibility. Consequently, instructors are unlikely to adopt AI technologies unless they believe the systems are dependable and appropriate for educational use. This finding supports recent studies highlighting trust as a critical determinant of Generative AI acceptance (Weis et al., 2026; Masrek et al., 2025).

5.4 From Technology Acceptance to Innovative Pedagogy Behavior

Unlike many previous technology acceptance studies that consider Behavioral Intention as the final outcome, this study extends existing theory by positioning Innovative Pedagogy Behavior as the ultimate consequence of AI acceptance. The findings indicate that Behavioral Intention exerted the strongest direct influence on Innovative Pedagogy Behavior, followed by Effort Expectancy and Trust.

This result confirms the central proposition of TAM and UTAUT that Behavioral Intention serves as the immediate antecedent of actual technology use (Davis, 1989; Venkatesh et al., 2003). More importantly, the findings demonstrate that acceptance of Generative AI can translate into meaningful pedagogical transformation. Instructors who intend to use AI are more likely to design innovative learning activities, experiment with AI-assisted instructional strategies, and share creative teaching practices with colleagues.

The significant contributions of Trust and Effort Expectancy further suggest that pedagogical innovation requires more than simple technology adoption. Educators must also feel confident that AI systems are reliable and sufficiently easy to integrate into their professional practice. Consequently, successful AI implementation should be viewed as a process of educational transformation rather than merely technological adoption.

5.5 Theoretical Contributions

This study makes several theoretical contributions to educational technology research. First, it demonstrates that integrating the Information Systems Success Model, TAM, UTAUT, and the Trust perspective provides a more comprehensive explanation of Generative AI acceptance than relying on a single theoretical framework. The integrated model captures technical quality, cognitive evaluation, social influence, and psychological trust simultaneously.

Second, the findings suggest that trust and social influence play more prominent roles in Generative AI adoption than traditional technology acceptance theories may predict. This indicates that the emergence of AI technologies introduces additional dimensions that should be incorporated into future acceptance models.

Third, by introducing Innovative Pedagogy Behavior as the final outcome construct, this study extends technology acceptance research beyond users' intention to adopt technology and emphasizes the educational value created through innovative teaching practices. This perspective aligns technology acceptance research more closely with the broader objectives of educational transformation and pedagogical innovation.

Finally, the positive Q^2predict values and satisfactory PLSpredict results demonstrate that the integrated framework possesses meaningful out-of-sample predictive capability, supporting its applicability for future educational technology research and practice.

5.6 Practical Interpretation

The findings suggest that successful implementation of Generative AI in vocational education requires a multidimensional strategy. Educational institutions should prioritize the development and adoption of reliable AI systems that provide high-quality educational outputs. At the same time, institutional leaders should establish supportive organizational cultures, provide continuous professional development opportunities, and promote responsible AI governance to strengthen instructors' trust.

The results also indicate that policies focusing exclusively on technological infrastructure may be insufficient. Social support, ethical guidelines, collaborative learning communities, and opportunities for pedagogical experimentation are equally important for promoting sustainable AI adoption. By addressing these dimensions simultaneously, vocational education institutions can move beyond simple technology implementation toward the development of innovative learning environments that better prepare learners for the demands of the digital economy and Industry 4.0.

6. Limitation of the Study and Future Research

This study has several limitations that should be acknowledged. First, the research employed a cross-sectional survey design, which captures respondents' perceptions at a single point in time and does not allow causal relationships or changes in technology acceptance behavior to be examined over time. Future studies should adopt longitudinal designs to investigate how instructors' acceptance of Generative AI evolves as they gain more experience with the technology.

Second, the participants were limited to private vocational education instructors in Thailand. Although the sample size was adequate and stratified random sampling enhanced representativeness, the findings may not be fully generalizable to public vocational institutions or other educational contexts and countries. Comparative studies across different educational sectors and cultural settings would strengthen the external validity of the proposed model.

Third, this study focused on self-reported perceptions and behavioral intentions rather than actual usage behavior. Future research should incorporate objective measures of Generative AI utilization and teaching performance. In addition, the proposed framework may be extended by including other influential factors, such as facilitating conditions, AI literacy, ethical concerns, privacy perceptions, digital competency, and organizational support. Multi-group analysis and mixed-methods approaches could also provide deeper insights into how different instructor characteristics influence the adoption and innovative use of Generative AI in vocational education.

7. Conclusion

This study investigated the acceptance of Generative Artificial Intelligence (Generative AI) for supporting innovative learning among private vocational education instructors in Thailand by integrating the Information Systems Success Model, the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Trust in Technology perspective. The empirical findings confirmed that the integrated model provides a robust framework for explaining instructors' adoption intentions and innovative pedagogical practices. Specifically, the model explained 62.2% of the variance in Behavioral Intention and 51.7% of the variance in Innovative Pedagogy Behavior, indicating satisfactory explanatory and predictive capability.

The results demonstrated that system/service quality and information quality significantly enhance performance expectancy and effort expectancy, while social influence and trust play particularly important roles in shaping instructors' intention to use Generative AI. Trust and social influence emerged as the strongest predictors of behavioral intention, whereas behavioral intention was the most influential determinant of innovative pedagogy behavior. These findings suggest that the successful implementation of Generative AI in vocational education depends not only on technological quality but also on organizational support, professional collaboration, and users' confidence in AI systems.

From a broader perspective, this study extends existing technology acceptance literature by integrating multiple theoretical foundations and positioning innovative pedagogy behavior as the ultimate outcome of AI adoption. The findings provide practical guidance for educational institutions and policymakers seeking to promote responsible and effective AI integration, ultimately supporting the transformation of vocational education toward more innovative, learner-centered, and digitally driven teaching practices in the era of Industry 4.0.

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Authors contributions

Ponprom Chooppawa, the first author, was responsible for conceptualization, instrument development, data collection, data analysis, and preparation of the original manuscript. Potsirin Limpinan, the advisor, was responsible for supervision, methodological guidance, validation, and critical review and revision of the manuscript. Thada Jantakoon, the co-advisor, critical review and revision of the manuscript. All authors read and approved the final manuscript.

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