Intention to Use Generative AI for Vocational College Administration

Porntep Chooppawa[1], Potsirin Limpinan[1,*] & Thada Jantakoon[1]

[1]Faculty of Science and Technology, Rajabhat Maha Sarakham University, Thailand

*Correspondence: Faculty of Science and Technology, Rajabhat Maha Sarakham University, Thailand

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Abstract

The increasing adoption of Generative Artificial Intelligence (GenAI) has transformed educational administration by supporting decision-making, information management, and organizational efficiency. Despite its growing importance, limited research has examined the factors influencing GenAI adoption among vocational college administrators, particularly from a governance and policy perspective. This study investigates the determinants of administrators' intention to use and actual use behavior of GenAI in vocational college administration by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) with Trust, Privacy Concern, and Institutional Policy Fit. A quantitative cross-sectional survey was conducted with 330 administrators and deputy directors of private vocational colleges in Thailand. Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM).

The findings revealed that Social Influence, Trust, Privacy Concern, and Institutional Policy Fit significantly influenced Behavioral Intention to use GenAI. In contrast, Performance Expectancy, Effort Expectancy, and Facilitating Conditions did not significantly affect Behavioral Intention. Behavioral Intention emerged as the strongest predictor of actual Use Behavior, while Facilitating Conditions exerted a significant direct effect on use behavior. The proposed model demonstrated substantial explanatory power, accounting for 82.8% of the variance in Behavioral Intention and 76.1% of the variance in Use Behavior. Predictive assessment further confirmed the model's satisfactory predictive capability.

The study contributes to technology acceptance literature by demonstrating that governance-oriented factors play a more influential role than traditional technology-related perceptions in explaining GenAI adoption among educational administrators. Unlike conventional UTAUT assumptions that emphasize usefulness and ease of use, the findings suggest that trust, privacy awareness, social endorsement, and policy alignment are critical determinants of GenAI acceptance in administrative contexts. Practically, the results highlight the importance of establishing clear institutional policies, strengthening AI governance mechanisms, and promoting responsible AI practices to facilitate sustainable GenAI implementation in vocational education institutions.

Keywords: generative artificial intelligence, vocational college administration, UTAUT, technology acceptance, educational administration, PLS-SEM

1. Introduction

The rapid advancement of Generative Artificial Intelligence (GenAI) has transformed how educational institutions operate, communicate, and make decisions. Unlike traditional artificial intelligence applications that primarily focus on data analysis and automation, GenAI can generate human-like content, synthesize information, support decision-making, and facilitate administrative processes through large language models and intelligent conversational systems (Dwivedi et al., 2020; Shailendra et al., 2024). Consequently, educational institutions worldwide have begun exploring the integration of GenAI not only in teaching and learning but also in institutional management and administrative operations (Jin et al., 2024; Kurtz et al., 2024; Yusuf et al., 2024).

Recent studies indicate that GenAI has become increasingly influential in higher education environments. Universities are developing institutional policies, governance frameworks, and operational guidelines to regulate the use of GenAI in teaching, research, assessment, and administration (An et al., 2025; Jin et al., 2024; Crescenzi et al., 2026). Evidence suggests that GenAI can enhance organizational productivity, improve information management, support strategic planning, and reduce administrative workload (Bamasoud et al., 2025; Ivanov et al., 2024).

Furthermore, the increasing adoption of GenAI has encouraged educational institutions to reconsider their digital transformation strategies and organizational readiness for artificial intelligence integration (Karran et al., 2024; Shailendra et al., 2024).

Within vocational education, the adoption of digital technologies has become particularly important because vocational institutions operate in rapidly changing environments characterized by industry-driven curricula, quality assurance requirements, workforce development responsibilities, and increasing demands for institutional efficiency (Regassa & Desissa, 2025; Zhao et al., 2025). Administrators and deputy directors of vocational colleges are expected to manage complex organizational functions, including academic administration, personnel management, budgeting, quality assurance, stakeholder engagement, and strategic planning. Consequently, Generative AI has the potential to support administrative effectiveness by facilitating information processing, policy development, report generation, and evidence-based decision-making.

Despite these opportunities, the successful implementation of GenAI depends largely on users' acceptance and actual usage behavior. Technology acceptance has therefore become a central research issue in educational technology and information systems research. Among the various theoretical perspectives, the Unified Theory of Acceptance and Use of Technology (UTAUT) remains one of the most widely applied frameworks for explaining technology adoption behavior (Venkatesh et al., 2003). Extensive studies have confirmed the applicability of UTAUT in educational settings, demonstrating factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influence behavioral intention and technology use (Bayaga & Du Plessis, 2023; Hakimi et al., 2024; Xue et al., 2024).

The growing popularity of artificial intelligence technologies has further stimulated the application of UTAUT in AI adoption research. Recent empirical studies have employed UTAUT and its extensions to explain acceptance of artificial intelligence, AI-assisted learning environments, ChatGPT, and Generative AI applications among students, teachers, and higher education stakeholders (Acosta-Enriquez et al., 2024; Ayyoub et al., 2025; Nikolic et al., 2024; Weis et al., 2026; Yan & Jafri, 2026). Meta-analytic evidence also supports the robustness of technology acceptance theories in explaining AI adoption across educational contexts (Ali et al., 2024; Dwivedi et al., 2020).

However, emerging evidence suggests that traditional UTAUT variables alone may not fully explain GenAI adoption because the use of AI-generated content involves substantial concerns regarding trust, privacy, security, accountability, and institutional governance (Rana et al., 2024; Shrivastava, 2025; Weis et al., 2026). Trust has been identified as a critical determinant of AI acceptance because users must rely on algorithm-generated outputs in situations characterized by uncertainty and limited transparency (Alzahrani et al., 2023; Jones et al., 2019). In educational environments, trust becomes especially important when AI systems influence institutional decisions, academic processes, and administrative operations (Khlaif et al., 2024; Karran et al., 2024).

Privacy concerns represent another significant challenge associated with AI adoption. The use of GenAI frequently involves the processing of sensitive institutional, staff, and student data, thereby raising concerns regarding confidentiality, data protection, and regulatory compliance (Dhagarra et al., 2020; Kelso et al., 2024; Kumi-Yeboah et al., 2023). Educational institutions have become increasingly aware of privacy risks associated with emerging technologies, particularly in contexts involving artificial intelligence, learning analytics, and digital governance (Durodolu et al., 2026; Kelso et al., 2025). Consequently, privacy concerns may substantially influence users' willingness to adopt GenAI technologies.

In addition, institutional policies and organizational governance structures play a crucial role in facilitating technology adoption. Recent studies emphasize that successful implementation of Generative AI requires clear institutional guidelines, strategic alignment, governance mechanisms, and policy support (An et al., 2025; Jin et al., 2024). Educational administrators are more likely to adopt AI technologies when institutional policies explicitly support their use and when AI initiatives align with organizational goals and administrative practices (Karran et al., 2024; Kurtz et al., 2024). Therefore, institutional policy fit may represent an important but underexplored determinant of GenAI adoption in educational administration.

Although a growing body of literature has investigated AI acceptance among students, teachers, and higher education stakeholders, empirical evidence focusing specifically on vocational college administrators remains limited. Most existing studies have concentrated on instructional applications of AI, teaching and learning contexts, or student adoption behaviors (Chan & Lee, 2023; Harimanto et al., 2025; Li et al., 2022; Wu et al., 2022). Comparatively little attention has been devoted to understanding how educational administrators evaluate and utilize Generative AI for administrative purposes. Furthermore, few studies have simultaneously examined traditional UTAUT factors together with trust, privacy concern, and institutional policy considerations within a single explanatory framework.

To address these gaps, the present study investigates the factors influencing administrators' intention to use and actual use behavior of Generative AI for vocational college administration in Thailand. Specifically, the study extends the UTAUT framework by integrating Trust, Privacy Concern, and Institutional Policy Fit to explain Behavioral Intention and Use Behavior among administrators and deputy directors of private vocational colleges. By doing so, the study contributes to the emerging literature on Generative AI adoption in educational administration and provides practical insights for policymakers, institutional leaders, and educational organizations seeking to implement AI technologies effectively and responsibly.

2. Theoretical Frameworks

2.1 Generative AI for Vocational College Administration

Generative artificial intelligence (Generative AI or GenAI) refers to a class of artificial intelligence systems capable of producing new content, including text, summaries, recommendations, plans, and decision-support outputs, based on large-scale language and data patterns. In educational organizations, GenAI has rapidly expanded from instructional support to administrative decision-making, strategic planning, communication, documentation, student services, and institutional quality assurance. Unlike traditional information systems that primarily process predefined data, GenAI can support administrators in generating policy drafts, summarizing institutional reports, preparing operational documents, analyzing managerial scenarios, and assisting evidence-informed decision-making.

In vocational college administration, the relevance of GenAI is particularly strong because vocational institutions operate in complex environments that require responsiveness to labor-market needs, curriculum changes, quality assurance demands, stakeholder coordination, and digital transformation. Administrators and deputy directors are expected to manage academic affairs, human resources, budgeting, institutional development, partnerships, and regulatory compliance. GenAI may therefore enhance administrative productivity by reducing routine paperwork, improving information synthesis, supporting planning processes, and enabling faster access to managerial knowledge. Prior studies suggest that large language models provide opportunities for education by supporting knowledge generation, personalized assistance, and decision support, while also raising concerns about accuracy, bias, transparency, ethics, and data protection (Dwivedi et al., 2023; Kasneci et al., 2023).

However, the adoption of GenAI in vocational college administration cannot be explained only by perceived usefulness or ease of use. Administrative use involves institutional responsibility, sensitive data, policy alignment, trust in AI-generated outputs, and compliance with governance requirements. In this context, administrators must evaluate whether GenAI is not only useful but also reliable, institutionally appropriate, ethically acceptable, and aligned with organizational policies. Therefore, this study conceptualizes GenAI adoption in vocational college administration as a governance-oriented technology acceptance phenomenon rather than a purely individual technology-use decision.

2.2 Technology Acceptance Research

Technology acceptance research explains why individuals intend to use and use information technologies. The Technology Acceptance Model (TAM) proposes that perceived usefulness and perceived ease of use are key determinants of behavioral intention toward technology use (Davis, 1989). TAM has been widely applied because it offers a parsimonious explanation of technology adoption across organizational and educational settings. However, as technology use became more embedded in organizational systems, later models incorporated social, facilitating, and contextual factors.

The Unified Theory of Acceptance and Use of Technology (UTAUT) integrates major acceptance theories and identifies performance expectancy, effort expectancy, social influence, and facilitating conditions as core determinants of behavioral intention and use behavior (Venkatesh et al., 2003). UTAUT is particularly suitable for organizational settings because it recognizes that technology adoption is shaped not only by individual perceptions but also by social pressure and resource availability. UTAUT2 later extended the model by incorporating additional determinants in consumer contexts and further confirmed the importance of behavioral intention and facilitating conditions in predicting technology use (Venkatesh et al., 2012).

Nevertheless, GenAI differs from conventional educational technologies because it generates outputs that may influence administrative judgments, institutional documents, and strategic decisions. Therefore, the present study extends UTAUT by integrating three additional constructs: trust, privacy concern, and institutional policy fit. Trust is essential because administrators must rely on GenAI output despite uncertainty about accuracy, consistency, and transparency. Prior research on technology-mediated environments shows that trust is a central determinant of technology acceptance when users face uncertainty and risk (Gefen et al., 2003). Privacy concern is also critical because administrative use of GenAI may involve sensitive institutional, personnel, and student-related information. Privacy concern reflects users' concerns about data collection, confidentiality, control, and regulatory compliance (Malhotra et al., 2004). Finally, institutional policy fit reflects the extent to which GenAI use aligns with organizational policy, strategy, and internal practices. This construct is conceptually related to task–technology fit, which argues that technology creates value when its capabilities fit users' tasks and organizational requirements (Goodhue & Thompson, 1995).

Accordingly, this study develops an integrated research model combining UTAUT with trust, privacy concern, and institutional policy fit to explain administrators' behavioral intention and use behavior regarding GenAI for vocational college administration.

Table 1. Integrated Research Constructs and Definitions

Construct	Abbreviation	Definition	Theoretical Basis
Performance Expectancy	PE	The degree to which administrators believe that GenAI improves administrative performance, decision-making, and work efficiency.	UTAUT
Effort Expectancy	EE	The degree to which administrators perceive GenAI as easy to learn and use for administrative tasks.	UTAUT
Social Influence	SI	The degree to which administrators perceive that important stakeholders, colleagues, senior administrators, and governing agencies support GenAI use.	UTAUT
Facilitating Conditions	FC	The degree to which administrators perceive that infrastructure, technical support, and resources are available to support GenAI use.	UTAUT
Trust	TR	The degree to which administrators believe that GenAI outputs are reliable, consistent, transparent, and sufficiently safe for administrative work.	Trust in Technology
Privacy Concern	PC	The degree to which administrators are concerned about confidentiality, personal data protection, and regulatory compliance when using GenAI.	Privacy Concern
Institutional Policy Fit	IPF	The degree to which GenAI use aligns with college policies, administrative strategies, and internal practices.	Institutional Fit / Task–Technology Fit
Behavioral Intention	BI	The degree to which administrators intend to continue, increase, and advocate GenAI use in administration.	TAM / UTAUT
Use Behavior	UB	The extent to which administrators actually use GenAI for routine administrative work, multiple administrative functions, and strategic decision-making.	UTAUT / Self-reported Use

2.3 Research Model and Hypotheses

The proposed model assumes that administrators' behavioral intention to use GenAI is influenced by both traditional technology acceptance factors and governance-related organizational factors. Based on UTAUT, performance expectancy is expected to influence behavioral intention because administrators who perceive GenAI as useful for improving administrative performance are more likely to intend to use it. Effort expectancy is also expected to influence behavioral intention because technologies perceived as easy to use tend to reduce cognitive burden and adoption resistance. Social influence is expected to affect behavioral intention because administrative decisions in vocational colleges are shaped by professional networks, senior management, institutional expectations, and governing agencies. Facilitating conditions are expected to influence both behavioral intention and use behavior because infrastructure, resources, and technical support may enable administrators to adopt and operationalize GenAI.

In addition to UTAUT constructs, trust is hypothesized to positively influence behavioral intention. In the context of GenAI, trust is important because administrators must evaluate whether AI-generated outputs can be used responsibly in institutional decision-making. Privacy concern is also hypothesized to influence behavioral intention. Although privacy concern is often treated as a barrier, in administrative contexts it may also reflect awareness of responsible and regulated technology use. Administrators who are highly aware of privacy and data protection issues may be more likely to intend to use GenAI under appropriate governance mechanisms. Institutional policy fit is expected to influence behavioral intention because administrators are more likely to adopt GenAI when its use aligns with institutional policies, strategic priorities, and internal administrative practices.

Finally, behavioral intention is hypothesized to positively influence use behavior. This relationship is central to TAM and UTAUT, where intention functions as the immediate antecedent of actual technology use. Facilitating conditions are also hypothesized to directly influence use behavior because even administrators with strong intention may not use GenAI regularly without adequate infrastructure, resources, and organizational support.

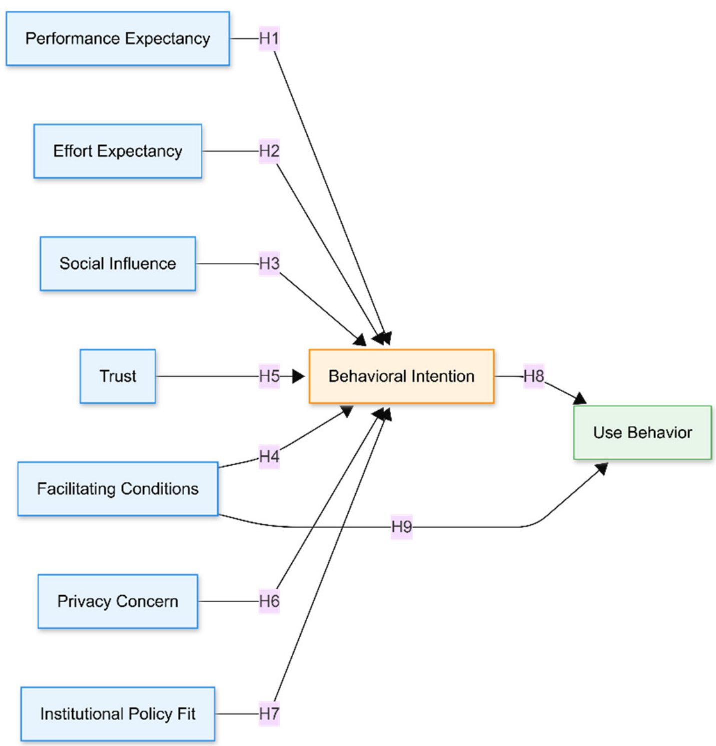

Figure 1. The Proposed Conceptual Model

Table 2. Hypotheses

Hypothesis	Path	Statement
H1	PE → BI	Performance expectancy positively influences administrators’ behavioral intention to use GenAI for vocational college administration.
H2	EE → BI	Effort expectancy positively influences administrators’ behavioral intention to use GenAI for vocational college administration.
H3	SI → BI	Social influence positively influences administrators’ behavioral intention to use GenAI for vocational college administration.
H4	FC → BI	Facilitating conditions positively influences administrators’ behavioral intention to use GenAI for vocational college administration.
H5	TR → BI	Trust positively influences administrators’ behavioral intention to use GenAI for vocational college administration.
H6	PC → BI	Privacy concern positively influences administrators’ behavioral intention to use GenAI for vocational college administration.
H7	IPF → BI	Institutional policy positively influences administrators’ behavioral intention to use GenAI for vocational college administration.
H8	BI → UB	Behavioral intention positively influences administrators’ use behavior of GenAI for vocational college administration.
H9	FC → UB	Facilitating conditions positively influence administrators’ use behavior of GenAI for vocational college administration.

3. Methodology

3.1 Research Design

This study employed a quantitative cross-sectional survey design to investigate factors influencing vocational college administrators’ intention to use and actual use behavior of Generative Artificial Intelligence (GenAI) for administrative purposes. The research framework was developed based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and extended by incorporating Trust (TR), Privacy Concern (PC), and Institutional Policy Fit (IPF) to provide a more comprehensive explanation of GenAI adoption in educational administration.

The proposed model consisted of nine latent constructs and nine hypothesized relationships. Given the predictive nature of the study and the complexity of the proposed model, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to test both the measurement model and the structural model. PLS-SEM is particularly appropriate for theory extension, prediction-oriented research, and studies involving multiple constructs and indicators (Hair et al., 2022). Data analysis was performed using SmartPLS 4 software.

3.2 Participants

The target population consisted of administrators and deputy directors of private vocational colleges in Thailand. These individuals play critical roles in institutional management, strategic planning, personnel administration, budgeting, quality assurance, and organizational decision-making.

A purposive sampling technique was employed to ensure that respondents possessed administrative responsibilities and sufficient experience in educational management. Eligible participants were required to hold administrative positions within private vocational institutions and have familiarity with digital technologies used in educational administration.

A total of 330 valid responses were obtained and included in the final analysis. The sample size exceeded the minimum recommendations for PLS-SEM and was considered adequate for estimating the proposed structural model and achieving sufficient statistical power (Hair et al., 2022).

Table 3. Demographic Information of Respondents (N = 330)

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	128	38.8
	Female	201	60.9
	Missing	1	0.3
Position	Director	159	48.2
	Deputy Director	171	51.8
Age	Below 30 years	130	39.4
	31–40 years	55	16.7
	41–50 years	56	17
	51–60 years	50	15.2
	Above 60 years	35	10.6
	Other/Invalid Response	4	1.2
Administrative Experience	Less than 5 years	71	21.5
	5–10 years	99	30
	More than 10 years	153	46.4
	Missing	7	2.1

The demographic profile indicates that female respondents constituted the majority of the sample (60.9%). Slightly more than half of the participants served as deputy directors (51.8%), while 48.2% were directors. Most respondents possessed substantial administrative experience, with 46.4% reporting more than ten years of experience. These characteristics suggest that the sample consisted of experienced educational administrators capable of providing informed perspectives regarding the adoption and use of Generative AI in vocational college administration.

3.3 Instrumentation

Data was collected using a structured questionnaire developed from established theories and validated instruments in technology acceptance research. The questionnaire consisted of two sections. The first section gathered demographic information, while the second section measured the constructs included in the proposed research model.

All items were measured using a seven-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). The instrument comprised 27 reflective indicators representing nine latent constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Trust (TR), Privacy Concern (PC), Institutional Policy Fit (IPF), Behavioral Intention (BI), and Use Behavior (UB).

Prior to data collection, the questionnaire was reviewed by experts in educational technology, artificial intelligence, and vocational education administration to establish content validity. Minor revisions were made to improve clarity, relevance, and contextual appropriateness.

Table 4. Items of Questionnaire

Construct	Code	Items	Source
Performance Expectancy	PE	3	UTAUT
Effort Expectancy	EE	3	UTAUT
Social Influence	SI	3	UTAUT
Facilitating Conditions	FC	3	UTAUT
Trust	TR	3	Trust in Technology
Privacy Concern	PC	3	Privacy Concern Theory
Institutional Policy Fit	IPF	3	Institutional Fit
Behavioral Intention	BI	3	TAM/UTAUT
Use Behavior	UB	3	Self-Reported Use
Total		**27**	

Table 5. Detailed Measurement Items

Construct	Item Code	Measurement Item
Performance Expectancy	PE1	GenAI improves my administrative performance.
	PE2	GenAI helps me make better decisions.
	PE3	GenAI reduces time spent on paperwork.
Effort Expectancy	EE1	GenAI is easy to use for administrative tasks.
	EE2	I can quickly learn to use GenAI for administration.
	EE3	GenAI usage procedures are clear.
Social Influence	SI1	Top management supports using GenAI.
	SI2	Colleagues expect me to use GenAI.
	SI3	Governing agencies encourage the use of GenAI.
Facilitating Conditions	FC1	Adequate digital infrastructure supports GenAI.

3.4 Ethical Considerations

Formal research ethics approval was not obtained for this study. Nevertheless, ethical safeguards were incorporated into the survey process. The introductory page of the questionnaire explained the purpose of the study, the voluntary nature of participation, participants' right to decline or discontinue without penalty, and the confidentiality of their responses. No directly identifying personal information was collected, and the data were analyzed and reported only in aggregate form. Submission of the completed questionnaire indicated informed consent to participate.

3.5 Data Analysis

Data analysis was conducted using SmartPLS 4 following the two-stage PLS-SEM procedure recommended by Hair et al. (2022).

Before model estimation, the responses were screened for completeness and invalid entries. The final analytical sample comprised 330 questionnaires with complete responses for all measurement-model indicators. Missing or invalid values occurred only in selected demographic fields (gender, age, and administrative experience). These values were retained and reported explicitly as "Missing" or "Other/Invalid Response" in Table 3; they were not imputed because the demographic variables were not used to estimate the measurement or structural models.

In the first stage, the measurement model was assessed to evaluate reliability and validity. Indicator reliability was examined using outer loadings. Internal consistency reliability was assessed using Cronbach's alpha, rho_A, and composite reliability (CR). Convergent validity was evaluated through the Average Variance Extracted (AVE), with values exceeding 0.50 indicating satisfactory convergent validity. Discriminant validity was assessed using the

Fornell–Larcker criterion, cross-loadings, and the Heterotrait–Monotrait ratio (HTMT).

In the second stage, the structural model was evaluated by examining collinearity statistics (Variance Inflation Factor: VIF), path coefficients (β), coefficients of determination (R^2), effect sizes (f^2), predictive relevance (Q^2), and predictive power using the PLSpredict procedure. The significance of the hypothesized relationships was assessed through bootstrapping with 5,000 resamples. Hypotheses were considered supported when p-values were below .05.

Following recent PLS-SEM reporting guidelines, the study additionally reported PLSpredict results to evaluate out-of-sample predictive performance. This procedure provided evidence regarding the model's ability not only to explain administrators' intention and use behavior but also to predict future observations. The overall model fit was assessed using the Standardized Root Mean Square Residual (SRMR), with values below .08 indicating acceptable model fit.

4. Results

4.1 Descriptive Statistics

Descriptive statistics were calculated to examine respondents' perceptions regarding the use of Generative Artificial Intelligence (GenAI) in vocational college administration. Table 6 presents the mean scores and standard deviations of all study constructs.

Overall, respondents reported favorable perceptions toward GenAI adoption, with all constructs means exceeding 5.60 on the seven-point Likert scale. Use Behavior (UB) exhibited the highest mean score (M = 5.80, SD = 1.48), followed by Behavioral Intention (BI) (M = 5.77, SD = 1.50), Privacy Concern (PC) (M = 5.76, SD = 1.53), and Institutional Policy Fit (IPF) (M = 5.75, SD = 1.46). These findings suggest that administrators not only demonstrated strong intentions to use GenAI but were also actively utilizing the technology in administrative activities.

Trust (TR) and Effort Expectancy (EE) also achieved relatively high mean scores (M = 5.73), indicating that respondents generally perceived GenAI as trustworthy and easy to use. Social Influence (SI), Facilitating Conditions (FC), and Performance Expectancy (PE) likewise received positive evaluations, suggesting broad organizational support for GenAI adoption.

Table 6. Descriptive Statistics of Study Constructs (N = 330)

Construct	Mean	SD	Interpretation
Performance Expectancy (PE)	5.68	1.58	High
Effort Expectancy (EE)	5.73	1.55	High
Social Influence (SI)	5.65	1.56	High
Facilitating Conditions (FC)	5.66	1.63	High
Trust (TR)	5.73	1.52	High
Privacy Concern (PC)	5.76	1.53	High
Institutional Policy Fit (IPF)	5.75	1.46	High
Behavioral Intention (BI)	5.77	1.5	High
Use Behavior (UB)	5.8	1.48	High

Note. Mean values were computed from the observed indicators using a seven-point Likert scale.

4.2 Factor Analysis

The measurement model was assessed through confirmatory factor analysis within the PLS-SEM framework. The results indicated that all indicators loaded strongly on their respective latent constructs. Outer loadings ranged from 0.928 to 0.963, substantially exceeding the recommended threshold of 0.70 (Hair et al., 2022).

Specifically, the factor loadings for Performance Expectancy ranged from 0.961 to 0.963, Effort Expectancy ranged from 0.935 to 0.953, Social Influence ranged from 0.934 to 0.945, Facilitating Conditions ranged from 0.942 to 0.955, Trust ranged from 0.931 to 0.942, Privacy Concern ranged from 0.944 to 0.952, Institutional Policy Fit ranged from 0.934 to 0.954, Behavioral Intention ranged from 0.932 to 0.953, and Use Behavior ranged from 0.928 to 0.946. All factor loadings exceeded the minimum recommended value, indicating strong indicator reliability and confirming that each indicator adequately represented its underlying construct. Consequently, no indicators were removed from the measurement model.

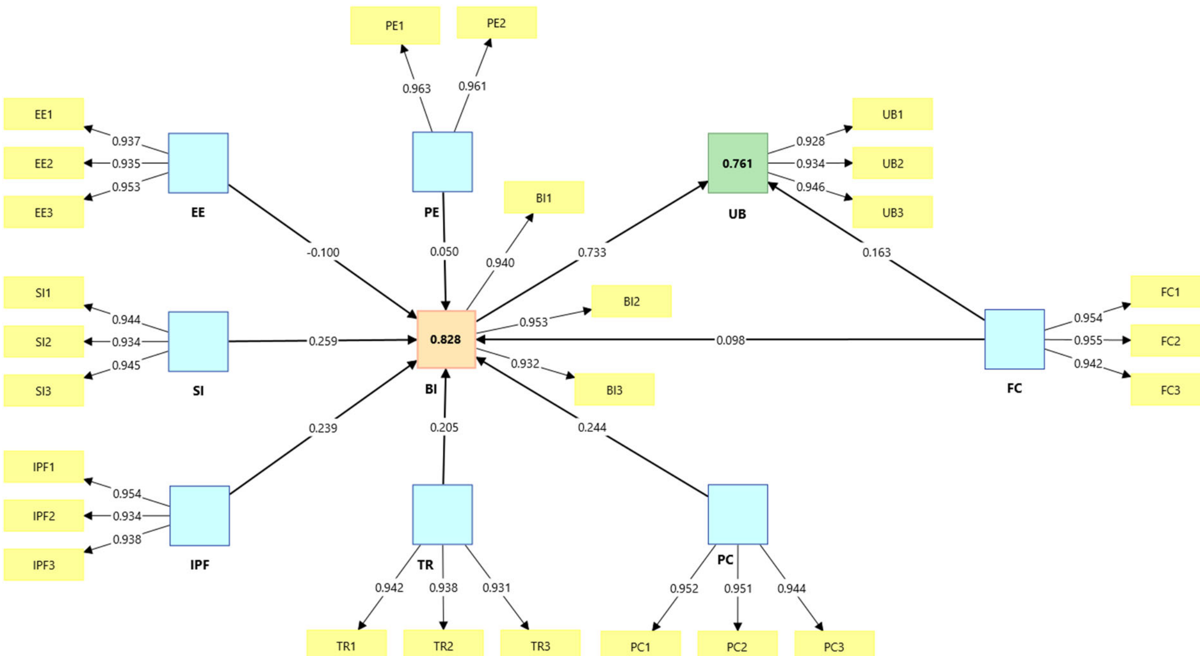

Figure 2. Presents the Final Measurement Model, Including the Standardized Outer Loadings of All Reflective Constructs

4.3 Evaluation of the Measurement Model

The measurement model was evaluated through assessments of internal consistency reliability, convergent validity, and discriminant validity.

Table 7. Construct Validity and Reliability

Construct	Cronbach's Alpha	rho_A	Composite Reliability	AVE
BI	0.936	0.937	0.959	0.887
EE	0.936	0.941	0.959	0.887
FC	0.947	0.947	0.966	0.904
IPF	0.937	0.939	0.96	0.888
PC	0.945	0.945	0.965	0.901
PE	0.92	0.92	0.961	0.926
SI	0.935	0.936	0.959	0.885
TR	0.93	0.932	0.956	0.878
UB	0.929	0.93	0.955	0.876

The results demonstrate excellent internal consistency, reliability and convergent validity. Cronbach's alpha values ranged from 0.920 to 0.947, while composite reliability values ranged from 0.955 to 0.966, both exceeding the recommended threshold of 0.70. Furthermore, AVE values ranged from 0.876 to 0.926, substantially exceeding the recommended criterion of 0.50, confirming convergent validity.

Table 8. Discriminant Validity: Fornell–Larcker Criterion

Construct	BI	EE	FC	IPF	PC	PE	SI	TR	UB
BI	**0.94**								
EE	0.762	**0.94**							
FC	0.824	0.828	**0.95**						
IPF	0.815	0.727	0.781	**0.94**					
PC	0.853	0.796	0.838	0.803	**0.95**				
PE	0.734	0.849	0.802	0.682	0.759	**0.96**			
SI	0.824	0.823	0.835	0.703	0.807	0.768	**0.94**		
TR	0.831	0.763	0.785	0.779	0.816	0.697	0.792	**0.94**	
UB	0.867	0.745	0.767	0.819	0.83	0.701	0.778	0.808	**0.94**

The square roots of AVE shown on the diagonal exceeded all corresponding inter-construct correlations, satisfying the Fornell–Larcker criterion and confirming discriminant validity.

Although several HTMT values slightly exceeded the conservative threshold of 0.90, the Fornell–Larcker criterion and cross-loading analysis confirmed that discriminant validity remained acceptable.

Table 9. Model Fit

	Saturated model	**Estimated model**
SRMR	0.027	0.035
d_ULS	0.261	0.422
d_G	0.713	0.764
Chi-square	1515.844	1576.262
NFI	0.873	0.868

The model demonstrated satisfactory fit. The SRMR value of 0.035 was well below the recommended threshold of 0.08, indicating an acceptable fit between the proposed model and the observed data. Furthermore, the NFI value of 0.868 suggests an acceptable level of model fit.

4.4 Evaluation of the Structural Model (Hypotheses Testing)

Table 10. Hypothesis Testing

Hypothesis	Path	β	t-value	p-value	Decision
H1	PE → BI	0.05	0.747	0.455	Not Supported
H2	EE → BI	-0.1	1.272	0.203	Not Supported
H3	SI → BI	0.259	2.924	0.003	Supported
H4	FC → BI	0.098	1.347	0.178	Not Supported
H5	TR → BI	0.205	2.643	0.008	Supported
H6	PC → BI	0.244	2.962	0.003	Supported
H7	IPF → BI	0.239	4.152	<0.001	Supported
H8	BI → UB	0.733	9.705	<0.001	Supported
H9	FC → UB	0.163	2.027	0.043	Supported

Prior to hypothesis testing, collinearity was assessed using the Variance Inflation Factor (VIF). The VIF values ranged from 3.448 to 5.259. Most values were below the commonly used threshold of 5.00; however, the maximum value of 5.259 slightly exceeded this criterion, indicating potential collinearity for at least one predictor. The corresponding path estimates were therefore interpreted cautiously, particularly for nonsignificant predictors and constructs with conceptually related antecedents.

The significance of the structural relationships was evaluated using bootstrapping with 5,000 subsamples.

The results indicate that Social Influence, Trust, Privacy Concern, and Institutional Policy Fit significantly influenced Behavioral Intention. In contrast, Performance Expectancy, Effort Expectancy, and Facilitating Conditions did not significantly affect Behavioral Intention. Behavioral Intention emerged as the strongest predictor of Use Behavior, while Facilitating Conditions also exerted a significant positive influence on actual usage.

Table 11. Coefficient of Determination (R^2)

Endogenous Construct	R^2	Adjusted R^2
Behavioral Intention (BI)	0.828	0.824
Use Behavior (UB)	0.761	0.759

Table 12. Effect Size (f^2)

Structural Path	f^2	Effect Size
PE → BI	0.004	Negligible
EE → BI	0.011	Negligible
FC → BI	0.01	Negligible
SI → BI	0.084	Small
TR → BI	0.061	Small
PC → BI	0.068	Small
IPF → BI	0.095	Small
FC → UB	0.036	Small
BI → UB	0.721	Large

The model explained 82.8% of the variance in Behavioral Intention and 76.1% of the variance in Use Behavior, indicating substantial explanatory power. Among all relationships, Behavioral Intention exerted the largest effect on Use Behavior ($f^2 = 0.721$), representing a large effect size.

Table 13. Predictive Relevance and PLSpredict Results

Indicator	Q^2predict	PLS-SEM RMSE	LM RMSE
BI1	0.716	0.838	0.864
BI2	0.751	0.728	0.802
BI3	0.682	0.826	0.876
UB1	0.623	0.941	1.005
UB2	0.641	0.888	0.873
UB3	0.687	0.805	0.823

All Q^2predict values were positive, indicating predictive relevance. Furthermore, the PLS-SEM model achieved lower RMSE values than the linear benchmark model for five of the six indicators. Following the guidelines of Hair et al. (2022), these results indicate medium-to-high predictive power. Therefore, the proposed model not only demonstrates strong explanatory capability but also possesses satisfactory out-of-sample predictive performance.

5. Discussion

This study examined the factors influencing vocational college administrators' intention to use and actual use behavior of Generative Artificial Intelligence (GenAI) for administrative purposes by extending the UTAUT framework with Trust, Privacy Concern, and Institutional Policy Fit. The findings provide important theoretical and practical insights into GenAI adoption in educational administration.

First, the results revealed that Social Influence significantly influenced Behavioral Intention. This finding suggests that administrators' decisions regarding GenAI adoption are strongly shaped by organizational expectations, professional networks, governing agencies, and leadership support. In vocational education settings, administrative practices are often guided by institutional policies and external regulations. Consequently, administrators may be more willing to adopt GenAI when they perceive endorsement from senior management, colleagues, and educational authorities. This finding is consistent with previous UTAUT studies emphasizing the importance of social and organizational pressures in technology adoption within educational institutions (Bayaga & Du Plessis, 2023; Hakimi et al., 2024; Xue et al., 2024; Da Silva Soares et al., 2024).

Second, Trust emerged as a significant predictor of Behavioral Intention. This result confirms that administrators are more likely to adopt GenAI when they perceive its output as reliable, accurate, and trustworthy. Unlike conventional educational technologies, GenAI can generate recommendations, reports, summaries, and decision-support information that may directly influence institutional management. Therefore, trust becomes a critical prerequisite for adoption. The finding supports previous studies highlighting trust as a key determinant of AI acceptance and technology-mediated decision-making (Alzahrani et al., 2023; Rana et al., 2024; Weis et al., 2026). It further suggests that successful implementation of GenAI in educational administration requires transparent AI systems, clear governance mechanisms, and opportunities for users to verify AI-generated outputs.

Third, Privacy Concern was found to have a significant positive influence on Behavioral Intention. Although privacy concern is traditionally viewed as a barrier to technology adoption, the present finding suggests a different interpretation within educational administration contexts. Administrators who are highly aware of privacy and data protection issues may not necessarily reject GenAI. Instead, they may be more willing to adopt the technology when appropriate governance frameworks, security mechanisms, and regulatory safeguards are in place. This result aligns with recent studies arguing that privacy awareness can coexist with technology acceptance when users perceive adequate institutional protection and responsible AI practices (Dhagarra et al., 2020; Kumar et al., 2022; Karran et al., 2024).

Fourth, Institutional Policy Fit demonstrated a significant positive effect on Behavioral Intention and represented one of the strongest predictors among the antecedent variables. This finding highlights the importance of organizational alignment in AI adoption. Administrators appear more willing to use GenAI when its application is consistent with institutional policies, strategic objectives, and administrative procedures. Unlike classroom technologies that are often adopted at the individual level, administrative technologies require formal organizational legitimacy. Therefore, institutional policy alignment plays a crucial role in facilitating adoption decisions. This finding extends previous research by demonstrating that organizational governance factors are particularly important in administrative AI adoption contexts (An et al., 2025; Jin et al., 2024; Kurtz et al., 2024).

An interesting finding is that Performance Expectancy and Effort Expectancy did not significantly influence Behavioral Intention. These results differ from the original UTAUT framework, which generally identifies perceived usefulness and ease of use as strong determinants of technology acceptance (Venkatesh et al., 2003). One possible explanation is that GenAI technologies have already become familiar and widely accessible through user-friendly interfaces such as ChatGPT and other AI platforms. As a result, administrators may already assume that GenAI is useful and relatively easy to use, reducing the explanatory power of these variables. This pattern is consistent with recent findings by Patil and Undale (2023), who observed that in contexts where technology use is compelled or rapidly normalized, the predictive influence of effort expectancy and performance expectancy on behavioral intention diminishes, while other contextual and organizational factors gain prominence. Additionally, Bervell and Umar (2017) suggested that the relationships between UTAUT's exogenous variables and behavioral intention may not be strictly linear, and that failing to account for non-linear effects could obscure significant predictive relationships in certain educational contexts. In this context, organizational and governance-related concerns may have become more influential than traditional technology acceptance factors.

Similarly, Facilitating Conditions did not significantly affect Behavioral Intention. This finding suggests that the availability of infrastructure and technical support may no longer be a primary concern among vocational college administrators. Most educational institutions have already established basic digital infrastructures, internet connectivity, and access to AI-enabled technologies. Consequently, facilitating conditions may function more as an operational enabler than as a motivational factor influencing adoption intention.

The strongest relationship identified in the model was between Behavioral Intention and Use Behavior. This finding strongly supports 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). The large effect size ($f^2 = 0.721$) further indicates that administrators who intend to use GenAI are highly likely to translate that intention into actual administrative practices. This result reinforces the importance of developing positive attitudes and intentions toward GenAI as a strategy for increasing practical adoption.

In addition, Facilitating Conditions exerted a significant positive influence on Use Behavior despite having no significant effect on Behavioral Intention. This finding suggests that while infrastructure and technical support may not motivate administrators to adopt GenAI, they remain essential for transforming intention into actual usage. Administrators who possess strong intentions may still encounter difficulties in regular implementation without adequate technological resources, institutional support, and organizational infrastructure. This result is consistent with the original UTAUT proposition that facilitating conditions play a direct role in supporting actual technology use.

Finally, the model demonstrated substantial explanatory and predictive capability. The high R^2 values for Behavioral Intention (0.828) and Use Behavior (0.761), together with positive Q^2predict values and favorable PLSpredict results, indicate that the proposed model successfully explains and predicts GenAI adoption among vocational college administrators. These findings contribute to the growing body of literature on AI acceptance by demonstrating that governance-oriented factors including trust, privacy concern, and institutional policy fit may be more important than traditional technology acceptance variables when explaining administrative adoption of Generative AI. The study therefore extends UTAUT beyond conventional educational technology contexts and provides a more comprehensive framework for understanding AI adoption in educational administration.

6. Limitation of the Study and Future Research

This study provides valuable insights into the adoption of Generative Artificial Intelligence (GenAI) for vocational college administration; however, several limitations should be acknowledged. First, the study employed a cross-sectional survey design, which captured respondents' perceptions at a single point in time. Consequently, causal relationships and changes in GenAI adoption behavior over time could not be fully examined. Future studies should consider longitudinal designs to investigate how administrators' perceptions, intentions, and actual usage evolve as GenAI technologies become more mature and widely institutionalized.

Second, the sample was limited to administrators and deputy directors of private vocational colleges in Thailand. Although this group represents key decision-makers in vocational education, the findings may not be generalizable to public vocational institutions, universities, schools, or other educational sectors. Future research should compare different educational contexts and administrative levels to determine whether the observed relationships remain consistent across organizational settings.

Third, the study relied on self-reported measures of use behavior, which may be influenced by social desirability bias and subjective perceptions. Future studies could incorporate objective indicators of GenAI usage, such as system logs, usage frequency records, or organizational performance metrics, to provide more robust evidence of actual adoption behavior.

Finally, the proposed model focused on UTAUT variables, Trust, Privacy Concern, and Institutional Policy Fit. Although these factors explained a substantial proportion of variance in Behavioral Intention ($R^2 = 0.828$) and Use Behavior ($R^2 = 0.761$), other relevant variables may also influence GenAI adoption. Future research should examine additional factors such as AI literacy, perceived risk, ethical concerns, algorithmic transparency, organizational culture, leadership support, and digital innovation capability. Furthermore, mixed-methods and qualitative studies may provide deeper insights into administrators' experiences, challenges, and decision-making processes regarding the implementation of Generative AI in educational administration.

7. Conclusion

This study investigated the factors influencing vocational college administrators' intention to use and actual use behavior of Generative Artificial Intelligence (GenAI) for administrative purposes by extending the Unified Theory of Acceptance and Use of Technology (UTAUT) with Trust, Privacy Concern, and Institutional Policy Fit. Using data collected from 330 administrators and deputy directors of private vocational colleges in Thailand and analyzed through PLS-SEM, the study provides both theoretical and practical contributions to the emerging field of AI adoption in educational administration.

The findings revealed that Social Influence, Trust, Privacy Concern, and Institutional Policy Fit significantly influenced Behavioral Intention to use GenAI. In contrast, Performance Expectancy, Effort Expectancy, and Facilitating Conditions did not significantly affect Behavioral Intention. Furthermore, Behavioral Intention emerged as the strongest predictor of Use Behavior, while Facilitating Conditions also demonstrated a significant positive effect on actual usage. The proposed model explained a substantial proportion of variance in both Behavioral Intention ($R^2 = 0.828$) and Use Behavior ($R^2 = 0.761$), indicating strong explanatory capability. In addition, the positive Q^2predict values and favorable PLSpredict results confirmed the model's predictive relevance and out-of-sample predictive power.

One of the most important contributions of this study is its challenge to the traditional assumptions of technology acceptance research. Unlike the original UTAUT framework, which emphasizes perceived usefulness and ease of use as primary determinants of technology adoption, the present findings suggest that administrators' acceptance of Generative AI is driven more strongly by governance-related considerations. Factors associated with organizational legitimacy, trustworthiness, privacy protection, and policy alignment appear to play a more influential role than conventional technology-related perceptions. This finding suggests that the adoption of Generative AI in educational administration represents not merely a technological decision but also an organizational and governance decision.

From a practical perspective, the findings indicate that educational institutions seeking to promote GenAI adoption should move beyond providing technical infrastructure and training alone. Institutional leaders should establish clear AI governance policies, strengthen trust through transparency and accountability mechanisms, address privacy and regulatory concerns, and ensure that AI initiatives are aligned with institutional strategies and administrative practices. Such efforts can foster stronger intentions to use GenAI and ultimately increase actual utilization within educational organizations.

In conclusion, the study demonstrates that the successful adoption of Generative AI in vocational college administration depends not only on technological characteristics but also on broader organizational, policy, and governance factors. As educational institutions continue to integrate AI technologies into administrative processes, understanding these multidimensional influences will be essential for ensuring effective, responsible, and sustainable implementation. The findings therefore provide a valuable foundation for future research and practice in AI-enabled educational administration and contribute to the growing literature on Generative AI adoption in organizational contexts.

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Author Statements

Author(s) declared the statement below:

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Author Contributions

Conceptualization: Asst. Prof. Dr Potsirin Limpinan., https://orcid.org/0000-0002-0748-1965

Methodology: Porntep Chooppawa, https://orcid.org/0009-0005-5419-5522

Formal analysis: Porntep Chooppawa, https://orcid.org/0009-0005-5419-5522

Investigation: Porntep Chooppawa, https://orcid.org/0009-0005-5419-5522

Writing – original draft: Porntep Chooppawa, https://orcid.org/0009-0005-5419-5522

Writing – review & editing: Asst. Prof. Dr. Thada Jantakoon, https://orcid.org/0000-0001-5935-5875

Supervision: Prof. Asst. Prof. Dr. Potsirin Limpinan, https://orcid.org/0000-0002-0748-1965

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed Consent

Informed consent was obtained from all participants involved in the study.

Ethics Approval

This study did not require formal ethical approval because it did not involve vulnerable populations, clinical interventions, or sensitive personal data. Ethical considerations, including informed consent, voluntary participation, and confidentiality, were fully observed throughout the study.

Data Availability Statement

Available upon request: The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Use of Artificial Intelligence

The authors used generative artificial intelligence (AI) tools solely for language editing and grammar improvement. All AI-assisted revisions were reviewed and verified by the authors, who take full responsibility for the final content of the manuscript.

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