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Generative AI Adoption in Educational Administration: An Extended UTAUT Model with Trust, Privacy Concern, and Institutional Policy Fit

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Abstract

Generative artificial intelligence (GenAI) is increasingly promoted as a tool for educational administration and administrative decision-making, yet evidence on why educational leaders adopt it remains scarce, particularly in technical and vocational education. Extending the unified theory of acceptance and use of technology (UTAUT) with trust, privacy concern, and institutional policy fit, this study examined the determinants of administrators' GenAI behavioral intention and use behavior. The study analyzed survey responses from 330 directors and deputy directors of Thai private vocational colleges, selected through two-stage stratified cluster sampling. The data were analyzed using generalized structured component analysis (GSCA) and bootstrapping. The measurement model showed satisfactory reliability and validity. The model fitted the data well and explained 82.9% of the variance in behavioral intention and 79.3% in use behavior. Social influence, trust, lower privacy concern, and institutional policy fit significantly predicted behavioral intention, whereas the unique direct effects of performance expectancy, effort expectancy, and facilitating conditions could not be separated from those of the correlated predictors; dominance analysis showed that these three determinants accounted for about one third of the explained variance in intention, almost all of it shared with the other predictors. Effort expectancy and facilitating conditions also shaped social influence, through which their influence reached intention. Behavioral intention, trust, and lower privacy concern predicted use behavior. Full-collinearity diagnostics indicated a risk of common method variance; a post hoc marker-variable analysis showed that the predictors of intention and the intention-use path were robust, whereas the direct effects of trust and privacy concern on use were not. Administrators' adoption of GenAI thus appears to depend on institutional legitimacy, normative endorsement, and data-governance assurance, which explain intention beyond what instrumental appraisal explains. Educational authorities seeking to promote GenAI in administration should therefore pair infrastructure investment with explicit institutional GenAI policies, guidelines for verifying GenAI outputs, and data-protection safeguards, because these conditions add to, rather than merely duplicate, beliefs about usefulness.

Keywords: educational leadership, AI governance, technology acceptance, technical and vocational education and training, social influence, generalized structured component analysis, Thailand

1. Introduction

1.1 Background and Problem Statement

Generative artificial intelligence (GenAI), exemplified by large language model chatbots that produce text, summaries, and analyses on demand, has diffused through education with a speed that has outpaced institutional governance. International guidance now urges education systems to regulate and deliberately integrate these tools rather than leave adoption to individual discretion (Miao & Holmes, 2023). Empirical scholarship has responded quickly, but it has concentrated overwhelmingly on students and, to a lesser extent, on teachers (Chan & Hu, 2023; Habibi et al., 2023; Strzelecki, 2024; Strzelecki & ElArabawy, 2024). This emphasis continues a longer pattern in which research on artificial intelligence in education has attended to learners and learning analytics while leaving the organizational actors who govern educational institutions comparatively invisible (Zawacki-Richter et al., 2019).

Educational administrators occupy a distinctive position in this transformation. Conceptual work suggests that AI can augment leadership decision-making through a symbiotic division of labor between human judgment and algorithmic processing (Wang, 2021), and early empirical work has documented how school leaders adopt and implement AI systems (Tyson & Sauers, 2021) and how far GenAI has penetrated managerial, instructional, and relational domains of school leadership (Berkovich, 2025). Nevertheless, the determinants of administrators' intention to use GenAI and of their actual use remain largely untheorized and untested. The gap is especially pronounced in technical and vocational education and training (TVET), where college directors and deputy directors carry heavy documentary, regulatory, and coordination burdens associated with enrolment, industry partnerships, quality assurance reporting, budgeting, and personnel management. These are precisely the text-intensive tasks for which GenAI is claimed to offer efficiency gains.

Administrative use of GenAI differs from students' or teachers' use in at least three respects. First, administrators process confidential personnel, student, and financial records, so their use is constrained by data-protection law; in Thailand, the Personal Data Protection Act B.E. 2562 (2019) imposes explicit obligations on data controllers. Second, administrators act within hierarchically governed organizations; in private vocational colleges, they answer both to college licensees and to the public regulator, so adoption decisions are shaped by governing agencies, institutional strategy, and peers. Research on AI in public and publicly regulated organizations shows that implementation raises tensions of transparency, fairness, and privacy (Madan & Ashok, 2023; Neumann et al., 2024). Third, administrators' outputs, such as reports, policy documents, and strategic decisions, carry institutional accountability, which makes the trustworthiness of GenAI outputs consequential. These features suggest that models explaining individual technology acceptance must be extended to capture institutional and risk-related considerations when applied to administrators.

1.2 Research Gaps and Purpose of the Study

The unified theory of acceptance and use of technology (UTAUT) remains the most integrative framework for explaining technology adoption (Venkatesh et al., 2003). Its core propositions, that performance expectancy, effort expectancy, and social influence shape behavioral intention, and that intention and facilitating conditions shape use, have been corroborated across thousands of applications (Dwivedi et al., 2019). Meta-analytic evidence, however, shows that UTAUT relationships vary considerably across settings, and that the theory gains explanatory power when it is extended with context-specific constructs (Blut et al., 2022; Venkatesh et al., 2016). Venkatesh (2022) accordingly proposed a research agenda for AI tools that calls for the incorporation of individual, technological, and environmental characteristics that are distinctive to AI, including trust and the organizational environment into which the tool is introduced.

Four gaps motivate the present study. The first is a population gap: no study, to our knowledge, has modeled GenAI acceptance among TVET administrators using a validated structural framework. The second is a theoretical gap: extant GenAI acceptance studies seldom integrate AI-specific beliefs (trust and privacy concern) with an organizational construct capturing the alignment between GenAI and institutional policy, even though the public-sector AI literature identifies organizational context and data-related tensions as central determinants of adoption (Madan & Ashok, 2023). The third is a specification gap: UTAUT treats its determinants as parallel antecedents of intention, whereas institutional theory suggests that, in hierarchical organizations, resources and usability may operate through the normative climate that they create (DiMaggio & Powell, 1983). The fourth is a methodological gap: acceptance research in educational technology relies almost exclusively on partial least squares path modeling, whereas generalized structured component analysis (GSCA) estimates composite-based models under a single global optimization criterion and yields overall indexes of model fit (Hwang & Takane, 2004; Hwang et al., 2020).

Accordingly, this study examined the determinants of GenAI behavioral intention and use behavior among

directors and deputy directors of private vocational colleges in Thailand. Four research questions guided the inquiry: (RQ1) To what extent do the UTAUT determinants predict administrators' intention to use GenAI? (RQ2) Do trust, privacy concern, and institutional policy fit explain intention and use beyond the UTAUT determinants? (RQ3) Do effort expectancy and facilitating conditions shape the social influence that administrators perceive? (RQ4) Which beliefs translate into actual use of GenAI in administrative work?

1.3 Theoretical Background and Relevant Scholarship

1.3.1 UTAUT and GenAI Acceptance

Since the public release of conversational GenAI, UTAUT and its consumer extension (Venkatesh et al., 2012) have become the dominant lenses for explaining its adoption. Studies of higher-education students in Poland and Egypt confirmed that the UTAUT predictors explain intention to use and use of GenAI, while demonstrating that gender and level of study condition selected paths (Strzelecki, 2024; Strzelecki & ElArabawy, 2024). Research outside education similarly identified performance expectancy as a key driver of intention to use ChatGPT (Camilleri, 2024). At the same time, extensions have repeatedly shown that the core predictors are insufficient on their own: relative risk perceptions and emotions add explanatory power (Lee et al., 2024), and institutional policy alters how intention translates into behavior (Polyportis & Pahos, 2025). Because nearly all of this evidence derives from students, the extent to which it generalizes to administrators, who use GenAI on behalf of an organization rather than for personal learning, is an open question.

1.3.2 Trust and Privacy Concern as GenAI-Specific Beliefs

Trust reduces the uncertainty that users face when they depend on a system whose inner workings they cannot inspect (Gefen et al., 2003; McKnight et al., 2002). This function is amplified for AI, whose outputs are probabilistic, opaque, and occasionally erroneous; reviews of human-AI interaction conclude that trust is a precondition for reliance on AI (Glikson & Woolley, 2020). Empirical studies have confirmed that trust in AI shapes intention to use AI technologies (Choung et al., 2023) and that trust is critical to the adoption and use of ChatGPT (Choudhury & Shamszare, 2023). Privacy concern, conversely, captures individuals' apprehension about the collection and secondary use of personal information (Smith et al., 1996). The privacy calculus perspective holds that such concerns are weighed against expected benefits and can suppress willingness to engage with information technologies (Dinev & Hart, 2006; Bélanger & Crossler, 2011). For administrators, whose prompts may contain confidential institutional data, privacy concern is therefore a salient inhibitor.

1.3.3 The Institutional Context of Administrative GenAI Adoption

Organizational adoption frameworks emphasize that technology adoption depends on the organizational context and on the compatibility of an innovation with existing values, practices, and strategy (Oliveira & Martins, 2011; Rogers, 2003; Tornatzky & Fleischer, 1990). In public organizations, AI adoption is conditioned by governance arrangements, organizational readiness, and ethical tensions (Madan & Ashok, 2023; Neumann et al., 2024). Institutional theory further explains why organizations converge on similar practices through coercive pressure from governing bodies, normative pressure from professional communities, and mimetic responses to uncertainty (DiMaggio & Powell, 1983). These perspectives imply that administrators' GenAI adoption will be shaped by whether GenAI fits institutional policy and strategy and by the normative signals that the organization sends. Table 1 synthesizes the evidence that informed the research model.

Table 1. Synthesis of Prior Evidence Informing the Research Model

Study	Context and sample	Design / analysis	Evidence relevant to the present model
Venkatesh et al. (2003)	Employees in organizations adopting new systems	Longitudinal field study; model comparison	PE, EE, and SI predict BI; BI and FC predict use; UTAUT integrates eight prior models.
Blut et al. (2022)	Cumulative UTAUT literature	Meta-analysis	UTAUT effects vary across contexts, supporting context-specific extension.
Venkatesh (2022)	AI tools in organizations	Conceptual research agenda	Calls for AI-specific individual, technology, and environmental characteristics in UTAUT.
Strzelecki & ElArabawy (2024)	University students, Poland and Egypt	PLS-SEM; multigroup analysis	UTAUT predictors explain GenAI intention and use; gender and study level moderate selected paths.
Lee et al. (2024)	ChatGPT users	PLS-SEM	Relative risk perception and emotions add to UTAUT in predicting attitudes and intention.
Polyportis & Pahos (2025)	355 students, Dutch higher education	SEM	PE, SI, and FC predict BI; institutional policy moderates the BI → use relationship.
Choung et al. (2023)	Users of AI voice assistants (two studies)	Path analysis; SEM	Trust in AI increases intention to use AI through usefulness and attitude.
Choudhury & Shamszare (2023)	ChatGPT users	SEM	Trust is critical to the adoption and actual use of ChatGPT.
Madan & Ashok (2023)	Public administration literature	Systematic review	Organizational and environmental context shape AI adoption; privacy and transparency tensions are salient.
Tyson & Sauers (2021)	School leaders in the United States	Qualitative	Documents contextual factors shaping leaders' adoption and implementation of an AI system.
Berkovich (2025)	302 school leaders in Israel	Descriptive survey	Maps GenAI diffusion stages and leadership domains affected; patterns vary by seniority and role.
Present study	330 directors and deputy directors of private vocational colleges, Thailand	GSCA with bootstrapping	Integrates UTAUT with TR, PC, and IPF and models SI as a conduit of EE and FC.

Note. BI = behavioral intention; EE = effort expectancy; FC = facilitating conditions; GSCA = generalized structured component analysis; IPF = institutional policy fit; PC = privacy concern; PE = performance expectancy; PLS-SEM = partial least squares structural equation modeling; SI = social influence; TR = trust.

1.4 Hypothesis Development and Research Model

The research model (Figure 1) retains the UTAUT core, adds two GenAI-specific beliefs (trust and privacy concern) and one institutional construct (institutional policy fit), and specifies social influence as an endogenous construct that transmits the effects of effort expectancy and facilitating conditions. Hypotheses H1 to H8 constitute the primary, theory-confirming tests; H9 to H12 represent theory-extending propositions derived from the administrative context.

UTAUT core determinants. Performance expectancy, the degree to which an individual believes that using a system will help attain gains in job performance, is the strongest predictor of intention in the original UTAUT validation and in subsequent meta-analyses (Blut et al., 2022; Venkatesh et al., 2003). Effort expectancy, the degree of ease associated with use, reduces the cognitive cost of adoption and is particularly influential when users are in the early stages of learning a technology (Venkatesh et al., 2003). Social influence reflects the degree to which

individuals perceive that important others believe they should use the system; in hierarchical settings, it operates through compliance and identification (Venkatesh et al., 2003). For administrators, the relevant referents are senior management, colleagues, and the governing agency. Facilitating conditions refer to the organizational and technical infrastructure that supports use; UTAUT2 theorizes that they also influence intention because users who perceive adequate support are more motivated to adopt (Venkatesh et al., 2012). Therefore:

H1: Performance expectancy positively influences behavioral intention to use GenAI.

H2: Effort expectancy positively influences behavioral intention to use GenAI.

H3: Social influence positively influences behavioral intention to use GenAI.

H4: Facilitating conditions positively influence behavioral intention to use GenAI.

GenAI-specific beliefs and institutional fit. Trust in GenAI denotes confidence that GenAI outputs are reliable, consistent, and free of unnecessary risk. Because administrators are accountable for decisions informed by GenAI, their willingness to rely on it should depend on trust (Choung et al., 2023; Glikson & Woolley, 2020). Privacy concern, in contrast, denotes apprehension about data confidentiality, personal data breaches, and regulatory compliance. Under the privacy calculus, such apprehension depresses willingness to use information technologies (Dinev & Hart, 2006). Institutional policy fit denotes the degree to which GenAI is consistent with college policies, administrative strategy, and internal practices. Drawing on the notion of compatibility (Rogers, 2003) and on organizational adoption theory (Oliveira & Martins, 2011; Tornatzky & Fleischer, 1990), we expect that administrators will intend to use GenAI when its use is legitimized by institutional policy, a proposition consistent with evidence that institutional policy conditions GenAI adoption (Polyportis & Pahos, 2025). Therefore:

H5: Trust in GenAI positively influences behavioral intention to use GenAI.

H6: Privacy concern negatively influences behavioral intention to use GenAI.

H7: Institutional policy fit positively influences behavioral intention to use GenAI.

From intention to behavior. Consistent with the theory of planned behavior and UTAUT, intention is the proximal antecedent of behavior (Ajzen, 1991; Venkatesh et al., 2003). Intentions do not always translate into behavior, however, and the gap tends to widen when behavior is constrained by factors outside volitional control (Sheeran, 2002). For administrators, two such factors are salient. Trust should affect use directly because reliance on GenAI in consequential tasks, such as policy and strategic decisions, requires confidence that exceeds a general intention (Choudhury & Shamszare, 2023; Glikson & Woolley, 2020). Privacy concern should constrain use directly because administrators may intend to use GenAI in general yet withhold it from tasks involving sensitive data (Dinev & Hart, 2006). Therefore:

H8: Behavioral intention positively influences use behavior of GenAI.

H9: Trust in GenAI positively influences use behavior of GenAI.

H10: Privacy concern negatively influences use behavior of GenAI.

Antecedents of social influence. Social influence is not an exogenous given in organizations; it is produced by organizational signals. Institutional theory holds that resources and structures communicate what an organization expects of its members (DiMaggio & Powell, 1983). When a college provides digital infrastructure, technical personnel, and budget for GenAI initiatives, administrators are likely to infer that superiors and governing agencies endorse its use, which intensifies perceived social influence. Effort expectancy may operate similarly. Diffusion theory indicates that innovations perceived as less complex spread more readily and become more observable within social systems (Rogers, 2003); an easy-to-use GenAI is thus more likely to be adopted and visibly modeled by colleagues, reinforcing the perception that important others expect its use. Therefore:

H11: Effort expectancy positively influences social influence.

H12: Facilitating conditions positively influence social influence.

The cross-sectional survey design permits tests of the hypothesized associations and of the model's overall consistency with the data; it does not, by itself, establish temporal precedence, a constraint that is addressed in the Discussion.

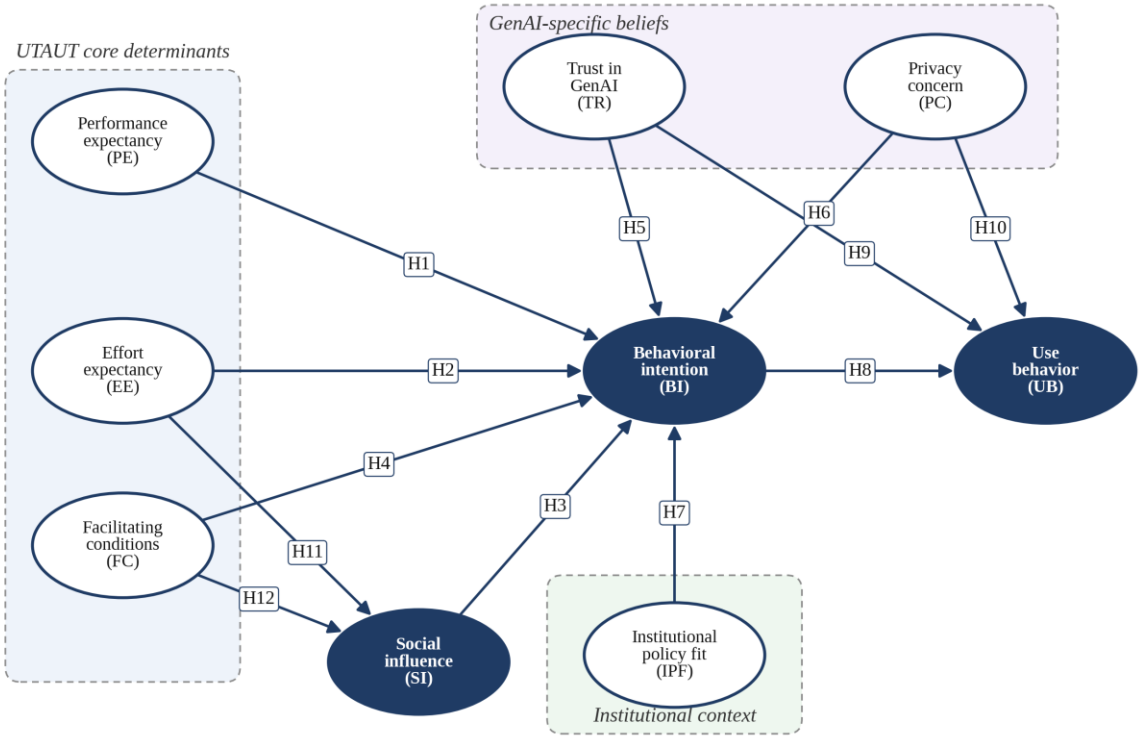

Figure 1. Research Model and Hypotheses

Note. Filled ellipses denote endogenous constructs. Privacy concern items were reverse-scored before analysis (see Section 2.3.2); hypotheses H6 and H10 are therefore supported by positive coefficients.

2. Methods

2.1 Research Design

The study adopted a cross-sectional, explanatory survey design. The hypothesized relationships were specified as a component-based structural equation model and estimated with GSCA. All constructs were operationalized with reflectively specified indicators, and inferential statistics were obtained by nonparametric bootstrapping. The analysis followed a two-step logic: the measurement model was evaluated first, and the structural model was interpreted only after reliability and validity had been established (Hair et al., 2019).

2.2 Participants and Setting

The target population comprised directors and deputy directors of private vocational colleges in Thailand, which operate under licences issued to private owners (licensees) and under the regulatory oversight of the Office of the Vocational Education Commission (OVEC). Private colleges were selected for two reasons. First, their executives hold combined strategic and managerial responsibilities and decide how administrative work is organized and which data may be processed with external tools. Second, private colleges operate under market pressure and comparatively tight resource constraints, so the efficiency gains promised by GenAI, as well as its data-protection risks, are directly salient to their administrators. Respondents were eligible if they held a director or deputy director position at the time of data collection. The final sample consisted of 330 administrators (159 directors and 171 deputy directors) from private vocational colleges across all regions of Thailand; their characteristics are reported in Section 3.1.

2.3 Sampling and Data Collection Procedures

A two-stage stratified cluster sampling design was used to obtain a nationally distributed sample. In the first stage, the sampling frame was the register of private vocational colleges under OVEC oversight. Colleges were stratified into five geographic regions (Northern, Northeastern, Central including Bangkok, Eastern, and Southern), and the number of colleges drawn from each stratum was allocated in proportion to the stratum's share of the frame. Within

each stratum, colleges were selected by simple random sampling using a computer-generated random number sequence. Stratification by region ensured that colleges in all parts of the country were represented and reduced the risk that regional differences in digital infrastructure would be confounded with the sampling process. In the second stage, each selected college was treated as a cluster, and all of its directors and deputy directors were invited to participate. This cluster design explains why the numbers of directors (159) and deputy directors (171) differ: colleges vary in the number of deputy positions, and not every invited executive responded.

Data were collected between March and April 2026 using a self-administered online questionnaire developed in Google Forms. The questionnaire was distributed through the official communication channels of the selected colleges. Participation was voluntary and anonymous. Respondents were informed of the study objectives, the voluntary nature of their participation, and their right to withdraw. No personally identifying information was collected. The study was reviewed by the Human Research Ethics Committee of Northeastern University, Khon Kaen, Thailand, which issued a research exemption determination on November 1, 2026 (Certificate No. 075/2569; Project No. 085/2569). Because respondents were nested within colleges, observations from the same college may not be fully independent; the sensitivity of the results to this clustering is quantified in Section 3.7.5 and considered in Section 4.4.

2.3.1 Sample Size and Statistical Power

Minimum sample size was determined with the inverse square root method, which derives the sample required to detect the smallest path coefficient of interest at a given significance level and power (Kock & Hadaya, 2018). Assuming a minimum path magnitude of 0.20, a 5% significance level, and 80% power, the required sample is 155 (i.e., $[2.486/0.20]^2$). The achieved sample of 330 exceeds this requirement by a factor of 2.1 and, inverting the same formula, permits the detection of path coefficients as small as $|\beta| \approx 0.137$ ($2.486/\sqrt{330}$). This threshold is relevant to the interpretation of nonsignificant paths in Section 4.

2.3.2 Measures

The questionnaire measured nine constructs with three items each (27 items). Items were written in Thai for administration and are reported in English in Appendix A. All items used a 7-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). The UTAUT constructs were anchored in Venkatesh et al. (2003, 2012) and contextualized to administrative tasks; trust was anchored in the trust literature (Choung et al., 2023; McKnight et al., 2002); privacy concern was anchored in information-privacy research (Dinev & Hart, 2006; Smith et al., 1996) and explicitly referred to compliance with the Personal Data Protection Act (2019); and institutional policy fit was anchored in the notions of compatibility and organizational context (Oliveira & Martins, 2011; Rogers, 2003). Table 2 defines each construct as operationalized in this study. The three privacy concern items were reverse-scored before analysis, so that higher PC scores denote lower privacy concern; consequently, the hypothesized negative effects of privacy concern (H6 and H10) are expected to appear as positive coefficients.

Table 2. Construct Definitions and Theoretical Anchors

Construct (code)	Operational definition in this study	Items	Theoretical anchor
Performance expectancy (PE)	Belief that GenAI improves administrative performance, decision quality, and paperwork efficiency	PE1-PE3	Venkatesh et al. (2003)
Effort expectancy (EE)	Perceived ease of learning and using GenAI for administrative tasks	EE1-EE3	Venkatesh et al. (2003)
Social influence (SI)	Perceived expectation of top management, colleagues, and governing agencies that GenAI be used	SI1-SI3	Venkatesh et al. (2003)
Facilitating conditions (FC)	Perceived availability of digital infrastructure, technical personnel, and budget for GenAI	FC1-FC3	Venkatesh et al. (2003, 2012)
Trust in GenAI (TR)	Confidence that GenAI outputs are reliable, consistent, transparent, and free of unnecessary risk	TR1-TR3	McKnight et al. (2002); Choung et al. (2023)
Privacy concern (PC)	Apprehension about data confidentiality, personal data breaches, and PDPA compliance (reverse-scored)	PC1-PC3 (R)	Smith et al. (1996); Dinev & Hart (2006)
Institutional policy fit (IPF)	Alignment of GenAI with college policies, administrative strategy, and internal practices	IPF1-IPF3	Rogers (2003); Oliveira & Martins (2011)
Behavioral intention (BI)	Intention to continue, increase, and advocate GenAI use in administration	BI1-BI3	Venkatesh et al. (2003)
Use behavior (UB)	Regularity, breadth, and strategic depth of GenAI use in administration	UB1-UB3	Venkatesh et al. (2003, 2012)

Note. (R) = reverse-scored before analysis. PDPA = Personal Data Protection Act B.E. 2562 (2019), Thailand. Full item wording is provided in Appendix A.

2.3.3 Analytical Approach

GSCA was selected for three reasons. First, the study aimed to explain variance in endogenous constructs within a theory-extending model, a purpose for which composite-based methods are well suited (Hwang et al., 2020). Second, unlike partial least squares path modeling, which estimates its parameters through a sequence of local regressions, GSCA estimates all weights, loadings, and path coefficients simultaneously by minimizing a single global least squares criterion (Hwang & Takane, 2004). Third, because GSCA has a global criterion, it provides indexes of overall model fit that allow the model to be evaluated as a whole (Cho et al., 2020). Let $\mathbf{Z}$ denote the $N \times J$ matrix of standardized indicators, $\mathbf{W}$ the matrix of component weights, $\mathbf{V} = [\mathbf{I}, \mathbf{W}]$, and $\mathbf{A} = [\mathbf{C}, \mathbf{B}]$ the matrix of loadings ($\mathbf{C}$) and path coefficients ($\mathbf{B}$). GSCA estimates $\mathbf{W}$ and $\mathbf{A}$ by minimizing

$$\varphi = \mathrm{SS}(\mathbf{ZV} - \mathbf{ZWA}), \tag{1}$$

where SS(·) denotes the sum of squares, subject to the constraint that each component is standardized (Hwang & Takane, 2004, 2014). The proportion of the total variance of all indicators and components explained by the model is expressed as

$$\mathrm{FIT} = 1 - \mathrm{SS}(\mathbf{ZV} - \mathbf{ZWA}) / \mathrm{SS}(\mathbf{ZV}), \tag{2}$$

and the adjusted index (AFIT) corrects FIT for model complexity. FIT can be decomposed into the variance of the indicators explained by their components ($\mathrm{FIT_M}$) and the variance of the components explained by their predictors ($\mathrm{FIT_S}$) (Hwang et al., 2023). Local effect sizes were computed as

$$f^2 = (R^2_{\text{included}} - R^2_{\text{excluded}}) / (1 - R^2_{\text{included}}), \tag{3}$$

with values of 0.02, 0.15, and 0.35 interpreted as small, medium, and large (Cohen, 1988). All analyses were conducted with the GSCA procedure implemented in SmartPLS 4 (Ringle et al., 2024), which was used to estimate the weights, loadings, and path coefficients, to compute the overall fit indexes (SRMR, FIT, AFIT, $\mathrm{FIT_S}$, and $\mathrm{FIT_M}$), and to perform bootstrapping.

2.3.4 Evaluation Procedures and Criteria

Because many of the evaluation metrics established for partial least squares path modeling also apply to GSCA, whereas overall model fit is assessed differently (Hwang et al., 2023), the measurement and structural models were

evaluated with the criteria summarized in Table 3, supplemented by the GSCA-specific fit indexes. Statistical significance was assessed with the GSCA bootstrapping procedure of SmartPLS 4 using 5,000 subsamples, percentile bootstrap confidence intervals, two-tailed tests at $\alpha = .05$, and a fixed random seed to ensure that the results can be reproduced. The distribution of each bootstrapped estimate was inspected to confirm that inference was not distorted by skewness or multimodality. Specific indirect effects were tested directly with the same bootstrap procedure, which makes no distributional assumption about the product of coefficients; the joint-significance test, which infers mediation when all constituent paths are significant (MacKinnon et al., 2002), was used as a corroborating check. Three supplementary analyses addressed threats identified in the diagnostics. First, because the predictors of intention were highly collinear, their relative importance was assessed with dominance analysis (Azen & Budescu, 2003), which decomposes R^2 into the average incremental contribution of each predictor across all possible subset models and, unlike partial coefficients, credits each predictor with its share of the variance it explains jointly with others; the joint contribution of the three instrumental determinants was also tested with a hierarchical R^2 change test and with a model in which they were merged into a single equally weighted composite. Second, because no marker variable had been included in the questionnaire, common method variance was assessed post hoc with the correlation-adjusted marker technique (Lindell & Whitney, 2001), using the smallest inter-construct correlation as a conservative estimate of method variance. Third, the sensitivity of inference to the clustering of respondents within colleges was quantified through the design effect (Kish, 1965). These analyses were computed from the component correlation matrix (Table 6); ordinary least squares regression on this matrix reproduced every GSCA path coefficient to within 0.003.

Table 3. Criteria for Evaluating the Measurement Model, Overall Fit, and Structural Model

Stage	Criterion	Threshold	Source
Measurement model	Indicator loading	≥ 0.708	Hair et al. (2019); Hwang et al. (2023)
	Cronbach's α; composite reliability (ρ_c)	0.70-0.95	Hair et al. (2019)
	Average variance extracted (AVE)	≥ 0.50	Fornell & Larcker (1981)
	Fornell-Larcker criterion	√AVE > inter-construct correlations	Fornell & Larcker (1981)
	Heterotrait-monotrait ratio (HTMT)	< 0.90; bootstrap 97.5% bound < 1.00	Henseler et al. (2015); Franke & Sarstedt (2019)
Collinearity	Outer (indicator) VIF	< 5 (reflective: high values signal redundancy)	Hair et al. (2019)
	Inner (predictor) VIF	< 5; ideally < 3	Hair et al. (2019)
	Full collinearity VIF	≤ 3.3	Kock (2015)
Overall fit	SRMR	≤ 0.08	Cho et al. (2020)
	FIT; AFIT	Proportion of variance explained; no fixed cutoff	Hwang & Takane (2004, 2014)
Structural model	Path coefficient (β)	Bootstrap $p < .05$ (two-tailed)	Hair et al. (2022)
	Coefficient of determination (R^2)	0.25 / 0.50 / 0.75 = weak / moderate / substantial	Hair et al. (2019)
	Effect size (f^2)	0.02 / 0.15 / 0.35 = small / medium / large	Cohen (1988)
	Specific indirect effect	Bootstrap $p < .05$ (two-tailed); constituent paths significant	Hair et al. (2022); MacKinnon et al. (2002)

Note. VIF = variance inflation factor; SRMR = standardized root mean square residual; FIT = proportion of total variance explained; AFIT = adjusted FIT.

3. Results

3.1 Respondent Profile

Table 4 presents the demographic characteristics of the 330 respondents. Women constituted 60.9% of the sample, and the two administrative ranks were almost equally represented (directors, 48.2%; deputy directors, 51.8%). Nearly half of the respondents (46.4%) reported more than 10 years of administrative experience. Missing demographic responses were rare (0.3% for gender and 2.1% for administrative experience), and four age

responses (1.2%) were invalid. The largest age group was younger than 30 years (39.4%), a profile consistent with the participation of a younger generation of executives in privately owned colleges; the remaining respondents were distributed relatively evenly across the older age bands.

Table 4. Demographic Characteristics of Respondents (N = 330)

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	17.0
	51-60 years	50	15.2
	Above 60 years	35	10.6
	Invalid response	4	1.2
Administrative experience	Less than 5 years	71	21.5
	5-10 years	99	30.0
	More than 10 years	153	46.4
	Missing	7	2.1

Note. Percentages may not sum to 100 because of rounding.

3.2 Measurement Model

Indicator reliability, internal consistency, and convergent validity. All 27 loadings ranged from 0.926 (UB1) to 0.957 (PE2 and FC3), well above the 0.708 threshold (Table 5). Cronbach's α ranged from 0.929 (UB) to 0.949 (PE), composite reliability (ρ_c) from 0.955 (UB) to 0.967 (PE), and AVE from 0.876 (UB) to 0.908 (PE). Bootstrapping confirmed that every AVE (t = 53.01-91.74) and every ρ_c (t = 145.18-257.59) differed significantly from zero ($p < .001$), and the bootstrap standard errors were small (AVE, 0.010-0.017; ρ_c, 0.004-0.007), indicating stable estimates. Reliability and convergent validity were therefore established. We note, however, that composite reliability exceeded 0.95 for all nine constructs (0.955-0.967). Hair et al. (2019) caution that values above 0.95 may signal semantically redundant items or response patterns such as straight-lining; this possibility is considered in Section 4.4.

Table 5. Indicator Loadings, Internal Consistency Reliability, and Convergent Validity

Construct	Item	Loading	α	ρ_c	AVE
Performance expectancy (PE)	PE1	0.952	0.949	0.967	0.908
	PE2	0.957			
	PE3	0.950			
Effort expectancy (EE)	EE1	0.937	0.936	0.959	0.887
	EE2	0.951			
	EE3	0.936			
Social influence (SI)	SI1	0.945	0.935	0.959	0.885
	SI2	0.946			
	SI3	0.931			
Facilitating conditions (FC)	FC1	0.940	0.947	0.966	0.904
	FC2	0.955			
	FC3	0.957			
Trust in GenAI (TR)	TR1	0.939	0.930	0.956	0.878
	TR2	0.940			
	TR3	0.932			
Privacy concern (R) (PC)	PC1	0.942	0.945	0.965	0.901
	PC2	0.954			
	PC3	0.952			
Institutional policy fit (IPF)	IPF1	0.934	0.937	0.960	0.888
	IPF2	0.954			
	IPF3	0.939			
Behavioral intention (BI)	BI1	0.930	0.936	0.959	0.887
	BI2	0.955			
	BI3	0.939			
Use behavior (UB)	UB1	0.926	0.929	0.955	0.876
	UB2	0.947			
	UB3	0.935			

Note. α = Cronbach's alpha; ρ_c = composite reliability; AVE = average variance extracted; (R) = reverse-scored. All loadings were significant at $p < .001$.

Indicator collinearity. Outer VIFs ranged from 3.448 (UB1) to 5.287 (PE2); three indicators exceeded 5 (PE2 = 5.287, FC2 = 5.259, FC3 = 5.128). For reflectively specified constructs, indicator collinearity is expected and does not bias the estimation of loadings, but values of this magnitude, together with composite reliabilities above 0.95, indicate that the items within some constructs are close to interchangeable (Hair et al., 2019).

Discriminant validity. Three complementary criteria were examined (Table 6). First, the square root of each construct's AVE (0.936-0.953) exceeded its correlations with all other constructs, the largest of which was 0.868 (BI-UB), thereby satisfying the Fornell-Larcker criterion. Second, every indicator loaded more strongly on its own construct than on any other construct (Appendix B, Table B1); the smallest margin was 0.110 (PE2, whose loading on PE exceeded its cross-loading on EE). Third, 33 of the 36 HTMT ratios fell below 0.90. The three exceptions were BI-UB (0.930; 95% bootstrap confidence interval [0.882, 0.968]), EE-PE (0.921; [0.859, 0.970]), and BI-PC (0.907; [0.848, 0.953]). Because the upper bounds of all 36 intervals were below 1.00, the HTMT inference test supports discriminant validity (Henseler et al., 2015). We acknowledge that this is the liberal variant of the test; under the more conservative criterion that the upper bound fall below 0.90 (Franke & Sarstedt, 2019), 24 of the 36 construct pairs would not be distinguished (Appendix B, Table B2). The three pairs above 0.90 are theoretically interpretable: the EE-PE overlap is consistent with the conversational interface of GenAI, in which ease of use and usefulness are experienced jointly; the BI-UB overlap reflects the continuation wording of the intention items among respondents who already use GenAI; and the BI-PC overlap suggests that assurance about data protection is integral to administrators' willingness to use GenAI. Because the BI-UB pair underpins H8, it was re-examined in detail. It did not meet the conservative criterion (upper bound 0.968), and the correlation between the two constructs ($r = .868$) means that they share 75.3% of their variance. They nonetheless remained separable at the item level: each BI item loaded on BI more strongly than on UB by at least 0.121, and each UB item loaded on UB more strongly than on BI by at least 0.120 (Table B1). Their overlap is largely a matter of wording, because the intention items refer to continuing and increasing current use, whereas the use items refer to its regularity,

breadth, and strategic depth. The BI → UB coefficient is therefore interpreted as the association between administrators' current use and their intention to sustain it, rather than as evidence that intention predicts subsequent behavior; developing items that separate prospective intention from current behavior is a priority for future research (Section 4.4).

Table 6. Discriminant Validity: Fornell-Larcker Criterion and Heterotrait-Monotrait Ratios

Construct	BI	EE	FC	IPF	PC	PE	SI	TR	UB
BI	**.942**	*.811*	*.875*	*.869*	*.907*[a]	*.797*	*.881*	*.889*	*.930*[a]
EE	.761	**.942**	*.879*	*.776*	*.845*	*.921*[a]	*.878*	*.816*	*.797*
FC	.824	.827	**.951**	*.828*	*.886*	*.873*	*.888*	*.835*	*.818*
IPF	.815	.727	.781	**.942**	*.853*	*.732*	*.750*	*.833*	*.877*
PC	.854	.795	.838	.803	**.949**	*.813*	*.859*	*.869*	*.885*
PE	.751	.868	.827	.690	.769	**.953**	*.835*	*.752*	*.760*
SI	.824	.823	.836	.702	.807	.787	**.941**	*.848*	*.834*
TR	.830	.762	.784	.778	.815	.707	.791	**.937**	*.868*
UB	.868	.745	.767	.820	.831	.714	.778	.808	**.936**

Note. Diagonal values (bold) are the square roots of AVE. Values below the diagonal are inter-construct correlations (Fornell-Larcker criterion); all were significant at $p < .001$. Values above the diagonal (italics) are HTMT ratios. [a] HTMT > 0.90; the 95% bootstrap confidence interval does not include 1.00.

3.3 Collinearity and Common Method Variance

Collinearity among predictors was assessed with inner VIFs, and common method variance was assessed with the full collinearity approach, in which each component is regressed on all other components and VIFs above 3.3 are taken as a warning sign of pathological collinearity or common method bias (Kock, 2015). Both sets of VIFs were derived from the component correlation matrix (Table 6): the full collinearity VIF of a component equals the corresponding diagonal element of the inverse of the full correlation matrix, and the inner VIF of a predictor equals the diagonal element of the inverse of the correlation matrix of the predictors of a given endogenous construct. Table 7 reports the results.

The inner VIFs for the predictors of social influence (3.164) and use behavior (3.711-4.604) were below 5. Among the seven predictors of behavioral intention, however, the inner VIFs ranged from 3.498 (IPF) to 5.726 (FC), and three exceeded 5 (FC = 5.726, EE = 5.612, PC = 5.074). The full collinearity VIFs ranged from 4.193 (IPF) to 6.642 (BI) and all exceeded 3.3. Two implications follow. First, the unique contributions of the correlated UTAUT determinants to behavioral intention are estimated imprecisely; the nonsignificant effects of performance expectancy, effort expectancy, and facilitating conditions, and in particular the negative sign of the effort expectancy coefficient despite its positive bivariate correlation with intention ($r = .761$), are consistent with suppression under collinearity; they are best read as unique effects that cannot be estimated precisely under this degree of collinearity rather than as evidence of no effect. Second, because every construct exceeded the 3.3 threshold, the full collinearity diagnostics constitute a substantive threat to validity: common method variance cannot be ruled out, and the magnitude of the structural relationships may be inflated. These issues were therefore examined directly with dominance analysis (Section 3.7.3) and a post hoc marker-variable analysis (Section 3.7.4), and they are revisited in Section 4.4.

Table 7. Collinearity Diagnostics: Inner and Full Collinearity Variance Inflation Factors

Construct	Inner VIF: predictors of BI	Inner VIF: predictors of UB	Inner VIF: predictors of SI	Full collinearity VIF
PE	4.866	—	—	4.904[b]
EE	5.612[a]	—	3.164	5.698[b]
SI	4.670	—	—	5.109[b]
FC	5.726[a]	—	3.164	5.846[b]
TR	4.002	3.711	—	4.325[b]
PC (R)	5.074[a]	4.265	—	5.603[b]
IPF	3.498	—	—	4.193[b]
BI	—	4.604	—	6.642[b]
UB	—	—	—	5.349[b]

Note. VIFs were computed from the GSCA component correlation matrix; values reported by the software may

differ marginally because of rounding. [a] Inner VIF > 5 (Hair et al., 2019). [b] Full collinearity VIF > 3.3 (Kock, 2015).

3.4 Overall Model Fit

Table 8 reports the overall fit of the estimated model. The SRMR of the estimated model (0.034) was only marginally larger than that of the saturated model (0.027) and well below the cutoff of 0.08 recommended for GSCA (Cho et al., 2020), indicating that the model-implied correlations closely reproduce the observed correlations. FIT indicated that the model explained 73.4% of the total variance of all indicators and components, and AFIT (0.732) showed that this value was almost unaffected by the adjustment for model complexity. The decomposition of FIT is instructive. FIT_M (0.890) equals the mean AVE across the nine constructs, confirming that the measurement component of the model accounts for 89.0% of the indicator variance. FIT_S (0.264) equals the mean R^2 across all nine components; because six components are exogenous (and thus have $R^2 = 0$ by construction), the maximum attainable value of FIT_S in this model is 3/9 = 0.333. Relative to this bound, the observed FIT_S corresponds to a mean R^2 of 0.792 across the three endogenous constructs. Consistent with its definition, FIT is the variance-weighted combination of the two components: (27 × 0.890 + 9 × 0.264) / 36 = 0.734.

Table 8. Overall Model Fit Indexes

Index	Saturated model	Estimated model	Interpretation
SRMR	0.027	0.034	Below 0.08; good fit
FIT	—	0.734	73.4% of total variance explained
AFIT	—	0.732	Negligible penalty for model complexity
FIT_M	—	0.890	Equals mean AVE across nine constructs
FIT_S	—	0.264	Equals mean R^2 across nine components (maximum 0.333)

Note. SRMR = standardized root mean square residual; FIT_M = measurement-model FIT; FIT_S = structural-model FIT. FIT-type indexes are not defined for the saturated model and are shown as 0.000 in the software output.

3.5 Structural Model and Hypothesis Testing

Table 9 and Figures 2 and 3 present the structural estimates and their bootstrap p values. Among the UTAUT determinants, social influence significantly predicted behavioral intention (β = 0.257, t = 2.860, p = .004), supporting H3. Performance expectancy (β = 0.081, t = 1.121, p = .262), effort expectancy (β = −0.118, t = 1.457, p = .145), and facilitating conditions (β = 0.084, t = 1.155, p = .248) did not have statistically significant unique direct effects on intention. Because these predictors were severely collinear (inner VIF = 4.866-5.726; Section 3.3) and each was strongly correlated with intention (r = .751-.824), these results do not show that the three determinants are unrelated to intention; rather, their unique effects could not be separated from those of the correlated predictors. H1, H2, and H4 are therefore classified as inconclusive rather than rejected, and the relative importance of these determinants is examined in Section 3.7.3. All three extension constructs significantly predicted intention: institutional policy fit (β = 0.240, t = 4.166, p < .001), privacy concern (reverse-scored; β = 0.246, t = 3.022, p = .003), and trust (β = 0.206, t = 2.639, p = .008), supporting H7, H6, and H5, respectively. Because privacy concern was reverse-scored, the positive coefficient indicates that lower privacy concern is associated with stronger intention, as hypothesized.

For use behavior, behavioral intention was the strongest predictor (β = 0.489, t = 4.502, p < .001), supporting H8. Privacy concern (reverse-scored; β = 0.256, t = 2.554, p = .011) and trust (β = 0.193, t = 1.972, p = .049) also exerted direct effects on use, supporting H10 and H9. The trust-use path, however, lay at the margin of conventional significance and should be interpreted with caution; as shown in Section 3.7.4, neither the trust-use nor the privacy concern-use path was robust to the most conservative adjustment for common method variance, and Section 3.7.5 shows that the trust-use path is also sensitive to clustering. Finally, facilitating conditions (β = 0.492, t = 6.032, p < .001) and effort expectancy (β = 0.416, t = 5.416, p < .001) strongly predicted social influence, supporting H12 and H11. Across all paths, the bootstrap means deviated from the original estimates by no more than 0.016, indicating negligible bootstrap bias.

Table 9. Structural Path Estimates and Hypothesis Testing

Hypothesis	Path	β	*M*	*SD*	*t*	*p*	Decision
H1	PE → BI	0.081	0.081	0.072	1.121	.262	Inconclusive[c]
H2	EE → BI	−0.118	−0.105	0.081	1.457	.145	Inconclusive[c]
H3	SI → BI	0.257	0.241	0.090	2.860	.004	Supported
H4	FC → BI	0.084	0.087	0.073	1.155	.248	Inconclusive[c]
H5	TR → BI	0.206	0.206	0.078	2.639	.008	Supported
H6	PC (R) → BI	0.246	0.250	0.082	3.022	.003	Supported
H7	IPF → BI	0.240	0.236	0.058	4.166	< .001	Supported
H8	BI → UB	0.489	0.479	0.109	4.502	< .001	Supported
H9	TR → UB	0.193	0.196	0.098	1.972	.049	Supported[d]
H10	PC (R) → UB	0.256	0.263	0.100	2.554	.011	Supported[d]
H11	EE → SI	0.416	0.421	0.077	5.416	< .001	Supported
H12	FC → SI	0.492	0.487	0.082	6.032	< .001	Supported

Note. β = original-sample path coefficient; *M* = bootstrap mean; *SD* = bootstrap standard deviation; *t* = |β / *SD*|; *p* = two-tailed bootstrap *p* value. PC (R): privacy concern reverse-scored, so a positive β indicates that lower privacy concern increases the outcome, consistent with the negative direction hypothesized for privacy concern. [c] Unique direct effect not significant and not separable from those of correlated predictors (inner VIF = 4.87-5.73); not interpreted as evidence of no effect (see Section 3.7.3). [d] Not robust to the most conservative marker-variable adjustment for common method variance (Section 3.7.4); interpret with caution.

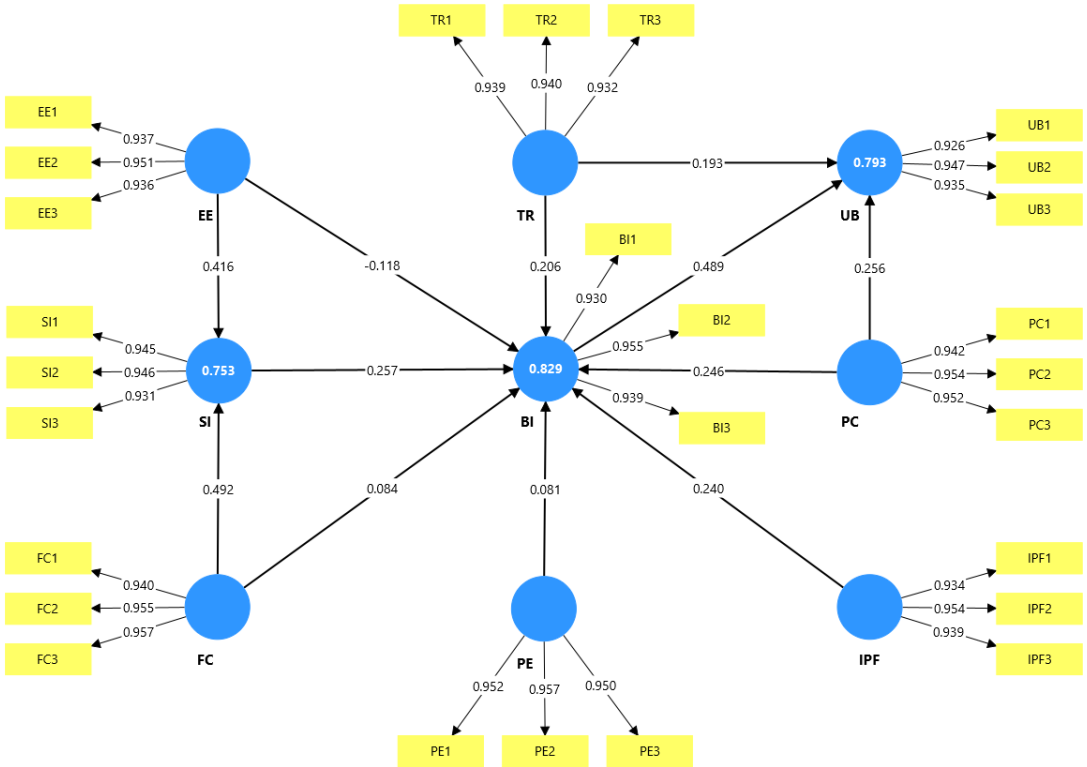

Figure 2. Estimated Structural Model: Path Coefficients, Outer Loadings, and R-Squared Values

Note. Values on the inner arrows are standardized path coefficients; values on the outer arrows are indicator loadings; values inside the endogenous constructs are R^2. Privacy concern (PC) was reverse-scored. Output from the GSCA procedure in SmartPLS 4.

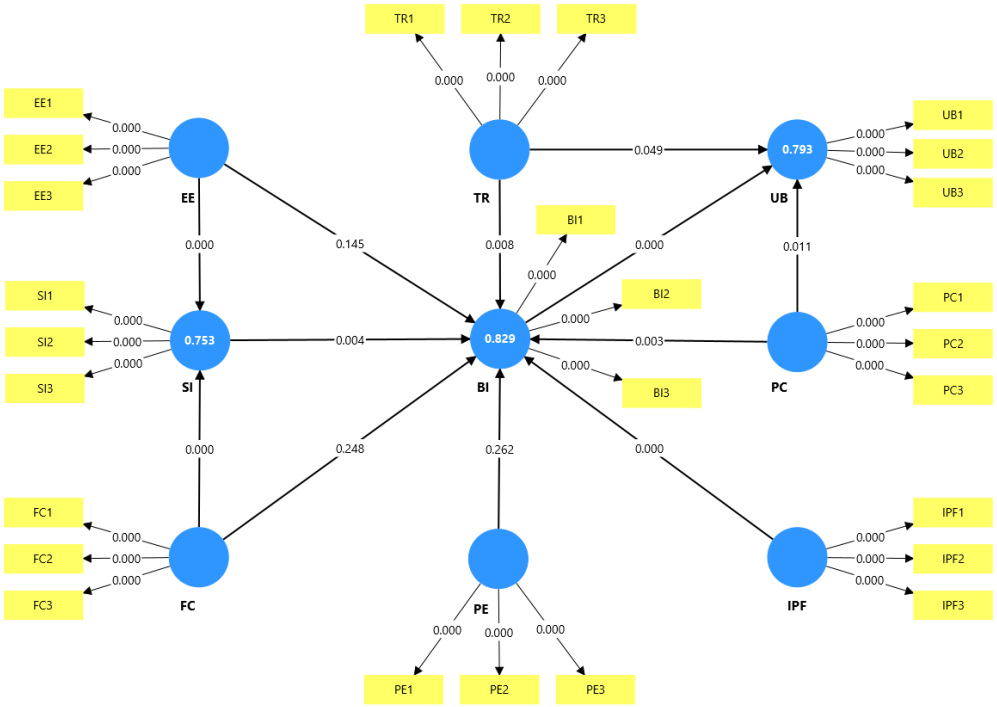

Figure 3. Bootstrap p Values of the Structural and Measurement Model (5,000 Subsamples)

Note. Values on the arrows are two-tailed *p* values from percentile bootstrapping; values inside the endogenous constructs are R^2. Output from the GSCA procedure in SmartPLS 4.

3.6 Explanatory Power and Effect Sizes

The model explained 82.9% of the variance in behavioral intention, 75.3% in social influence, and 79.3% in use behavior (Table 10). All three R^2 values were significant ($p < .001$) and substantial by conventional benchmarks (Hair et al., 2019). The effect sizes clarify the relative contribution of each predictor. BI → UB ($f^2 = 0.251$), FC → SI (0.310), and EE → SI (0.221) were medium effects. Among the predictors of intention, institutional policy fit had the largest effect (0.097), followed by social influence (0.083), privacy concern (0.070), and trust (0.062), all small. Privacy concern (0.075) and trust (0.048) exerted small effects on use behavior. The effects of performance expectancy (0.008), facilitating conditions (0.007), and effort expectancy (0.014) on intention were below the threshold for a small effect, which reflects the small amount of variance that each contributes uniquely once the other predictors are controlled. Because f^2 measures unique contribution, it is subject to the same collinearity as the path coefficients; Section 3.7.3 therefore reports a decomposition that also credits shared variance.

Table 10. Coefficients of Determination and Effect Sizes

Endogenous construct	R^2	*SD*	*t*	*p*	Predictor	f^2	Magnitude
Behavioral intention (BI)	0.829	0.025	32.854	< .001	PE	0.008	None
					EE	0.014	None
					SI	0.083	Small
					FC	0.007	None
					TR	0.062	Small
					PC (R)	0.070	Small
					IPF	0.097	Small
Social influence (SI)	0.753	0.043	17.556	< .001	EE	0.221	Medium
					FC	0.310	Medium
Use behavior (UB)	0.793	0.031	25.166	< .001	BI	0.251	Medium
					TR	0.048	Small
					PC (R)	0.075	Small

Note. R^2 significance is based on bootstrapping. f^2 magnitudes follow Cohen (1988): ≥ 0.02 small, ≥ 0.15 medium, ≥ 0.35 large.

3.7 Additional Analyses

3.7.1 Indirect and Total Effects

Because the model contains two mediating constructs, 11 specific indirect effects were tested with bootstrapping (Table 11). Two effects operated through social influence: effort expectancy (β = 0.107, t = 2.409, p = .016) and facilitating conditions (β = 0.127, t = 2.854, p = .004) both influenced behavioral intention indirectly through social influence. Because their direct effects on intention were nonsignificant, the pattern is consistent with indirect-only mediation, although the collinearity reported in Section 3.3 means that the absence of direct effects should not be overstated. The negative direct estimate for effort expectancy (−0.118) offsets its positive indirect effect, yielding a total effect on intention close to zero (−0.011); given the inner VIF of effort expectancy (5.612), this offsetting pattern is more plausibly attributed to suppression under collinearity than to a substantive negative effect.

Four antecedents reached use behavior indirectly through behavioral intention: privacy concern (reverse-scored; β = 0.120, t = 2.752, p = .006), institutional policy fit (β = 0.117, t = 2.583, p = .010), trust (β = 0.101, t = 2.524, p = .012), and social influence (β = 0.126, t = 2.173, p = .030). The corresponding indirect effects of performance expectancy (p = .287), effort expectancy (p = .174), and facilitating conditions (p = .250) through intention were nonsignificant. Of the two serial effects, facilitating conditions → social influence → behavioral intention → use behavior was significant (β = 0.062, t = 2.271, p = .023), whereas the corresponding effect of effort expectancy was not (β = 0.052, t = 1.877, p = .061). Thus, within this model, the effect of organizational resources on actual use is transmitted mainly through the normative climate they create. When direct and indirect paths were combined, privacy concern had the largest total effect on use behavior (0.376), followed by trust (0.294), whereas the total effects of institutional policy fit (0.117) and social influence (0.126) operated entirely through intention. All significant bootstrap results were corroborated by the joint-significance test (MacKinnon et al., 2002).

Table 11. Bootstrapped Specific Indirect Effects

Specific indirect effect	β	*M*	*SD*	*t*	*p*	Decision
EE → SI → BI	0.107	0.102	0.044	2.409	.016	Significant
FC → SI → BI	0.127	0.116	0.044	2.854	.004	Significant
SI → BI → UB	0.126	0.119	0.058	2.173	.030	Significant
TR → BI → UB	0.101	0.097	0.040	2.524	.012	Significant
PC (R) → BI → UB	0.120	0.118	0.044	2.752	.006	Significant
IPF → BI → UB	0.117	0.116	0.045	2.583	.010	Significant
PE → BI → UB	0.039	0.039	0.037	1.066	.287	Not significant
EE → BI → UB	−0.057	−0.051	0.042	1.358	.174	Not significant
FC → BI → UB	0.041	0.040	0.036	1.150	.250	Not significant
FC → SI → BI → UB	0.062	0.057	0.027	2.271	.023	Significant
EE → SI → BI → UB	0.052	0.050	0.028	1.877	.061	Not significant

Note. β = original-sample specific indirect effect; *M* = bootstrap mean; *SD* = bootstrap standard deviation; $t = |\beta / SD|$; p = two-tailed percentile bootstrap p value (5,000 subsamples). PC (R): privacy concern reverse-scored.

3.7.2 Robustness of Bootstrap Inference

Figure 4 displays the bootstrap distribution of the strongest structural path (BI → UB). The distribution was unimodal and approximately normal, centered on 0.479 (original estimate 0.489; bias = −0.010), with a standard deviation of 0.109. Nearly all bootstrap estimates lay between approximately 0.15 and 0.75, and none approached zero, which indicates that the effect of intention on use is robust to resampling rather than an artefact of a few influential cases.

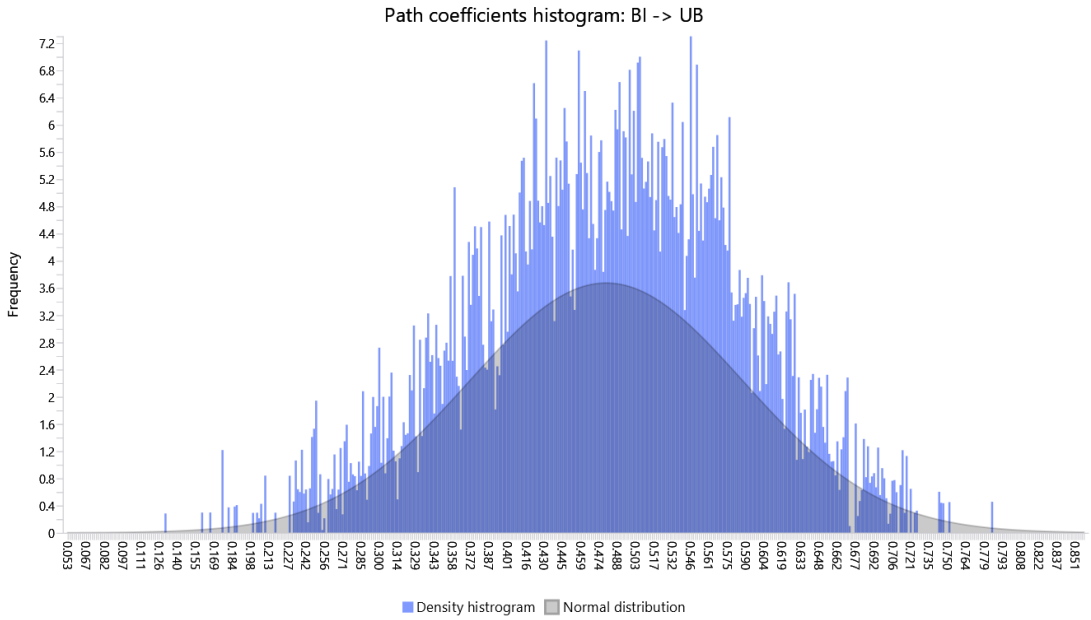

Figure 4. Bootstrap Distribution of the Path Coefficient From Behavioral Intention to Use Behavior

Note. Bars show the density histogram of bootstrap estimates; the grey curve shows the fitted normal distribution. Output from SmartPLS 4.

3.7.3 Relative Importance of the Predictors of Intention

Because the nonsignificant direct effects of performance expectancy, effort expectancy, and facilitating conditions could reflect collinearity rather than irrelevance, the variance in behavioral intention was decomposed with dominance analysis (Table 12). Each general dominance weight is the average increase in R^2 that a predictor produces when added to all possible subsets of the other predictors, and the weights sum to the total R^2 (0.829). The three instrumental determinants together accounted for 35.4% of the explained variance (performance expectancy, 10.6%; effort expectancy, 10.7%; facilitating conditions, 14.1%), and on their own they explained 70.2% of the variance in intention. Their importance was therefore substantial, but it was almost entirely shared: their conditional contributions fell to 0.009 or less once two other predictors were in the model, and jointly they added only $\Delta R^2 = .004$ beyond social influence, trust, privacy concern, and institutional policy fit ($F(3, 322) = 2.56$, $p = .055$). Conversely, the four legitimacy-and-assurance constructs added $\Delta R^2 = .128$ beyond the three instrumental determinants ($F(4, 322) = 60.25$, $p < .001$), and they were the four most important predictors (15.4%-17.3% each). When performance expectancy, effort expectancy, and facilitating conditions were merged into a single equally weighted instrumental composite, which correlated .824 with intention, the composite had no significant unique effect ($\beta = 0.040$, $p = .470$), whereas social influence (0.253), trust (0.195), privacy concern (0.258), and institutional policy fit (0.247) remained significant ($p < .001$), and R^2 was virtually unchanged (0.826). The defensible conclusion is therefore not that the instrumental determinants have no effect, but that their unique effects are not separable and that the legitimacy-and-assurance constructs carry explanatory information that the instrumental determinants do not.

Table 12. Dominance Analysis of the Predictors of Behavioral Intention

Predictor	*r* with BI	β	General dominance weight	Share of R^2 (%)	Rank
PE	.751	0.081	0.088	10.6	7
EE	.761	−0.118	0.089	10.7	6
FC	.824	0.084	0.117	14.1	5
SI	.824	0.257	0.128	15.4	4
TR	.830	0.206	0.133	16.0	2
PC (R)	.854	0.246	0.143	17.3	1
IPF	.815	0.240	0.131	15.8	3
Total			0.829	100.0	

Note. General dominance weights are the average incremental R^2 of each predictor across all 64 subset models of the remaining predictors (Azen & Budescu, 2003), computed from the component correlation matrix; they sum to the total R^2. β = GSCA path coefficient (Table 9). PC (R): privacy concern reverse-scored.

3.7.4 Post Hoc Test of Common Method Variance

Because the full collinearity VIFs exceeded 3.3 for every construct and no marker variable had been included in the questionnaire, common method variance was tested post hoc with the correlation-adjusted marker technique (Lindell & Whitney, 2001). The smallest inter-construct correlation (r = .690, PE-IPF) was used as the estimate of method variance (r_M), which is a deliberately conservative choice: it assumes that the whole of the weakest relationship in the model is attributable to the common method. Every correlation in Table 6 was adjusted as $(r - r_M) / (1 - r_M)$, the three structural equations were re-estimated, and each adjusted coefficient was evaluated against the bootstrap standard deviation of the original estimate (Table 13). The adjustment reduced the explained variance substantially (R^2 for BI, 0.829 → 0.450; UB, 0.793 → 0.371; SI, 0.753 → 0.282), confirming that shared method variance may inflate the magnitude of the relationships. However, all four significant predictors of intention (SI, TR, PC, and IPF), the BI → UB path, and both antecedents of social influence remained significant, and the instrumental determinants remained nonsignificant. Only the direct effects of trust (β = 0.115, p = .241) and privacy concern (β = 0.184, p = .066) on use behavior lost significance. Under a less extreme marker estimate (r_M = .30), every originally significant path remained significant. Thus, the central conclusions regarding intention are robust to a conservative adjustment for common method variance, whereas the direct effects of trust and privacy concern on use (H9 and H10) should be regarded as tentative.

Table 13. Structural Paths Before and After Correlation-Adjusted Marker Analysis (rM = .690)

Path	Original β	Adjusted β	*t*	*p*	Robust
SI → BI	0.257	0.252	2.80	.005	Yes
TR → BI	0.206	0.200	2.56	.010	Yes
PC (R) → BI	0.246	0.248	3.02	.002	Yes
IPF → BI	0.240	0.235	4.05	< .001	Yes
PE → BI	0.081	0.074	1.03	.304	n.s. in both
EE → BI	−0.118	−0.117	1.44	.149	n.s. in both
FC → BI	0.084	0.085	1.16	.244	n.s. in both
BI → UB	0.489	0.425	3.90	< .001	Yes
TR → UB	0.193	0.115	1.17	.241	No
PC (R) → UB	0.256	0.184	1.84	.066	No
EE → SI	0.416	0.275	3.57	< .001	Yes
FC → SI	0.492	0.350	4.27	< .001	Yes

Note. r_M = smallest inter-construct correlation (PE-IPF), used as the estimate of method variance (Lindell & Whitney, 2001). Adjusted β = coefficient re-estimated from the marker-adjusted correlation matrix; t = adjusted β divided by the bootstrap standard deviation of the original estimate (Table 9); p = two-tailed. Adjusted R^2: BI = 0.450, UB = 0.371, SI = 0.282.

3.7.5 Sensitivity to the Clustering of Respondents

Because respondents were nested within colleges and the analysis treated them as independent, the standard errors may be underestimated by a factor of √DEFF, where the design effect is $DEFF = 1 + (\bar{m} - 1)\rho$, $\bar{m}$ is the average number of respondents per college, and ρ is the intraclass correlation (Kish, 1965). Rather than assume a value of

ρ, we computed for each significant effect the critical design effect, $DEFF_{crit} = (t / 1.96)^2$, above which the effect would cease to be significant at α = .05. The core effects were robust to substantial clustering: FC → SI ($DEFF_{crit}$ = 9.47), EE → SI (7.64), BI → UB (5.28), and IPF → BI (4.52) would remain significant even if the variance of their estimates were more than quadrupled, and PC → BI (2.38), SI → BI (2.13), and FC → SI → BI (2.12) would remain significant if it were doubled. The weaker effects were more fragile: TR → BI (1.81), PC → UB (1.70), EE → SI → BI (1.51), FC → SI → BI → UB (1.34), and especially TR → UB (1.01) could lose significance under modest within-college dependence. These effects, which overlap with those that were sensitive to common method variance, should be replicated with multilevel designs.

4. Discussion

4.1 Interpretation of the Principal Findings

This study set out to explain why vocational college administrators intend to use, and actually use, GenAI in administrative work. The model accounted for a large share of variance in intention and use, and the pattern of effects departs in instructive ways from the canonical UTAUT account. Administrators' intention was driven by institutional policy fit, social influence, privacy assurance, and trust, whereas the unique direct effects of the instrumental and resource-based determinants of UTAUT, namely performance expectancy, effort expectancy, and facilitating conditions, could not be separated from those of the other predictors. Dominance analysis showed that these three determinants are far from irrelevant, because together they accounted for about one third of the explained variance in intention, but that almost all of their predictive information was shared with the legitimacy-and-assurance constructs, which in turn added substantial explanatory power beyond them. We therefore interpret the pattern not as evidence that instrumental appraisal has no effect, but as evidence that administrative adoption of GenAI depends on legitimacy and assurance in ways that an individual appraisal of the tool's utility does not capture.

Performance expectancy. The nonsignificant unique effect of performance expectancy (H1) contrasts with its status as the most robust UTAUT predictor (Blut et al., 2022; Venkatesh et al., 2003) and with findings from student samples (Strzelecki & ElArabawy, 2024). Three explanations merit consideration. First, performance expectancy was strongly correlated with intention at the bivariate level (r = .751); its null effect is therefore a null *unique* effect, reflecting the substantial variance it shares with effort expectancy (r = .868), facilitating conditions (r = .827), and social influence (r = .787). Second, in a population in which the usefulness of GenAI for document-intensive work is widely acknowledged, performance expectancy may no longer discriminate between administrators who do and do not intend to use it; what discriminates is whether such use is sanctioned and safe. Third, the predictors of intention were substantially collinear (inner VIF of performance expectancy = 4.866; Table 7), and the estimated coefficient (0.081) lies below the smallest effect the sample could reliably detect (≈ 0.137), so a small positive effect cannot be ruled out. Future studies should use more distinct measures and test whether performance expectancy operates through institutional policy fit or trust.

Effort expectancy and facilitating conditions. Neither construct affected intention directly (H2 and H4), but both strongly shaped social influence (H11 and H12), through which they reached intention. This pattern is consistent with institutional theory (DiMaggio & Powell, 1983): when a college invests in infrastructure, technical personnel, and budget, administrators read these investments as signals of organizational endorsement rather than merely as enabling resources. Likewise, consistent with diffusion theory (Rogers, 2003), GenAI that is easy to learn is more readily adopted and displayed by colleagues, which strengthens perceived normative expectations. Because the inner VIFs of effort expectancy (5.612) and facilitating conditions (5.726) exceeded 5, their nonsignificant direct effects, and the negative sign of the effort expectancy estimate, should be read as evidence that their unique direct contributions cannot be separated from those of correlated predictors rather than as evidence that they are irrelevant; the robust finding is that both constructs strongly predict social influence, a relationship estimated with acceptable collinearity (VIF = 3.164). The bootstrapped indirect effects of both constructs on intention through social influence were significant, and facilitating conditions reached actual use through the full sequence of social influence and intention (β = 0.062, p = .023), which indicates that resource provision translates into behavior only through the normative signal it sends. The contrast with student samples, in which facilitating conditions predicted intention directly (Polyportis & Pahos, 2025), underscores that the function of resources depends on the adopter's organizational role.

Social influence and institutional policy fit. The significant effects of social influence (H3) and institutional policy fit (H7) point to the importance of the organizational environment emphasized in Venkatesh's (2022) research agenda for AI tools. Institutional policy fit had the largest effect size among the predictors of intention, indicating that administrators, who are accountable to governing agencies, commit to GenAI when its use is congruent with

college policy, strategy, and internal practice. This finding extends evidence that institutional policy shapes GenAI adoption among students (Polyportis & Pahos, 2025) to the administrators who write and enforce such policy, and it is consistent with the view that organizational context is a principal determinant of AI adoption in public administration (Madan & Ashok, 2023; Neumann et al., 2024).

Trust and privacy concern. Trust (H5) and lower privacy concern (H6) both strengthened intention, and both also acted directly on use behavior (H9 and H10). These results corroborate the centrality of trust in AI acceptance (Choung et al., 2023; Glikson & Woolley, 2020) and in the actual use of ChatGPT (Choudhury & Shamszare, 2023), and they align with the privacy calculus (Dinev & Hart, 2006). Two features are notable. First, privacy concern had the largest total effect on use behavior of any antecedent (0.376), which suggests that, for administrators handling personal data under the Personal Data Protection Act (2019), data-protection assurance may be the most consequential belief for translating GenAI into practice, although part of this total effect rests on a direct path that was sensitive to common method variance (Section 3.7.4). Second, the direct effects of privacy concern and trust on use, over and above intention, are consistent with the argument that intentions translate into behavior less completely when behavior is constrained by factors beyond volitional control (Sheeran, 2002). Administrators may hold favorable intentions yet refrain from using GenAI for sensitive or strategic tasks unless they are confident that outputs are dependable and data are protected. The marginal significance of the trust-use path (p = .049), however, warrants replication. Moreover, neither direct effect on use survived the most conservative marker-variable adjustment (Section 3.7.4), and the trust-use path would lose significance under virtually any clustering-induced design effect (Section 3.7.5); these direct effects should therefore be regarded as tentative.

From intention to use. Behavioral intention was the strongest predictor of use behavior (H8), with a medium effect size, confirming the intention-behavior link that anchors UTAUT (Ajzen, 1991; Venkatesh et al., 2003). The bootstrap distribution of this path was symmetric and well separated from zero, indicating that the relationship is robust. Because BI and UB were not distinguished under the conservative HTMT criterion and the intention items refer to continuing current use, this coefficient is best read as the concurrent association between current use and the intention to sustain it rather than as a prospective prediction, which makes the intention-behavior link partly definitional in this study.

4.2 Theoretical Implications

The study makes three contributions. First, it provides a context-specific extension of UTAUT for educational administrators (Venkatesh et al., 2016). The results distinguish two conceptually distinct sets of beliefs: an instrumental set (performance expectancy, effort expectancy, and facilitating conditions), which has been the principal driver in student and consumer samples, and a legitimacy-and-assurance set (institutional policy fit, social influence, trust, and privacy assurance). Among administrators, the two sets overlapped strongly, but only the latter contributed substantial explanatory power beyond the other (ΔR^2 = .128 vs. .004). The contribution is therefore not a claim that the instrumental pathway is inoperative, because its unique effects could not be separated under collinearity, but the finding that legitimacy and assurance carry explanatory information that instrumental appraisal does not. Theories of AI adoption in educational organizations should specify the adopter's organizational role as a boundary condition that determines which set of beliefs carries unique explanatory weight. Second, the study respecifies social influence as an endogenous construct produced by organizational resources and usability. This respecification reveals an indirect route that the parallel structure of UTAUT conceals and offers a mechanism linking UTAUT to institutional theory. Third, methodologically, the study demonstrates the value of GSCA for acceptance research and shows that its structural fit index must be read relative to the model's structure: because FIT_S averages R^2 over all components, it is bounded by the proportion of endogenous components, and a seemingly modest FIT_S (0.264) may coexist with substantial explanatory power (mean endogenous R^2 = 0.792).

4.3 Practical Implications

For OVEC, college licensees, and college leadership, the findings imply that promoting GenAI by emphasizing its benefits or ease of use is unlikely to be sufficient, because administrators already appear to accept that GenAI is useful. Adoption depends instead on institutional sanction and data assurance. Four actions follow. First, colleges should articulate GenAI policies that explicitly align its administrative use with institutional strategy and specify legitimate use cases. Second, authorities should issue data-governance guidance that operationalizes the Personal Data Protection Act (2019) for GenAI, including rules for data classification, approved tools, and prohibitions on entering personal data into public models, consistent with international guidance (Miao & Holmes, 2023). Third, trust should be cultivated through verification protocols and human-in-the-loop review of GenAI outputs rather than through exhortation. Fourth, investments in infrastructure, technical support, and training should be made

visible and accompanied by explicit leadership endorsement, because their effect on adoption operates through the normative signals they send.

4.4 Limitations

Several limitations qualify the conclusions. First, the cross-sectional design precludes causal inference and cannot establish temporal ordering between intention and use; longitudinal designs are needed. Second, all constructs were measured by self-report from a single source at a single time. The full collinearity VIFs (4.193-6.642) exceeded the 3.3 threshold for every construct (Kock, 2015), so common method variance cannot be ruled out and may have inflated the structural estimates (Podsakoff et al., 2003). The post hoc correlation-adjusted marker analysis indicated that the predictors of intention and the intention-use path were robust, but that the direct effects of trust and privacy concern on use were not; because the marker was a post hoc proxy rather than an a priori, theoretically unrelated variable, this result mitigates but does not eliminate the threat (Lindell & Whitney, 2001); future studies should separate the measurement of predictors and outcomes in time, include a marker variable, and use objective indicators of use. In addition, the inner VIFs of three predictors of intention exceeded 5, which limits the precision of their unique effects. Third, composite reliabilities above 0.95 and the HTMT ratios above 0.90 for three construct pairs suggest item redundancy and limited empirical separation between some constructs, particularly performance and effort expectancy; under the conservative HTMT test, 24 of the 36 construct pairs, including BI-UB, were not distinguished, so the intention-use link is partly definitional; future research should use more heterogeneous items that separate prospective intention from current use. Fourth, use behavior was self-reported; system log data would provide a stronger criterion. Fifth, the sample was drawn from private vocational colleges in a single national TVET system, so the findings may not generalize to public vocational colleges, whose governance and budgeting differ, or to other countries. Because administrators were nested within colleges and the analysis did not model this clustering, standard errors may be underestimated; the design-effect analysis (Section 3.7.5) showed that the core effects are robust to substantial clustering but that the weaker effects are not, and multilevel designs with college identifiers would address this issue. Finally, the study did not test moderators such as administrative rank or experience, which may condition the legitimacy-and-assurance pathway.

5. Conclusion

This study examined the determinants of GenAI adoption among administrators of Thai private vocational colleges by extending UTAUT with trust, privacy concern, and institutional policy fit, and by estimating the model with GSCA. The central conclusion is that administrators' intention to use GenAI and their subsequent use are shaped less by what the technology can do for them than by whether its use is institutionally sanctioned, normatively expected, trustworthy, and safe with respect to data. Institutional policy fit, social influence, trust, and privacy assurance predicted intention, whereas the unique direct effects of performance expectancy, effort expectancy, and facilitating conditions could not be separated from those of the other predictors in the presence of substantial collinearity; these determinants shared most of their predictive information with the legitimacy-and-assurance constructs, and effort expectancy and facilitating conditions operated clearly through the social influence they generate. Intention, trust, and privacy assurance jointly explained most of the variance in use behavior, although the direct effects of trust and privacy assurance on use were sensitive to common method variance. These findings contribute a role-sensitive, institutionally embedded account of GenAI acceptance to the literature on educational leadership and technology. Future research should test the legitimacy-and-assurance pathway longitudinally, with objective usage data and across national TVET systems, and should examine whether explicit GenAI governance policies shorten the distance between administrators' intention and their use of GenAI in consequential decisions. For vocational education systems seeking to realize the administrative potential of GenAI, the evidence points to governance as the lever that adds most beyond persuasion about usefulness.

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Author contributions

Theenida Buntornwon (first author) conceptualized the study, designed the research model and methodology, collected the data, conducted the formal analysis, and drafted the original manuscript.

Orawan Pariwat (corresponding author) contributed to the conceptualization and research design, validated the

data analysis and the interpretation of the results, revised the manuscript, and was responsible for communication with the journal throughout submission and revision.

Pichai Rawengwan, Phanuwat Ruangkulsap, and Wantipa Unarat contributed to the development and content validation of the research instrument, facilitated data collection, assisted with the literature review and the interpretation of the findings, and reviewed and edited the manuscript.

Thada Jantakoon supervised the project and critically revised the manuscript for important intellectual content.

All authors read and approved the final manuscript and agree to be accountable for all aspects of the work.

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Competing interests

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

Obtained. Participation was voluntary and anonymous; all respondents were informed of the purpose of the study and of their right to withdraw before completing the online questionnaire.

Ethics approval

The Publication Ethics Committee of the Canadian Center of Science and Education.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

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The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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Appendixes

Appendix A. Measurement Instrument

All items were rated on a 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). Items were administered in Thai; the English wording is reported here. Items marked (R) were reverse-scored before analysis.

Table A1. Constructs and Measurement Items

Construct	Code	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.
	FC2	Technical personnel are available for GenAI.
	FC3	Budget/resources for GenAI initiatives are available.
Trust in GenAI	TR1	I trust GenAI outputs for administrative work.
	TR2	GenAI is sufficiently consistent and transparent.
	TR3	GenAI will not introduce unnecessary risks in administration.
Privacy concern	PC1 (R)	I worry about data confidentiality when using GenAI in administration.
	PC2 (R)	I am concerned about personal data breaches when using GenAI.
	PC3 (R)	I worry about PDPA/regulatory compliance when using GenAI.
Institutional policy fit	IPF1	College policies align with GenAI use.
	IPF2	GenAI aligns with the college's administrative strategy.
	IPF3	Internal practices facilitate GenAI adoption.
Behavioral intention	BI1	I intend to continue using GenAI in administration.
	BI2	I will increase my use of GenAI in administration.
	BI3	I will advocate for broader GenAI use in my unit.
Use behavior	UB1	I regularly use GenAI for administrative tasks.
	UB2	I use GenAI across various administrative areas.
	UB3	I use GenAI for policy/strategic decision-making.

Note. PDPA = Personal Data Protection Act B.E. 2562 (2019).

Appendix B. Supplementary Discriminant Validity Evidence

Table B1. Indicator Cross-Loadings

Item	BI	EE	FC	IPF	PC	PE	SI	TR	UB
BI1	**.930**	.710	.772	.759	.777	.716	.755	.759	.806
BI2	**.955**	.739	.787	.789	.829	.724	.786	.801	.834
BI3	**.939**	.699	.769	.752	.803	.682	.788	.785	.810
EE1	.674	**.937**	.769	.666	.725	.819	.745	.709	.674
EE2	.770	**.951**	.813	.696	.779	.835	.814	.746	.739
EE3	.702	**.936**	.754	.691	.741	.798	.763	.697	.688
FC1	.777	.772	**.940**	.742	.784	.772	.769	.738	.721
FC2	.776	.809	**.955**	.735	.786	.808	.802	.732	.730
FC3	.797	.779	**.957**	.750	.818	.780	.812	.765	.737
IPF1	.745	.671	.714	**.934**	.756	.654	.649	.710	.741
IPF2	.808	.707	.775	**.954**	.791	.693	.690	.753	.806
IPF3	.747	.677	.716	**.939**	.722	.604	.645	.736	.768
PC1	.797	.760	.791	.745	**.942**	.745	.763	.764	.753
PC2	.816	.747	.800	.770	**.954**	.720	.762	.776	.814
PC3	.816	.758	.796	.771	**.952**	.726	.773	.780	.796
PE1	.698	.808	.764	.654	.725	**.952**	.724	.658	.671
PE2	.736	.847	.821	.662	.739	**.957**	.772	.680	.692
PE3	.714	.826	.779	.657	.734	**.950**	.754	.682	.677
SI1	.767	.767	.802	.650	.748	.763	**.945**	.727	.714
SI2	.795	.786	.789	.671	.759	.742	**.946**	.761	.741
SI3	.765	.769	.768	.662	.772	.716	**.931**	.745	.741
TR1	.750	.731	.689	.705	.743	.664	.726	**.939**	.734
TR2	.817	.728	.758	.752	.798	.680	.766	**.940**	.783
TR3	.766	.683	.757	.730	.750	.643	.731	**.932**	.753
UB1	.795	.679	.707	.743	.760	.662	.720	.738	**.926**
UB2	.827	.704	.738	.811	.782	.667	.738	.785	**.947**
UB3	.814	.707	.709	.745	.790	.676	.727	.743	**.935**

Note. Bold values denote loadings on the intended construct. Each indicator loads more highly on its own construct than on any other construct.

Table B2. Heterotrait-Monotrait Ratios With 95% Bootstrap Confidence Intervals

Construct pair	HTMT	2.5%	97.5%	Construct pair	HTMT	2.5%	97.5%
EE - BI	.811	.728	.883	SI - IPF	.750	.651	.833
FC - BI	.875	.805	.932	SI - PC	.859	.781	.921
FC - EE	.879	.811	.936	SI - PE	.835	.749	.904
IPF - BI	.869	.800	.923	TR - BI	.889	.826	.941
IPF - EE	.776	.678	.856	TR - EE	.816	.718	.900
IPF - FC	.828	.732	.904	TR - FC	.835	.747	.908
PC - BI	.907	.848	.953	TR - IPF	.833	.742	.907
PC - EE	.845	.765	.913	TR - PC	.869	.798	.925
PC - FC	.886	.812	.947	TR - PE	.752	.644	.847
PC - IPF	.853	.783	.909	TR - SI	.848	.765	.917
PE - BI	.797	.704	.875	UB - BI	.930	.882	.968
PE - EE	.921	.859	.970	UB - EE	.797	.703	.875
PE - FC	.873	.802	.930	UB - FC	.818	.725	.894
PE - IPF	.732	.620	.826	UB - IPF	.877	.803	.937
PE - PC	.813	.725	.887	UB - PC	.885	.817	.941
SI - BI	.881	.823	.928	UB - PE	.760	.653	.849
SI - EE	.878	.813	.932	UB - SI	.834	.758	.896
SI - FC	.888	.817	.942	UB - TR	.868	.788	.934

Note. Confidence intervals are percentile bootstrap intervals. All upper bounds are below 1.00 (HTMT inference; Henseler et al., 2015); upper bounds above 0.90 indicate pairs that would not meet the conservative criterion (Franke & Sarstedt, 2019).