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Modeling behavioral intention toward generative AI use in higher education English language teaching

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Introduction: The rapid emergence of generative artificial intelligence (AI) presents new opportunities and challenges for English language teaching (ELT) in higher education, particularly in developing and resource-diverse contexts. Responding to limited empirical evidence from Philippine higher education, this study examines the behavioral intention of higher education English language teachers in Cebu to adopt generative AI in instructional practice. Guided by an integrated framework combining the Unified Theory of Acceptance and Use of Technology (UTAUT) and Expectancy–Value Theory (EVT), and extended with perceived knowledge of AI and perceived privacy concerns, the study adopts a predictive, theory-guided design.
Methods: Survey data were collected from 488 higher education teachers across urban and rural state universities and local colleges in Cebu and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM).
Results: Results show that performance expectancy predicts perceived attainment value, effort expectancy predicts perceived utility value, and social influence shapes perceived attainment value, perceived intrinsic value, and perceived cost. Facilitating conditions predict both perceived utility value and perceived cost. Among downstream mechanisms, perceived attainment value and perceived utility value significantly predict perceived knowledge of AI, which emerges as the strongest direct predictor of behavioral intention. Perceived intrinsic value does not significantly predict perceived knowledge of AI, and perceived privacy concerns do not significantly predict behavioral intention after accounting for value-based and knowledge-based predictors. Moderation analysis indicates that age does not significantly moderate any structural relationships, while sex moderates only the relationship between effort expectancy and perceived utility value.
Discussion: Overall, the findings indicate that behavioral intention to adopt generative AI in higher education ELT is primarily driven by performance-related beliefs, value-based appraisals, and self-assessed AI competence, rather than by demographic characteristics or privacy concerns alone. The study contributes a context-sensitive, theory-integrated explanation of AI adoption intentions and offers implications for AI literacy, professional development, and responsible institutional integration in higher education English language teaching.

KEYWORDS
behavioral intention, English language teaching, Expectancy–Value Theory, generative artificial intelligence, higher education, partial least squares structural equation modeling, unified theory of acceptance and use of technology

1 Introduction

Generative artificial intelligence (GAI) is increasingly reshaping educational practices through personalized content generation, adaptive instruction, and automated assessment. Tools such as ChatGPT have expanded pedagogical possibilities by enabling real-time feedback, interactive material development, and responsiveness to diverse learner needs. Earlier research on AI-based technology in education highlights the role of predictive analytics and automated instructional support (Chen et al., 2020), while more recent studies extend these insights to generative AI applications in instructional planning and feedback (Ahmad et al., 2023; Leiker and Cukurova, 2023; AlAli et al., 2024). Despite these advancements, persistent concerns about equity, access, and ethical use continue to shape debates over AI integration in education (Konstantinova et al., 2023).

In the Philippine context, interest in GAI adoption is growing but remains uneven. The Philippine National AI Strategy reflects institutional recognition of AI's potential in national development (Jose et al., 2022), while recent educational technology initiatives aim to mitigate teacher shortages and address learning gaps (Rosales et al., 2020; Amuga, 2023; Estrellado and Miranda, 2023). However, the integration of generative AI in English Language Teaching (ELT) within higher education has lagged behind global developments (Aborot et al., 2022; Alharbi, 2023). In Cebu, a central Philippine province characterized by a mix of urban and rural higher education institutions, the adoption of AI-assisted writing tools and adaptive platforms remains conservative, particularly within English-related programs.

Several structural and contextual barriers contribute to this slow uptake. These include limited faculty training, uneven technological infrastructure, and insufficient familiarity with AI-based instructional tools (Bautista et al., 2024). While prior research has extensively examined technology acceptance through constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003), and has separately explored motivational dimensions such as attainment value, intrinsic value, utility value, and perceived cost (Eccles and Wigfield, 2024), few studies have integrated these perspectives within regional, multilingual ELT settings in developing contexts. Moreover, ethical considerations, particularly data privacy and fairness, remain underexamined in routine instructional practice despite their growing relevance (Konstantinova et al., 2023). These gaps highlight the need for a localized, theory-integrated analysis of AI adoption in higher education English language teaching.

Responding to these gaps, this study examines the behavioral intention of higher education English language teachers in Cebu, Philippines, to adopt generative artificial intelligence in instructional practice. Specifically, the study aims to (1) examine the structural relationships among technology-related enablers and value-based motivational constructs influencing behavioral intention, (2) identify the direct and indirect predictors of teachers' intention to use generative AI, (3) assess the moderating roles of age and sex in shaping these relationships, and (4) derive pedagogical and institutional implications for the responsible integration of AI in English language teaching across diverse higher education contexts.

Guided by these objectives, the study addresses the following research questions: (1) which technology-related and motivational factors significantly predict higher education English teachers' behavioral intention to use generative AI; (2) how do expectancy–value constructs mediate the effects of UTAUT-based enablers on behavioral intention, (3) do age and sex significantly moderate the relationships among key constructs in the proposed model; (4) what pedagogical and institutional implications can be drawn from the identified predictors of behavioral intention in Cebu's higher education English language teaching context.

To ensure theoretical clarity and avoid conceptual diffusion, the study adopts an integrated framework combining the Unified Theory of Acceptance and Use of Technology (UTAUT) and Expectancy–Value Theory (EVT), with clearly delineated roles. UTAUT is employed to explain external and system-oriented enablers of technology adoption, including performance expectancy, effort expectancy, social influence, and facilitating conditions. In contrast, EVT accounts for internal, value-based motivational appraisals, specifically attainment value, intrinsic value, utility value, and perceived cost, which shape teachers' evaluative judgments toward adopting generative AI. This integrated framework is further extended through perceived knowledge of AI, reflecting teachers' self-assessed competence, and perceived privacy concerns, capturing ethical and risk-related considerations that are particularly salient in resource-constrained and policy-evolving educational environments.

To empirically test the proposed model, the study employs Structural Equation Modeling (SEM) using a Partial Least Squares approach. This method is appropriate given the model's latent-variable structure, multiple interrelated constructs, and inclusion of moderating effects. PLS-SEM supports a predictive, theory-guided analytical orientation, allowing simultaneous evaluation of measurement reliability and structural relationships, including direct, indirect, and moderated effects. Through this approach, the study provides a strong and context-sensitive explanation of the factors shaping English language teachers' behavioral intention to adopt generative AI across urban and rural higher education institutions in Cebu.

2 Literature review and hypothesis development

2.1 Unified theory of acceptance and use of technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), integrates multiple technology acceptance models into four core predictors of technology adoption: performance expectancy, effort expectancy, social influence, and facilitating conditions. In higher education, these constructs explain how teachers evaluate the functional usefulness, ease of use, social legitimacy, and institutional support of emerging technologies such as generative artificial intelligence (GAI).

Empirical studies consistently demonstrate UTAUT's strength across educational contexts. Manswar et al. (2024) synthesized two decades of UTAUT-based research in education and confirmed its sustained explanatory power amid the expansion of digital and AI-assisted learning. Feng and Xiaoyu (2024) reported that performance expectancy, effort expectancy, and social influence significantly predicted AI-related acceptance in Malaysian humanities education, while facilitating conditions exerted weaker but still relevant effects. Similarly, Julio (2024) found that all four UTAUT constructs predicted AI adoption among university teachers, with pedagogical beliefs further strengthening these relationships. Xinhua and Thitinant (2024) observed that teaching experience and IT proficiency moderated UTAUT effects among preschool teachers, underscoring the framework's sensitivity to contextual and demographic factors. In English-language teaching contexts, Anabel et al. (2024) noted that social norms and personal attitudes outweighed infrastructure constraints, while Lanying and Chunming (2023) demonstrated that UTAUT predicts not only behavioral intention but also affective outcomes such as learner satisfaction.

Although UTAUT has been extensively validated, most prior studies treat its constructs as direct predictors of behavioral intention, with limited attention to the motivational mechanisms through which these enablers shape teachers' evaluative judgments. Moreover, UTAUT research on AI adoption has largely focused on technologically advanced or monolingual contexts, leaving regional, multilingual English-language teaching environments underexplored. In Philippine higher education, particularly in Cebu, where institutional resources and professional norms vary across urban and rural campuses, there is a need to examine how UTAUT-based enablers indirectly influence adoption through teachers' value-based appraisals rather than solely through direct effects.

2.2 Expectancy-value theory

Expectancy–Value Theory (EVT) complements UTAUT by emphasizing internal motivational processes, proposing that individuals' behavior is shaped by their expectations for success and the subjective value they assign to tasks (Goegan et al., 2021). In instructional contexts, this implies that teachers adopt generative AI not solely because it is usable or supported, but because it aligns with their professional goals, interests, and perceived costs.

Empirical evidence supports the relevance of EVT in educational technology adoption. Durk et al. (2024) demonstrated that female physics lecturers sustained technology use when they perceived strong educational value, even in the presence of challenges. Wong and Chapman (2024) further strengthened EVT's applicability by developing the Expectancy–Value Higher Education Instrument (EVHEI), which reliably measures expectancy and task value constructs in academic settings. In AI-specific contexts, Prema et al. (2023) found that perceived task value strongly predicted students' intention to use ChatGPT, although existing studies have focused predominantly on learners rather than educators.

Despite EVT's explanatory potential, few studies have systematically applied its four core value components, attainment value, intrinsic value, utility value, and perceived cost, to teachers' adoption of generative AI. More importantly, EVT is rarely integrated with UTAUT in a way that theoretically distinguishes external enablers from internal motivational appraisals. This study addresses these gaps by positioning EVT constructs as mediating mechanisms through which UTAUT-based enablers influence behavioral intention, thereby extending EVT to professional ELT contexts and strengthening theoretical integration.

2.3 Perceived knowledge of AI and perceived privacy concerns

To capture the confidence-based and ethical dimensions of AI adoption, this study extends UTAUT and EVT by incorporating perceived knowledge of AI (PKA) and perceived privacy concerns (PPC) as distinct explanatory constructs. Perceived knowledge of AI (PKA) is operationally defined as teachers' subjective evaluation of their own understanding, familiarity, and perceived capability to use generative AI tools for instructional purposes. This construct reflects self-assessed confidence in navigating AI applications, interpreting outputs, and applying them in teaching contexts, rather than objectively measured technical proficiency or formally assessed competence. Prior research indicates that higher levels of perceived knowledge increase educators' likelihood of experimenting with and adopting AI technologies (Yue et al., 2024; Oran, 2023).

Perceived privacy concerns (PPC) are operationalized as teachers' anticipated perceptions of ethical, legal, and data-related risks associated with the use of generative AI in educational settings (Alashoor et al., 2023). These concerns include apprehensions regarding student data protection, confidentiality, informed consent, and compliance with institutional and national data privacy regulations. In contexts with developing or unevenly enforced data governance frameworks, such as the Philippines, heightened privacy concerns may constrain teachers' willingness to engage with AI technologies (Gella, 2024). Importantly, PPC represents risk perception rather than actual policy knowledge, capturing teachers' subjective sensitivity to potential ethical implications of AI use.

Motivational factors interact with these constructs. Teachers who perceive high utility value in AI tools are more inclined to develop AI-related competence, thereby strengthening perceived knowledge (Ibrahim and Shiring, 2022). Conversely, high perceived cost, conceptualized as a negative task valuation encompassing time demands, effort, and perceived professional or ethical risk, may heighten perceived privacy concerns, particularly in settings where institutional safeguards and clear guidelines are limited (Mahama et al., 2024; Wagman et al., 2023).

2.4 Hypotheses development

Performance expectancy (PE) is a key construct in the Unified Theory of Acceptance and Use of Technology (UTAUT), referring to the extent to which teachers believe generative AI will enhance their teaching effectiveness (Venkatesh et al., 2003). In higher education, this relates directly to the perceived attainment value, which is the belief that AI use leads to meaningful professional outcomes (Chiu and Wang, 2008). Teachers who anticipate benefits such as automated assessment, personalized feedback, and efficient content delivery are more likely to view AI as valuable in achieving instructional goals (Chan and Tsi, 2024; Rajak et al., 2024). However, this relationship is influenced by factors such as institutional support, training, and alignment with pedagogical goals (Wang et al., 2021). Therefore, performance expectancy can only translate into perceived attainment value when barriers like limited AI literacy and ethical concerns are addressed (Pedro et al., 2019). Thus, this study has a hypothesis that:

> *H01*: Performance expectancy positively affects perceived attainment value.

Effort expectancy (EE) influences perceived utility value (UV) in instructional practice (Venkatesh et al., 2003). Teachers are more likely to perceive generative AI as useful when it is accessible, intuitive, and easy to integrate into lesson planning and assessment tasks (Cabero-Almenara et al., 2024; Wu et al., 2022). Simplified interfaces and responsive institutional support further enhance willingness to engage with AI tools, particularly in resource-limited settings (Manswar et al., 2024). Conversely, perceptions of technological complexity have been associated with less favorable evaluations of instructional technologies, which may attenuate perceived utility (Anabel et al., 2024). Thus, user-friendly design and targeted training are expected to enhance perceived utility. This paper hypothesizes that:

> *H02*: Effort expectancy positively affects perceived utility value.

Within the Unified Theory of Acceptance and Use of Technology, social influence (SI) reflects the extent to which significant others, such as colleagues, institutional leaders, and professional communities, shape individuals' evaluations of a technology's legitimacy and relevance. However, rather than exerting a direct effect on behavioral intention, social influence is theorized to operate indirectly by shaping teachers' value-based appraisals, as conceptualized in Expectancy–Value Theory. In collectivist-oriented professional environments, normative endorsement and peer modeling contribute to the internalization of shared goals and standards (Hennessy et al., 2022), thereby increasing the perceived importance (attainment value) and enjoyment (intrinsic value) associated with adopting generative AI (Lan, 2024). When respected colleagues or administrators frame AI use as aligned with professional expectations or pedagogical excellence, teachers are more likely to see AI as meaningful to their roles and identities as educators.

Furthermore, institutional advocacy and leadership support signal the instrumental relevance of generative AI for accomplishing instructional tasks, thereby strengthening perceived utility value (UV) (Chounta et al., 2022). Although Chounta et al. (2022) examined AI perceptions in K–12 education, the study underscores how institutional norms and leadership endorsement influence educators' evaluations of emerging technologies, a mechanism also relevant to higher education ELT. Through these mechanisms, social influence does not merely encourage compliance but reshapes how teachers evaluate the professional worth, practical usefulness, and experiential appeal of AI technologies. Consequently, social influence is expected to affect behavioral intention indirectly through its impact on attainment value, intrinsic value, and utility value, rather than through a direct pathway. Accordingly, this study hypothesizes that:

> *H03*: Social influence positively affects perceived attainment value.
>
> *H04*: Social influence positively affects perceived intrinsic value.
>
> *H05*: Social influence positively affects perceived utility value.

Facilitating conditions (FC), including infrastructure, technical support, and ongoing training, enable teachers to use generative AI effectively (Ibrahim and Shiring, 2022). Although Ibrahim and Shiring (2022) adopt a TAM-based framework, their findings on perceived usefulness and support structures conceptually align with facilitating conditions and utility value as modeled in UTAUT and EVT. These factors significantly affect perceived utility value (UV) and perceived cost (PC). Teachers are more likely to find AI beneficial when institutions provide structured support for implementation (Hojeij et al., 2024). Findings from emergency remote learning contexts (Wagman et al., 2023) suggest that limited support can amplify perceptions of technical burden, a concern that may also arise in AI adoption within higher education. Well-supported environments reduce perceived barriers and increase the likelihood of integration. This hypothesizes that:

> *H06*: Facilitating conditions positively affect perceived utility value.
>
> *H07*: Facilitating conditions positively affect perceived cost.

Within Expectancy–Value Theory, perceived attainment value (AV) reflects the degree to which engaging in a task is considered important for one's professional identity, goals, and sense of accomplishment. When teachers perceive the use of generative AI as instrumental to their effectiveness, professional growth, or instructional relevance, they are more likely to invest cognitive and motivational resources in learning how the technology works. This value-driven investment encourages deliberate effort, sustained engagement, and self-directed exploration, which in turn enhances teachers' perceived knowledge of AI (PKA), defined as their self-assessed confidence and understanding of AI tools. Prior research supports this mechanism, showing that educators who assign high professional importance to instructional technologies are more inclined to pursue skill development and instructional innovation (Alegre, 2023; Assassi, 2025). Accordingly, this study hypothesizes that:

> *H08*: Perceived attainment value positively affects perceived knowledge of AI.

Perceived intrinsic value (IV), or enjoyment from using AI, encourages sustained engagement and skill development. Teachers who find AI intellectually stimulating are more willing to explore it further and apply it creatively in teaching (Sharma and Srivastava, 2020; Zimmerman, 2018). This curiosity leads to a deeper understanding and broader application in their perceived knowledge of AI (PKA). Hence, this paper hypothesizes that:

> *H09*: Perceived intrinsic value positively affects perceived knowledge of AI.

Perceived utility value (UV) is defined as teachers' evaluation of generative AI as instrumentally useful and efficient for accomplishing instructional tasks, such as providing feedback, generating learning materials, or supporting assessment. Teachers who perceive high utility value are more motivated to invest effort in learning and experimenting with AI tools, which strengthens their perceived knowledge of AI (PKA) and self-assessed competence (Mah and Groß, 2024). At the same time, increased engagement with AI systems may heighten teachers' awareness of ethical and data-related risks, thereby intensifying their perceived privacy concerns (PPC) (Popenici and Kerr, 2017). This dual influence positions utility value as a mechanism that simultaneously promotes technical confidence and ethical sensitivity. Accordingly, this study proposes the following hypotheses:

> *H10*: Perceived utility value positively affects perceived knowledge of AI.
>
> *H11*: Perceived utility value positively affects perceived privacy concerns.

Perceived cost (PC) is operationalized as a negative task valuation reflecting teachers' perceptions of the time investment, effort, cognitive load, and potential ethical or professional risks associated with the use of generative AI in instructional practice. When perceived cost is high, educators may become more attentive to possible data protection and ethical compliance issues, thereby intensifying their perceived privacy concerns (PPC) (Mahama et al., 2024; Wagman et al., 2023). This relationship is particularly salient in under-resourced educational settings, where limited institutional safeguards and unclear implementation guidelines may amplify risk sensitivity. Accordingly, this study theorizes that:

> *H12*: Perceived cost positively affects perceived privacy concerns.

Perceived knowledge of AI (PKA) is operationalized as teachers' subjective self-assessment of their understanding, familiarity, and perceived capability (Gado et al., 2021), to use generative AI tools for instructional purposes, rather than as objectively measured technical competence. This construct reflects educators' confidence in navigating AI applications, interpreting AI-generated outputs, and applying them appropriately in teaching and assessment contexts. Teachers with higher perceived knowledge are more likely to integrate AI into their instructional practices and express stronger behavioral intention (BI) to use AI tools (Oran, 2023). Professional training, hands-on exposure, and guided practice play a critical role in strengthening perceived knowledge, thereby facilitating adoption (Shao et al., 2024). Accordingly, this study assumes that:

> *H13*: Perceived knowledge of AI positively affects behavioral intention to use AI.

Perceived privacy concerns (PPC) are operationalized as teachers' subjective perceptions of ethical, legal, and data-related risks associated with the use of AI technologies in instructional contexts, including concerns about student data protection, confidentiality, consent, and regulatory compliance (Alashoor et al., 2023). Even when generative AI is perceived as pedagogically beneficial, heightened privacy concerns may reduce teachers' willingness to use such technologies if adequate safeguards and clear guidelines are perceived to be lacking (Aldboush and Ferdous, 2023). In the Philippine higher education context, where awareness of data privacy regulations varies across institutions, alignment with national privacy laws and institutional policies is critical for fostering trust and supporting responsible AI adoption (Gella, 2024). Accordingly, this study assumes that:

> *H14*: Perceived privacy concerns positively affect behavioral intention to use AI.

Age is examined as a moderating variable that may influence the strength of relationships among the key constructs in the proposed model. Prior research suggests that age shapes how educators evaluate technology usability, respond to social support, and develop confidence in using digital tools (Morris and Venkatesh, 2000; Tewathia et al., 2020). Differences in professional experience, prior exposure to educational technologies, and learning preferences may lead teachers of different age groups to interpret the benefits, costs, and risks of generative AI differently. Accordingly, age is modeled as a moderator across the structural relationships specified in this study. Thus, this paper hypothesizes that age moderates the relationships among the constructs in the proposed model.

> *H15–H28*: Age moderates each construct pathway in this framework.

Sex is also examined as a moderating variable in the proposed model. Prior research indicates that male and female educators may differ in how they evaluate technology-related factors such as performance expectancy, effort expectancy, and social influence, reflecting variations in socialization, professional experiences, and institutional contexts (Ong and Lai, 2006; Arthur et al., 2024). Rather than assuming inherent differences in adoption behavior, this study treats sex as a contextual moderator that may influence the strength of relationships among the model constructs. Accordingly, sex is modeled as a moderator across all structural relationships specified in this study. Thus, this paper further proposes that sex moderates the relationships among the constructs in the proposed model.

> *H29–H42*: Sex moderates each construct pathway in this framework.

By integrating UTAUT, EVT, perceived knowledge of AI, perceived privacy concerns, and the moderating factors of age and sex, this study proposes a comprehensive and a novel model to understand behavioral intention to use generative AI among higher education teachers in the Philippines (see Figure 1).

Figure 1 illustrates the proposed structural model integrating the Unified Theory of Acceptance and Use of Technology (UTAUT), Expectancy–Value Theory (EVT), perceived knowledge of AI, perceived privacy concerns, and demographic moderators to explain higher education teachers' behavioral intention to use generative AI. The model is organized into three conceptual layers. The first layer consists of UTAUT-based external enablers, including performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). These constructs do not directly predict behavioral intention but are theorized to shape teachers' value-based motivational appraisals. The second layer comprises EVT constructs, namely perceived attainment value (AV), perceived intrinsic value (IV), perceived utility value (UV), and perceived cost (PC), which capture teachers' evaluative judgments regarding the importance, enjoyment, usefulness, and negative trade-offs associated with generative AI use. In the third layer, perceived knowledge of AI (PKA) and perceived privacy concerns (PPC) represent downstream cognitive and ethical mechanisms linking value appraisals to behavioral intention to use AI (BI). Solid arrows indicate hypothesized direct effects, while dashed arrows represent moderation effects. Age and sex are modeled as moderators influencing all structural relationships, reflecting potential demographic differences in how teachers evaluate and respond to behavioral intention toward generative AI adoption. Overall, the model specifies an indirect, theory-driven pathway in which external enablers influence behavioral intention primarily through motivational, cognitive, and ethical processes rather than through direct effects alone.

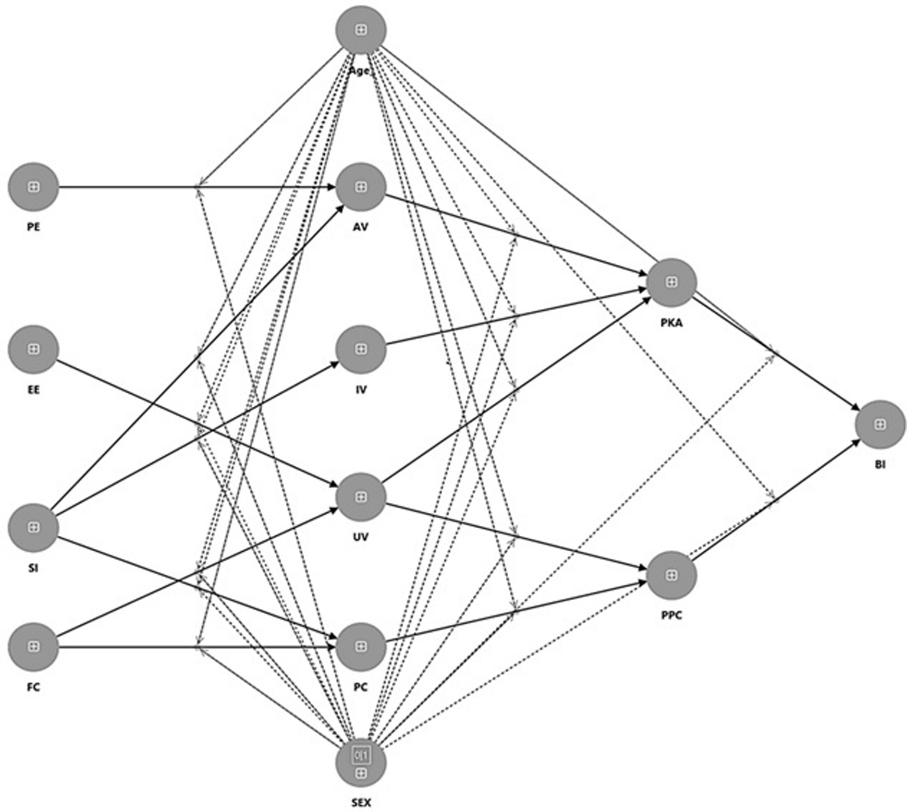

FIGURE 1
The proposed structural model. PE, performance expectancy; EE, effort expectancy; SI, social influence; FC, facilitating conditions; AV, perceived attainment value; IV, perceived intrinsic value; UV, perceived utility value; PC, perceived cost; PPC, perceived privacy concerns; PKA, perceived knowledge of AI; BI, behavioral intention to use AI.

3 Methods

3.1 Research design

This study employed a quantitative, non-experimental research design, specifically a predictive correlational design, to examine the structural relationships among latent variables derived from the Unified Theory of Acceptance and Use of Technology (UTAUT), Expectancy–Value Theory (EVT), and additional constructs, such as perceived knowledge of AI (PKA) and perceived privacy concerns (PPC).

The study is explicitly predictive in orientation with theory-guided testing, aiming to explain and estimate the strength of relationships among constructs rather than to confirm a single established causal model. Partial Least Squares Structural Equation Modeling (PLS-SEM) was therefore selected because it is well-suited for prediction-oriented research involving complex models with multiple latent variables and moderating effects.

PLS-SEM was used to analyze both the measurement and structural models, including moderation effects from demographic variables such as age and sex. This design enabled the researcher to quantify associations among constructs and predict teachers' behavioral intention to adopt generative AI tools in English language instruction, rather than actual usage behavior. PLS-SEM is particularly appropriate for models that integrate multiple theoretical frameworks and emphasize prediction and variance explanation in social science contexts (Cortez et al., 2024).

3.2 Research environment

The study was conducted in Cebu, a province in the central Philippines that offers a heterogeneous higher education environment encompassing both urban and rural campuses. Cebu was selected because it hosts a mix of metropolitan institutions located in highly urbanized cities and satellite campuses situated in semi-urban and rural municipalities, allowing the study to capture variability in institutional resources, technological infrastructure, and instructional contexts relevant to behavioral intention in AI adoption.

Two state universities were included: State University 1 (SU1) and State University 2 (SU2), each operating multiple campuses across Cebu, providing both rural and urban backdrops. SU1, the largest technological university in Cebu, contributed the most respondents, while SU2 primarily focused on teacher education programs. In addition, five local colleges were included: three city colleges (CitC1, CitC2, and CitC3) and two community colleges (ComC1, ComC2). Collectively, these institutions represent state and local higher education sectors across diverse geographic and institutional settings, thereby strengthening the study's capacity to examine behavioral intention toward generative AI adoption in both rural and urban English language teaching environments.

3.3 Research respondents

The study employed purposive sampling, selecting 488 higher education teachers from state universities and local colleges in Cebu.

Inclusion criteria required participants to have taught English-related courses within the past two academic years and to report prior exposure to generative AI tools (e.g., ChatGPT, Grammarly, and Bard). English-related courses included grammar, composition, linguistics, literature, English for Specific Purposes (ESP), and interdisciplinary courses delivered in English, such as purposive communication and research writing.

The sample comprised both formally trained English instructors and educators from other disciplines who regularly handled English-medium instruction, reflecting the instructional realities of Philippine higher education institutions. Representation across institutions ensured participation from urban-based campuses with stronger digital infrastructure as well as rural and semi-urban campuses with more limited technological resources, thereby enhancing contextual representativeness (see Table 1).

Minimum sample size requirements were met using the rule of 10 cases per estimated parameter in SEM, and the power analysis further confirmed the adequacy of the sample (Kline, 2023). Only complete responses from participants with prior AI exposure were retained for analysis to ensure the reliability and validity of the findings.

3.4 Research instruments

The study adapted validated instruments to measure all constructs. The UTAUT section was based on An et al. (2023) and measured performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention.

Behavioral intention was operationally defined as teachers' self-reported intention to use generative AI tools in future English language teaching activities, rather than current usage or instructional effectiveness.

EVT constructs, perceived attainment value, perceived intrinsic value, perceived utility value, and perceived cost, were adapted from Ka et al. (2023). Perceived knowledge of AI was measured using a six-item scale developed by Gado et al. (2021) that captures teachers' subjective confidence and understanding of AI tools. Perceived privacy concerns were measured using Coopamootoo's (2023) instrument, focusing on anticipated ethical and data-related risks. All items were rated on a 5-point Likert scale. The instruments underwent expert validation for clarity, content relevance, and theoretical alignment. Reliability and validity were assessed during data analysis using established SEM criteria.

3.5 Data gathering procedures

Data were collected over a one-month period following approval from the institutional research ethics committee. Formal permission was obtained from participating institutions through transmittal letters outlining the study's objectives, procedures, and ethical safeguards. A hybrid data collection approach was employed, combining Google Forms for online respondents and printed questionnaires for on-site administration at campuses with limited internet access.

All participants provided informed consent and were assured of voluntary participation, confidentiality, and anonymity. Pretesting was conducted with a small group of respondents to ensure clarity and appropriate survey length. Paper-based responses were digitized and merged with online data for consistency. Ethical protocols, including anonymization and secure data handling, were strictly followed throughout the data collection process.

3.6 Data analysis

Descriptive statistics were generated using SPSS version 20. Structural model analysis was conducted using SmartPLS 4.0. Measurement model evaluation included assessment of convergent validity through Average Variance Extracted (AVE $\geq$ 0.50) and discriminant validity using the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio. Internal consistency was assessed using Cronbach's alpha, composite reliability, and rho_C, all exceeding the recommended threshold of 0.70.

Structural relationships were tested using bootstrapping with 5,000 resamples. Moderation analysis was performed using the product-indicator approach in PLS-SEM. Age was modeled as a continuous moderator, and sex as a categorical moderator, with interaction terms created between each moderator and the corresponding predictor constructs.

Significance was evaluated using t-values $\geq$ 1.96 and p-values < 0.05. This analytical approach enabled robust testing of both direct and moderated relationships across UTAUT, EVT, and the extended constructs, ensuring theoretical precision and empirical rigor in explaining teachers' behavioral intention to adopt generative AI.

TABLE 1 Demographic distribution of the respondents.

Higher education institution	Total respondents	Female	Male	Non-binary	English teachers	Handling English-related courses
SU1	309	261	46	2	167	142
SU2	71	49	18	4	34	37
CitC1	32	19	13	0	19	13
CitC2	41	24	16	1	25	16
CitC3	21	18	3	0	15	6
ComC1	8	7	1	0	7	1
ComC2	6	6	0	0	6	0
Total	488	384	97	7	273	215

4 Results and discussions

4.1 Psychometric properties of the measurement model

This section reports the measurement model's psychometric properties, including construct reliability and validity, to ensure an accurate representation of the theoretical domains. Three types of validity were assessed: discriminant validity, convergent validity, internal consistency reliability, and predictive validity assessment following the guidance of Hair et al. (2020).

4.1.1 Discriminant validity

Discriminant validity was established using the Fornell-Larcker criterion and the HTMT ratio.

As shown in Table 2, all constructs met the Fornell-Larcker criterion. For instance, the square root of the AVE for performance expectancy (PE) (0.873) exceeded its correlations with attainment value (0.697) and behavioral intention (BI) (0.685), confirming conceptual uniqueness. Effort expectancy (EE) (0.862) and social influence (SI) (0.849) also demonstrated adequate discriminant validity, with correlations lower than their respective AVEs. Despite their theoretical proximity, constructs such as perceived intrinsic value (IV), perceived utility value (UV), and perceived attainment value (AV) maintained distinctiveness (e.g., IV–UV $r = 0.714$; $\sqrt{\text{AVE}} = 0.858$ and 0.860, respectively). Low correlations for perceived cost (PC) (max $r = 0.249$; $\sqrt{\text{AVE}} = 0.810$) and perceived privacy concerns (PPC) ($\sqrt{\text{AVE}} = 0.876$) further supported discriminant validity. Even the strong correlation between perceived knowledge of AI (PKA) and behavioral intention (BI) ($r = 0.775$) remained below the $\sqrt{\text{AVE}}$ of 0.798, confirming distinctiveness.

HTMT ratios (Table 3), all of which were ≤0.90, reaffirmed these findings.

Following Henseler et al. (2015), the HTMT ≤0.90 criterion was adopted, given the theoretical relatedness of the motivational and cognitive constructs in the model. All HTMT values ranged from 0.156 (PC–EE) to 0.874 (PKA–BI), remaining below the ≤0.90 threshold. The strongest association between perceived knowledge of AI and behavioral intention (HTMT = 0.874) supports theoretical expectations without compromising discriminant validity. Moderate HTMT values (e.g., PE–AV at 0.780; IV–UV at 0.833) reflect conceptual overlap yet preserve construct distinctiveness. Lower values for perceived cost (e.g., PC–EE = 0.156; PC–PKA = 0.166) confirm its unique position in the model. These findings, supported by both Fornell–Larcker and HTMT criteria, validate the discriminant structure of the integrated UTAUT-EVT model. Prior research (e.g., Teo and Noyes, 2014; Chatterjee et al., 2025) similarly affirms the robustness of HTMT in educational technology contexts. This reinforces the empirical distinctiveness of motivational, cognitive, and ethical constructs within AI adoption models, particularly among higher education teachers in Cebu.

4.1.2 Convergent validity and reliability

Convergent validity was confirmed through AVE scores, all of which exceeded the recommended threshold of 0.50, ranging from 0.560 to 0.768. Reliability was assessed using Cronbach's alpha and composite reliability, both of which exceeded their minimum thresholds across all constructs ($\alpha > 0.70$; CR > 0.80). Performance expectancy showed the strongest reliability ($\alpha = 0.922$; CR = 0.941), while facilitating conditions recorded the lowest acceptable AVE (0.560).

Table 4 confirms that all constructs exhibited strong psychometric properties. Factor loadings exceeded 0.70, with PE4 (0.897) having the highest value and FC3 (0.710) the lowest, reflecting consistent item reliability. Cronbach's alpha values ranged from 0.745 to 0.922, and composite reliability from 0.835 to 0.941, indicating high internal consistency. AVE values (0.560 to 0.768) exceeded the 0.50 threshold, confirming convergent validity. Performance expectancy (PEP and behavioral intention (BI) showed the strongest metrics, while facilitating conditions (FC) had lower but still acceptable scores, indicating comparatively weaker measurement strength for that construct in this sample.

These results validate the measurement properties of the integrated UTAUT–EVT model, including perceived knowledge of AI and privacy concerns, without extending interpretation beyond psychometric adequacy. Accordingly, reliability and validity indicators are interpreted strictly as evidence of construct measurement quality

TABLE 2 Fornell and Larcker criterion.

Constructs	PE	EE	SI	FC	AV	IV	UV	PC	PPC	PKA	BI
PE	0.873										
EE	0.648	0.862									
SI	0.392	0.423	0.849								
FC	0.507	0.516	0.64	0.748							
AV	0.697	0.549	0.608	0.603	0.837						
IV	0.595	0.433	0.426	0.454	0.661	0.858					
UV	0.745	0.577	0.359	0.478	0.674	0.714	0.86				
PC	0.183	0.139	0.249	0.247	0.182	0.184	0.223	0.81			
PPC	0.347	0.353	0.325	0.409	0.43	0.367	0.396	0.177	0.876		
PKA	0.685	0.567	0.495	0.564	0.741	0.588	0.68	0.151	0.528	0.798	
BI	0.685	0.497	0.424	0.509	0.685	0.625	0.707	0.176	0.386	0.775	0.871

PE, performance expectancy; EE, effort expectancy; SI, social influence; FC, facilitating conditions; AV, perceived attainment value; IV, perceived intrinsic value; UV, perceived utility value; PC, perceived cost; PPC, perceived privacy concerns; PKA, perceived knowledge of AI; BI, behavioral intention to use AI.

TABLE 3 Heterotrait-Monotrait (HTMT) ratio of correlation.

Constructs	PE	EE	SI	FC	AV	IV	UV	PC	PPC	PKA	BI
PE		0.712	0.434	0.576	0.78	0.681	0.825	0.187	0.38	0.764	0.753
EE			0.48	0.603	0.626	0.506	0.645	0.156	0.392	0.65	0.552
SI				0.806	0.703	0.497	0.406	0.267	0.365	0.571	0.475
FC					0.74	0.546	0.558	0.285	0.485	0.685	0.594
AV						0.781	0.774	0.194	0.489	0.855	0.779
IV							0.833	0.192	0.424	0.687	0.725
UV								0.235	0.444	0.769	0.795
PC									0.175	0.166	0.181
PPC										0.61	0.428
PKA											0.874
BI											

PE, performance expectancy; EE, effort expectancy; SI, social influence; FC, facilitating conditions; AV, perceived attainment value; IV, perceived intrinsic value; UV, perceived utility value; PC, perceived cost; PPC, perceived privacy concerns; PKA, perceived knowledge of AI; BI, behavioral intention to use AI.

rather than as reflections of institutional infrastructure or contextual conditions.

4.1.3 Predictive validity assessment

The predictive validity of the structural model was evaluated using the coefficient of determination (R^2), effect size (f^2), and predictive relevance indicators, following established guidelines for Partial Least Squares Structural Equation Modeling.

The model demonstrated moderate to substantial explanatory power for key endogenous constructs. The coefficient of determination showed that the model explained 61.7% of the variance in perceived attainment value (AV) and 60.1% of the variance in behavioral intention to use AI (BI), indicating strong predictive accuracy for both motivational valuation and adoption intention. Similarly, perceived knowledge of AI (PKA) showed an R^2 of 0.609, indicating that the proposed predictors accounted for a substantial proportion of the variance in teachers' self-assessed AI competence. Perceived utility value (UV) showed a moderate level of explained variance ($R^2 = 0.377$), while perceived intrinsic value (IV) and perceived privacy concerns (PPC) demonstrated lower but acceptable explanatory power ($R^2 = 0.181$ and 0.166, respectively). In contrast, perceived cost (PC) yielded a low R^2 value (0.075), indicating that additional unmodeled factors may contribute to teachers' cost perceptions.

Effect-size analysis further clarified the relative contributions of individual predictors. Large effect sizes were observed for performance expectancy on perceived attainment value ($f^2 = 0.648$) and for perceived knowledge of AI on behavioral intention ($f^2 = 1.131$), underscoring the central role of perceived usefulness and self-assessed competence in shaping behavioral adoption intention. Social influence (SI) also exerted meaningful effects on value-based constructs, with medium effect sizes on perceived attainment value (AV) ($f^2 = 0.345$) and perceived intrinsic value (IV) ($f^2 = 0.221$). Effort expectancy (EE) demonstrated a moderate effect on perceived utility value (UV) ($f^2 = 0.238$), while facilitating conditions (FC) showed a small effect on perceived utility value (UV) ($f^2 = 0.071$) and a negligible effect on perceived cost (PC) ($f^2 = 0.014$).

Perceived utility value (UV) exhibited small-to-moderate effects on downstream constructs, including perceived knowledge of AI (PKA) ($f^2 = 0.109$) and perceived privacy concerns (PPC) ($f^2 = 0.161$), supporting its dual role in promoting competence development and ethical awareness. In contrast, perceived cost (PC) and perceived privacy concerns (PPC) displayed negligible effects on behavioral intention (BI) ($f^2 = 0.002$), indicating limited predictive contribution once knowledge-based factors were accounted for.

Overall, the pattern of R^2 and f^2 values supports the predictive adequacy of the proposed model, particularly in explaining teachers' behavioral intention (BI) to adopt generative AI through motivational and knowledge-based mechanisms. These findings are consistent with the study's predictive, theory-guided orientation and demonstrate that perceived knowledge of AI and value-based constructs are the most substantive drivers of adoption intention in the proposed framework.

Predictive relevance was further assessed using the Stone–Geisser Q^2 criterion, with nonzero values indicating adequate predictive relevance for the endogenous constructs. Full results are detailed in Table 5.

4.2 Structural model assessment

This section evaluates the hypothesized relationships among latent variables using PLS-SEM with bootstrapping (5,000 subsamples). Significance was determined at $t > 1.96$ and $p < 0.05$. Twelve of fourteen hypotheses were supported.

Table 6 summarizes the structural model results, with 12 of 14 hypotheses supported through bootstrapping (5,000 subsamples). Statistically significant paths affirmed the model's predictive validity, particularly among core constructs from UTAUT, EVT, and the extended variables.

Performance expectancy (PE) significantly predicted attainment value (H01) ($\beta = 0.542$), and effort expectancy (EE) influenced perceived utility value (UV) (H02) ($\beta = 0.450$), confirming that perceptions of usefulness and ease of use shape motivational appraisals. This is consistent with the work of Farhan et al. (2019), who emphasized that simplicity in digital tool design can directly enhance user adoption, especially in education systems with varying levels of technological proficiency.

Social influence (SI) significantly affected perceived attainment value (AV) (H03) ($\beta = 0.395$), perceived intrinsic value (IV) (H04) ($\beta = 0.426$), and perceived cost (PC) (H05) ($\beta = 0.153$), reinforcing the impact of peer and institutional support on both motivation and

TABLE 4 Convergent validity and reliability results.

Constructs	Items	FL	Cronbach (α)	CR	AVE
Performance expectancy	PE1	0.874	0.922	0.941	0.761
	PE2	0.881			
	PE3	0.862			
	PE4	0.897			
	PE5	0.848			
	PE1	0.874			
Effort expectancy	EE1	0.869	0.886	0.921	0.744
	EE2	0.850			
	EE3	0.881			
	EE4	0.849			
Social influence	SI1	0.843	0.871	0.912	0.721
	SI2	0.879			
	SI3	0.858			
	SI4	0.816			
Facilitating conditions	FC1	0.735	0.745	0.835	0.560
	FC2	0.781			
	FC3	0.710			
	FC4	0.765			
Perceived attainment value	AV1	0.862	0.856	0.903	0.701
	AV2	0.836			
	AV3	0.892			
	AV4	0.752			
Perceived intrinsic value	IV1	0.863	0.822	0.894	0.737
	IV2	0.849			
	IV3	0.863			
Perceived utility value	UV1	0.879	0.882	0.919	0.739
	UV2	0.843			
	UV3	0.882			
	UV4	0.833			
Perceived cost	PC1	0.887	0.767	0.851	0.656
	PC2	0.787			
	PC3	0.750			
Perceived knowledge of AI	PKA1	0.720	0.858	0.897	0.637
	PKA2	0.791			
	PKA3	0.822			
	PKA4	0.814			
	PKA5	0.837			
Perceived privacy concerns	PPC1	0.867	0.898	0.929	0.768
	PPC2	0.924			
	PPC3	0.915			
	PPC4	0.792			
Behavioral intention	BI1	0.898	0.894	0.926	0.759
	BI2	0.897			
	BI3	0.872			
	BI4	0.816			

FL, factor loadings; CR, composite reliability; AVE, average variance extracted.

TABLE 5 Predictive validity assessment.

Endogenous construct	R^2	Adjusted R^2	Predictor → endogenous	f^2
AV	0.617	0.616	PE → AV	0.648
			SI → AV	0.345
BI	0.601	0.599	PKA → BI	1.131
			PPC → BI	0.002
IV	0.181	0.180	SI → IV	0.221
PC	0.075	0.071	FC → PC	0.014
			SI → PC	0.015
PKA	0.609	0.607	AV → PKA	0.321
			IV → PKA	0.001
			UV → PKA	0.109
PPC	0.166	0.162	PC → PPC	0.010
			UV → PPC	0.161
UV	0.377	0.374	EE → UV	0.238
			FC → UV	0.071

R^2 indicates the variance explained in the endogenous construct. f^2 reflects effect sizes based on PLS-SEM guidelines.

TABLE 6 Structural model assessment.

Structural model		β	*t*-value	*p*-value	Result
H01	PE → AV	0.542	15.826	0.000	S
H02	EE → UV	0.450	9.880	0.000	S
H03	SI → AV	0.395	12.432	0.000	S
H04	SI → IV	0.426	10.712	0.000	S
H05	SI → PC	0.153	2.242	0.025	S
H06	FC → UV	0.247	5.880	0.000	S
H07	FC → PC	0.151	2.161	0.032	S
H08	AV → PKA	0.512	12.146	0.000	S
H09	IV → PKA	0.022	0.496	0.620	NS
H10	UV → PKA	0.319	6.913	0.000	S
H11	UV → PPC	0.375	9.432	0.000	S
H12	PC → PPC	0.095	2.150	0.032	S
H13	PKA → BI	0.791	27.942	0.000	S
H14	PPC → BI	−0.033	0.918	0.358	NS

S, supported; NS, not supported; β, standardized path coefficient; *t* values, test statistics; *p*-values, probability values.

perceived barriers. These findings align with Zamiri and Esmaeili (2024), who found that peer and institutional encouragement are particularly influential in academic environments where shared norms and collaborative learning drive innovation. When teachers see colleagues using AI meaningfully or receive leadership endorsement, their sense of purpose and control increases. The implications are clear: professional learning communities, peer mentoring, and visible administrative support can go a long way in building confidence and motivation to adopt AI.

Facilitating conditions (FC) influenced perceived utility value (UV) (H06) ($\beta = 0.247$) and perceived cost (PC) (H07) ($\beta = 0.151$), emphasizing the role of institutional support. These results are echoed by Zhao and Zhao et al. (2024), who found that infrastructure, access to training, and consistent tech support are critical in sustaining teacher engagement with AI tools. Notably, the structural environment in which teachers operate affects how they calculate both the benefits and the effort required for technology use in rural settings, such as one of the environments in this study.

Perceived attainment value (AV) predicted perceived knowledge of AI (PKA) (H08) ($\beta = 0.512$), supporting Bandura's (2015) concept of self-efficacy, where mastery expectations are shaped by perceived goal relevance, as cited in Bardach et al. (2019). However, perceived intrinsic value (IV) did not affect perceived knowledge of AI (PKA) (H09) ($\beta = 0.022$), indicating that enjoyment alone does not drive competence. This echoes the findings of Novak and Schwan (2021), who argue that while affective responses can foster curiosity, they must be paired with hands-on learning experiences to result in actual knowledge gains.

Perceived utility value (UV) positively influenced both perceived knowledge of AI (PKA) (H10) ($\beta = 0.319$) and perceived privacy concerns (PPC) (H11) ($\beta = 0.375$), suggesting that practical engagement increases both confidence and ethical awareness. The outcome aligns with recent insights by Durango et al. (2024), who note that higher engagement with AI increases users' sensitivity to data-related risks, even as it fosters skill development.

Perceived cost (PC) also predicted perceived privacy concerns (PPC) (H12) ($\beta = 0.095$) indicating that teachers who anticipate a high investment of time or effort may also feel more cautious about data exposure (Beirat et al., 2025). These insights underscore the need for proactive digital ethics training that is closely tied to usability and accessibility.

The strongest path emerged between perceived knowledge of AI (PKA) and behavioral intention (BI) (H13) ($\beta = 0.791$), confirming that self-assessed competence is the primary driver of adoption. This finding aligns with studies by Kelly et al. (2023) and Kim and Lee (2022), which emphasize that knowledge, rather than general positivity, is a stronger predictor of AI engagement in educational settings.

Two hypotheses were not supported. First is perceived intrinsic value (IV) did not affect perceived knowledge of AI (PKA) (H09) ($\beta = 0.022$). In addition to what was stated above, this result

TABLE 7 Moderating effects of age on the relationships between constructs.

Interaction path		β	t-value	p-value	Result
H15	Age × PE → AV	0.137	1.189	0.235	NS
H16	Age × EE → UV	−0.025	0.148	0.882	NS
H17	Age × SI → AV	0.044	0.447	0.655	NS
H18	Age × SI → IV	0.178	1.173	0.241	NS
H19	Age × SI → PC	−0.121	0.491	0.623	NS
H20	Age × FC → UV	0.043	0.234	0.815	NS
H21	Age × FC → PC	−0.020	0.085	0.932	NS
H22	Age × AV → PKA	0.020	0.136	0.892	NS
H23	Age × IV → PKA	0.049	0.336	0.737	NS
H24	Age × UV → PKA	−0.157	0.952	0.341	NS
H25	Age × UV → PPC	−0.057	0.282	0.778	NS
H26	Age × PC → PPC	0.026	0.190	0.849	NS
H27	Age × PKA → BI	−0.064	0.486	0.627	NS
H28	Age × PPC → BI	−0.008	0.053	0.958	NS

S, supported; NS, not supported; β, standardized path coefficient; t values, test statistics; p-values, probability values.

TABLE 8 Moderating effects of sex on the relationships between constructs.

Interaction path		β	t-value	p-value	Result
H29	Sex × PE → AV	−0.011	0.103	0.918	NS
H30	Sex × EE → UV	0.243	2.419	0.016	S
H31	Sex × SI → AV	0.063	0.75	0.454	NS
H32	Sex × SI → IV	0.046	0.456	0.648	NS
H33	Sex × SI → PC	0.251	1.512	0.131	NS
H34	Sex × FC → UV	0.005	0.058	0.954	NS
H35	Sex × FC → PC	−0.26	1.629	0.103	NS
H36	Sex × AV → PKA	−0.102	0.931	0.352	NS
H37	Sex × IV → PKA	0.037	0.375	0.707	NS
H38	Sex × UV → PKA	0.046	0.384	0.701	NS
H39	Sex × UV → PPC	−0.089	0.771	0.441	NS
H40	Sex × PC → PPC	−0.054	0.506	0.613	NS
H41	Sex × PKA → BI	0.021	0.258	0.796	NS
H42	Sex × PPC → BI	−0.034	0.431	0.667	NS

S, supported; NS, not supported; β, standardized path coefficient; t values, test statistics; p-values, probability values.

suggests that curiosity alone does not guarantee understanding without training. This finding aligns with recent studies indicating that enjoyment and interest alone foster engagement but do not automatically lead to increased confidence or competence (Zhao et al., 2022; Lim and Wang, 2023). In other words, teachers are curious and enthusiastic about experimenting with generative AI, but without formal training or structured learning experiences, that enthusiasm does not translate into a solid sense of understanding. This highlights the need for institutions to go beyond sparking interest and offer sustained professional development programs that cultivate engagement and mastery.

Secondly, perceived privacy concerns (PPC) did not significantly influence behavioral intention (BI) (H14) ($\beta = -0.033$), because in resource-constrained contexts like the Philippines, perceived usefulness outweighs ethical reservations. This indicates that, in the present model, PPC does not explain additional variance in BI beyond that accounted for by other predictors, particularly perceived knowledge of AI (PKA) and the perceived value constructs. The nonsignificant effect should be interpreted as a model-based result rather than as evidence that privacy does not matter in practice; it suggests that privacy concerns may operate through alternative mechanisms (e.g., shaping institutional policy preferences or actual usage behavior) that were not directly tested in this study."

These findings suggest that affective interest and ethical concerns, while relevant, do not directly translate into behavioral intention to adopt without supportive infrastructure and capacity-building. Institutions should therefore prioritize teacher training, recognize the value of alignment, and strengthen environmental supports while embedding privacy education into broader AI literacy programs. Together, the findings confirm that behavioral intention is driven by the interplay of cognitive, motivational, and contextual factors, requiring localized, multifaceted implementation strategies.

Throughout the structural model assessment, behavioral intention is treated as a cognitive–motivational outcome representing teachers' future willingness to use generative AI, rather than as evidence of actual AI adoption or usage behavior.

4.2.1 Moderating effects

To analyze moderating effects, the study tested whether Age and Sex moderated relationships among key constructs using interaction terms generated through the product indicator method and the two-stage approach, respectively. Moderation analysis using PLS-SEM and 5,000-sample bootstrapping assessed whether demographic characteristics altered the strength or direction of effects between independent and dependent variables. This analysis helps determine whether AI integration strategies should be uniform or tailored to specific teacher profiles, based on factors such as age or gender.

Table 7 presented that Age did not significantly moderate any relationships among the key constructs, indicating that AI-related perceptions and intentions were consistent across age groups. This suggests that generational differences in AI adoption are less influential when institutional support and perceived value are strong (Erdmann and Toro-Dupouy, 2025). Similarly, Sex was examined for its moderating role across constructs, highlighting the importance of identifying potential gender-based differences in shaping behavioral intention, though most effects remained statistically nonsignificant.

This study further examined whether key relationships in the model varied by sex, particularly regarding constructs such as effort expectancy (EE), social influence (SI), and perceived privacy concerns (PPC). Identifying such gender-based differences helps clarify how demographic profiles may influence the adoption of generative AI in higher education (see Table 8).

Of the 14 tested interaction effects involving Sex, only one was statistically significant: Sex moderated the relationship between effort expectancy (EE) and perceived utility value (UV) (H30) ($\beta = 0.243$, $p = 0.016$), suggesting that females may be more influenced by ease of use when evaluating AI's practicality. This supports earlier findings (Ravula et al., 2024; Venkatesh and Morris, 2000) that women often

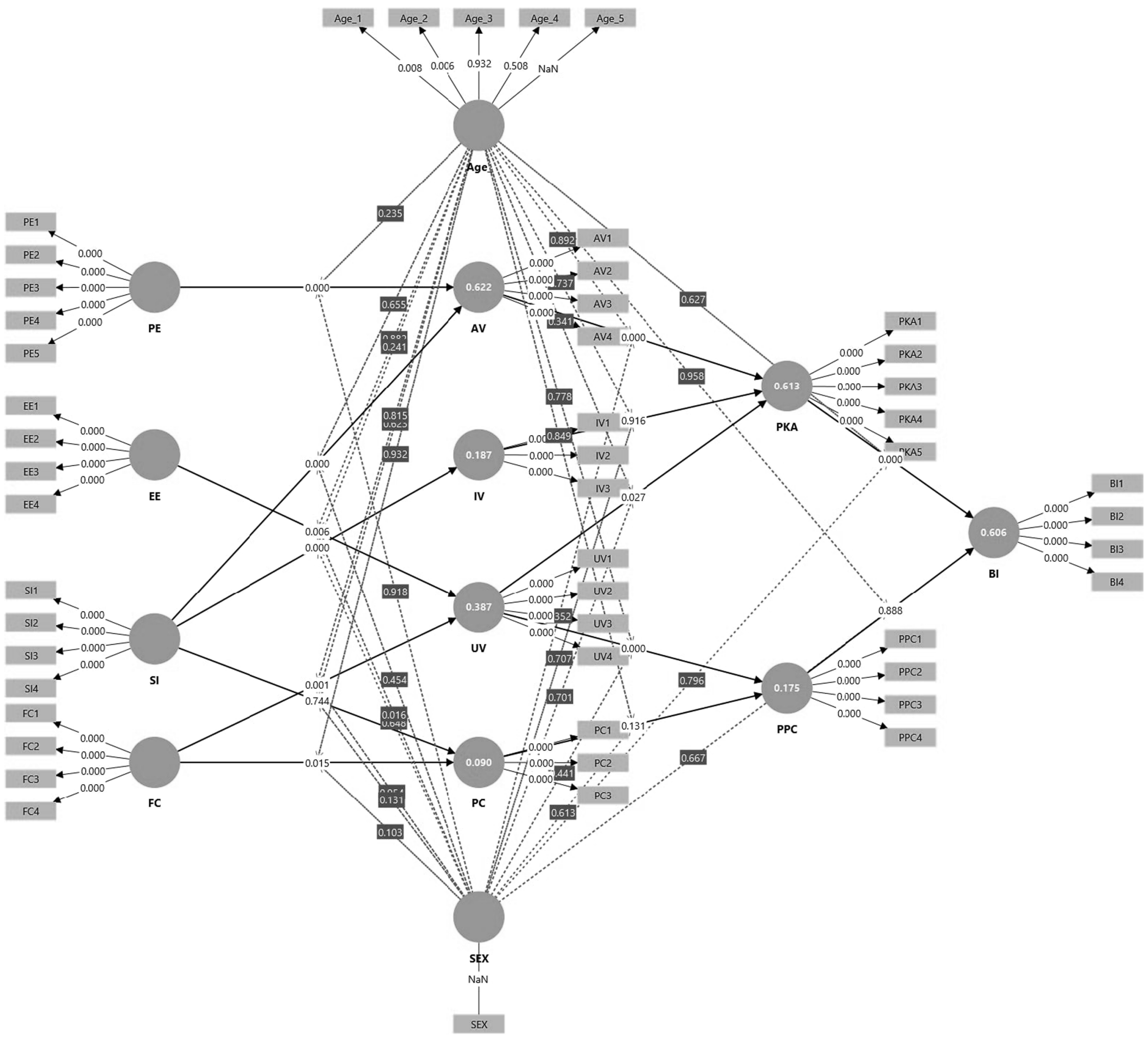

FIGURE 2
The final structural model. PE, performance expectancy; EE, effort expectancy; SI, social influence; FC, facilitating conditions; AV, perceived attainment value; IV, perceived intrinsic value; UV, perceived utility value; PC, perceived cost; PPC, perceived privacy concerns; PKA, perceived knowledge of AI; BI, behavioral intention to use AI.

prioritize usability when forming their attitudes towards technology, highlighting the need for gender-responsive support strategies, such as hands-on training and simplified onboarding.

Other interactions, although not significant, showed suggestive patterns: social influence (SI) on perceived cost (PC) (H33) ($\beta = 0.251$) and facilitating conditions (FC) on perceived cost (PC) (H35) ($\beta = -0.260$), indicating possible gender-based variations in interpreting peer encouragement and institutional support. Overall, the core model relationships appear strong across sexes, but tailoring AI integration to address subtle gender differences may enhance adoption outcomes and promote inclusive implementation across diverse educational settings.

The moderation analysis showed that Age had no significant effect, whereas Sex moderated the relationship between effort expectancy (EE) and (perceived) utility value, underscoring the need for gender-sensitive AI adoption strategies. The final structural model offers a comprehensive view of the factors shaping AI adoption in higher education, highlighting the interplay of demographic, psychological, and contextual influences on behavioral intention (see Figure 2).

Figure 2 presents the final structural model, clearly distinguishing between supported and unsupported hypothesized paths in the context of generative AI adoption among higher education English language teachers in Cebu, Philippines. The results show that performance expectancy (PE) significantly predicts perceived attainment value (AV), indicating that teachers who believe generative AI enhances instructional performance are more likely to view its use as important to their professional roles. Effort expectancy (EE) significantly predicts perceived utility value (UV), suggesting that ease of use strengthens perceptions of AI's practical usefulness in English language teaching tasks. Social influence (SI) significantly predicts perceived attainment value (AV), perceived intrinsic value (IV), and perceived cost (PC), reflecting the role of peer norms and institutional signals in shaping teachers' evaluations of AI. Facilitating conditions (FC) significantly predict perceived utility value (UV) and perceived cost (PC), underscoring the importance of institutional support and resources in shaping both the benefits and the perceived burdens of AI use. In turn, perceived attainment value (AV) and perceived utility value (UV) significantly predict perceived knowledge of AI (PKA), indicating that teachers who regard AI as professionally important and instructionally useful are more likely to develop confidence in their understanding of AI tools. Perceived knowledge of AI (PKA) significantly predicts behavioral intention (BI) and is the strongest direct predictor of teachers' intention to use generative AI. Additionally, perceived utility value (UV) and perceived cost (PC) significantly predict perceived privacy concerns (PPC), suggesting that greater engagement is associated with increased ethical awareness. By contrast, perceived intrinsic value (IV) does not significantly predict perceived knowledge of AI (PKA), and perceived privacy concerns (PPC) do not significantly predict behavioral intention, indicating that enjoyment and ethical concerns alone do not directly shape intention once usefulness and competence are accounted for in this context.

With respect to moderating effects, the findings indicate that Age does not significantly moderate any of the structural relationships, including paths involving performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), perceived values (AV, IV, UV), perceived knowledge of AI (PKA), perceived privacy concerns (PPC), and behavioral intention (BI). This suggests that, across age groups, higher education teachers in Cebu form relatively similar evaluations of generative AI when motivational and institutional factors are taken into account. In contrast, Sex moderates only one pathway, namely the relationship between effort expectancy (EE) and perceived utility value (UV), indicating that perceptions of ease of use translate into judgments of practical usefulness differently for male and female teachers. All other interaction effects involving Sex are not statistically significant, suggesting that the relationships among performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), perceived values (AV, IV, UV), perceived knowledge of AI (PKA), perceived privacy concerns (PPC), and behavioral intention (BI) are largely stable across genders. Overall, these results indicate that, in the Philippine higher education ELT context, behavioral intention to use generative AI is primarily shaped by cognitive, motivational, and institutional factors, while demographic characteristics play a limited, highly specific moderating role.

4.3 Implications

This section enumerates the practical and pedagogical implications of the study's findings. The implications enumerated from this study focus on factors shaping behavioral intention to use generative AI and do not assume actual adoption or implementation outcomes.

Drawing on the Unified Theory of Acceptance and Use of Technology (UTAUT), Expectancy-Value Theory (EVT), and extended constructs such as perceived knowledge of AI (PKA) and perceived privacy concerns (PPC), the study offers a nuanced understanding of how English language teachers in higher education evaluate and adopt generative AI. The discussion is organized under two thematic categories: enhancing pedagogical strategies and integrating technology into the curriculum.

First, the study confirms that performance expectancy (PE), perceived utility value (UV), and perceived knowledge of AI (PKA) significantly influence behavioral intention (BI). Teachers are more likely to adopt AI when they perceive it as pedagogically useful and feel confident in its use. AI tools like ChatGPT and Grammarly support personalized writing feedback and revision, especially in large classes (Zhou et al., 2023). Teachers can frame AI suggestions as springboards for discussion, promoting learner autonomy and metalinguistic awareness (García-Sánchez et al., 2023). Similarly, reflective tasks using AI-generated perspectives can foster critical thinking, provided students are guided to evaluate the credibility and tone of such content (Meihami and Meihami, 2023). The study shows that perceived intrinsic value (IV) alone does not predict perceived knowledge of AI (PKA), suggesting that enjoyment must be accompanied by structured reflection to yield meaningful learning. Teachers' confidence also enables them to curate AI-generated output for differentiated instruction, especially in multilingual classrooms (Tuan, 2023; Belda-Medina and Goddard, 2024), while minimizing reliance on flawed or culturally misaligned content.

Second, perceived knowledge of AI (PKA) emerged as the strongest predictor of behavioral intention (BI), underscoring the need to institutionalize AI literacy within English language teaching programs. Curricula can include modules on AI-assisted summarization, vocabulary expansion, and lesson planning tailored to local linguistic contexts (Sandoval, 2024). Faculty development programs are essential to ensure that instructors are equipped to deliver these components effectively (Florendo and Alvarez, 2023). At the same time, assessment redesign is critical. Since AI can perform basic tasks like summarization and grammar correction, instructors should prioritize synthesis, critique, and ethical analysis to encourage higher-order thinking (Valbuena and Tongco, 2024). Perceived privacy concerns (PPC), although not statistically significant in predicting behavioral intention (BI), remain moderately present and warrant curriculum-embedded discussions on the ethical use of AI and data protection (Dizon and Espina, 2023).

Third, the study correspondingly finds that social influence (SI) positively affects perceived attainment value (AV) and perceived intrinsic value (IV), highlighting the importance of peer communities. Institutions can establish AI Teaching Circles to foster collaborative experimentation and informal mentoring, which build faculty confidence (Marquez and Austria, 2024). However, these communities require institutional recognition and resource support to be sustainable. Infrastructure disparities also pose a barrier. Teachers in rural or under-resourced campuses may lack access to reliable internet or AI subscriptions. In contexts such as Philippine higher education, institutions must audit technological needs and consider alternatives such as offline AI tools or localized content banks (Rivera and Mallari, 2024). Even incremental improvements in usability and support systems can significantly boost utility value.

Furthermore, this study found that even when teachers are aware of potential privacy or data risks associated with AI, these concerns do not significantly deter them from intending to use it. This result contrasts with earlier studies conducted in Western contexts, where privacy and surveillance issues are often cited as key barriers to AI adoption (Dwivedi et al., 2021; Mittelstadt, 2019). However, in developing or resource-constrained settings like the Philippines, the urgency to improve teaching tools and access to innovative technologies may outweigh abstract concerns about data security, reflecting a contextual prioritization of usefulness over risk among Cebu-based educators. This is similar to results in other third-world contexts, where perceived benefits often outweigh abstract concerns about data security (Ifinedo, 2012).

Lastly, consistent with findings from higher education studies in Arab contexts, where perceived usefulness and self-efficacy consistently outweigh privacy concerns in predicting intention (Sallam et al., 2025; Al-Emran et al., 2025; Salah and Ayyash, 2025), the present results suggest that teachers prioritize instructional value and competence development when forming intentions to use AI. These comparative findings indicate that across diverse cultural settings, including the Philippines and Arab higher education systems, motivational and cognitive factors exert stronger influence on behavioral intention than ethical risk perceptions at the intention-formation stage.

Overall, the study's findings suggest that the effectiveness of AI integration in ELT is largely determined by perceived instructional benefits, confidence, and institutional support, rather than intrinsic interest or demographic variables. Teachers are willing to adopt AI when it is pedagogically relevant, ethically grounded, and institutionally supported. Ethical concerns, while secondary in behavioral prediction, should still be addressed through proactive training and policy safeguards. A triadic approach anchored in pedagogical design, digital ethics, and infrastructural support will help ensure that AI serves as a strategic partner in advancing language education outcomes in Philippine higher education.

5 Conclusion, limitations, and research direction

5.1 Conclusion

Responding to gaps in the literature on generative AI adoption in English language teaching, this study examined the behavioral intention of higher education English language teachers in Cebu, Philippines, by integrating UTAUT, EVT, and extended constructs of perceived AI knowledge and perceived privacy concerns. The findings show that technology-related enablers influence behavioral intention indirectly through value-based motivational mechanisms. Performance expectancy predicts perceived attainment value; effort expectancy predicts perceived utility value; social influence shapes perceived attainment value, intrinsic value, and perceived cost; and facilitating conditions influence perceived utility value and perceived cost. Among downstream mechanisms, perceived attainment value and perceived utility value significantly predict perceived knowledge of AI, which emerges as the strongest direct predictor of behavioral intention. In contrast, perceived intrinsic value does not significantly predict perceived knowledge of AI, and perceived privacy concerns do not significantly predict behavioral intention, indicating that enjoyment and ethical concerns alone do not directly shape intention once perceived usefulness and self-assessed competence are considered.

With respect to demographic influences, age does not moderate any of the structural relationships, suggesting that teachers' evaluations of generative AI are consistent across age groups in this context. Sex moderates only the relationship between effort expectancy and perceived utility value, while all other pathways remain invariant across genders. Taken together, these findings indicate that behavioral intention to adopt generative AI in English language teaching is primarily shaped by perceived usefulness, value alignment, and confidence, rather than by demographic characteristics. The study underscores the importance of institutional strategies that prioritize AI literacy, professional development, and supportive implementation environments to enable responsible and pedagogically aligned AI integration across diverse higher education contexts.

5.2 Limitations

Several limitations should be acknowledged when interpreting the findings. First, the study employed a cross-sectional research design, which limits the ability to draw causal inferences or to examine changes in teachers' perceptions and intentions over time. Behavioral intention was measured at a single point, and shifts in intention as teachers gain more experience with generative AI were not captured.

Second, all constructs were measured using self-reported data, which may be subject to social desirability bias and common method variance. In particular, perceived knowledge of AI reflects teachers' subjective confidence rather than objectively assessed competence, and behavioral intention does not necessarily translate into actual classroom use.

Third, the study is geographically bounded to higher education institutions in Cebu, Philippines. While Cebu provides a diverse mix of urban and rural campuses, the findings may not be fully generalizable to other regions of the Philippines or to higher education systems with different policy environments, infrastructure conditions, or cultural norms. These limitations suggest the need for cautious interpretation beyond the studied context.

5.3 Research direction

Future research may extend this work in several directions. Longitudinal studies are needed to examine how behavioral intention evolves into actual AI adoption and sustained use, particularly as institutional policies, training initiatives, and AI literacy programs mature. Such designs would allow researchers to test whether perceived knowledge of AI continues to predict usage behavior over time.

Comparative and cross-regional studies are also recommended to assess whether the integrated UTAUT–EVT framework operates similarly across different Philippine regions and in other higher education contexts, both developed and developing. Expanding the model to include objective measures of AI competence, classroom implementation data, or policy awareness may further strengthen explanatory power. Finally, future research could explore additional moderators, such as teaching experience, disciplinary background, or institutional AI governance maturity, to refine the understanding of how contextual conditions shape teachers' engagement with generative AI.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by Cebu Normal University Ethics Review Committee. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

RK: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that Generative AI was used in the creation of this manuscript. Generative artificial intelligence (AI) tools, specifically ChatGPT (OpenAI) and Grammarly, were utilized to aid in language refinement and ensure editorial consistency during the manuscript's preparation. ChatGPT was employed to enhance clarity, grammar, and conciseness in sentence wording, and to ensure adherence to academic style conventions. Grammarly was used for minor proofreading and syntax corrections. No AI tool was used to generate research ideas, conduct data analysis, present results, or draw interpretations. The author maintains full responsibility for the content, accuracy, and integrity of the manuscript.

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References

Aborot, J., Neverida, M. P., Abonita, J. K. C., and Osiana, V. O., "Gul.Ai: AI- and IoT-enabled plant-growing system for boosting STEM education in the Philippines," In: *2022 20th International Conference on ICT and Knowledge Engineering (ICT&KE)*, 2022, New York, NY: IEEE

Ahmad, K., Iqbal, W., El-Hassan, A., Qadir, J., Benhaddou, D., Ayyash, M., et al. (2023). Data-driven artificial intelligence in education: a comprehensive review. *IEEE Trans. Learn. Technol.* 17, 12–31. doi: 10.1109/TLT.2023.3314610

AlAli, R., Wardat, Y., Al-Saud, K., and Alhayek, K. A. (2024). Generative AI in education: best practices for successful implementation. *Int. J. Relig.* 5, 1016–1025. doi: 10.61707/pkwb8402

Alashoor, T., Keil, M., Smith, H. J., and McConnell, A. R. (2023). Too tired and in too good of a mood to worry about privacy: explaining the privacy paradox through the lens of effort level in information processing. *Inf. Syst. Res.* 34, 1415–1436. doi: 10.1287/isre.2022.1182

Aldboush, H. H., and Ferdous, M. (2023). Building trust in fintech: an analysis of ethical and privacy considerations in the intersection of big data, AI, and customer trust—international journal of financial studies. *11* 11:90. doi: 10.3390/ijfs11030090

Alegre, E. M. (2023). Technology-driven education: analyzing the synergy among innovation, motivation, and student engagement. *Int. J. Membr. Sci. Technol.* 10, 1477–1485. doi: 10.15379/ijmst.v10i2.1507

Al-Emran, M., Al-Sharafi, M. A., Foroughi, B., Al-Qaysi, N., Mansoor, D., Beheshti, A., et al. (2025). Evaluating the influence of generative AI on students' academic performance through the lenses of TPB and TTF using a hybrid SEM-ANN approach. *Educ. Inf. Technol.* 30, 17557–17587. doi: 10.1007/s10639-025-13485-w

Alharbi, W. (2023). AI in the foreign language classroom: a pedagogical overview of automated writing assistance tools. *Educ. Res. Int.* 2023, 1–15. doi: 10.1155/2023/4253331

Amuga, E. O. (2023). *Artificial intelligence in education.* Palmdale: IGI Global Scientific Publishing.

An, X., Chai, C. S., Li, Y., Zhou, Y., Shen, X., Zheng, C., et al. (2023). Modelling English teachers' behavioral intention to use artificial intelligence in middle schools. *Educ. Inf. Technol.* 28, 5187–5208. doi: 10.1007/s10639-022-11286-z

Anabel, D., Silva, S., Moya, L. S., and Barker, J. (2024). Recontextualising the unified theory of acceptance and use of technology (UTAUT) framework to higher education online marking. *J. Univ. Teach. Learn. Pract.* 21, 1–26. doi: 10.53761/7ft8x880

Arthur, F., Salifu, I., and Abam Nortey, S. (2024). Predictors of higher education students' behavioural intention and usage of ChatGPT: the moderating roles of age, gender and experience. *Interact. Learn. Environ.* 33, 993–1019. doi: 10.1080/10494820.2024.2362805

Assassi, T. (2025). ESP practitioners' perspectives on the efficiency of using artificial intelligence 'ChatGPT' in needs analysis. *Comput. Assist. Lang. Learn.*, 1–32. doi: 10.1080/09588221.2024.2428943

Bandura, A. (2015). "Self-efficacy conception of anxiety" in *Anxiety and self-focused attention* (Abingdon: Routledge), 89–110.

Bardach, L., Popper, V., Hochfellner, E., and Lüftenegger, M. (2019). Associations between vocational students' perceptions of goal structures, mastery goals, and self-efficacy in five subjects—practical relevance as a potential mediator. *Empir. Res. Vocat. Educ. Train.* 11:9. doi: 10.1186/s40461-019-0084-0

Bautista, A., Estrada, C., Jaravata, A. M., Mangaser, L. M., Narag, F., Soquila, R., et al. (2024). Preservice teachers' readiness towards integrating AI-based tools in education: a TPACK approach. *Educ. Process. Int. J.* 13, 40–68. doi: 10.22521/edupij.2024.133.3

Beirat, M. A., Tashtoush, D. M., Khasawneh, M. A., Az-Zo'bi, E. A., and Tashtoush, M. A. (2025). The effect of artificial intelligence on enhancing education quality and reduce the levels of future anxiety among Jordanian teachers. *Appl. Math.* 19, 279–290. doi: 10.18576/amis/190205

Belda-Medina, J., and Goddard, M. B. (2024). AI-driven digital storytelling: a strategy for creating English as a foreign language (EFL) materials. *Int. J. Linguist. Stud.* 4, 40–49. doi: 10.32996/ijls.2024.4.1.4

Cabero-Almenara, J., Palacios-Rodríguez, A., Loaiza-Aguirre, M. I., and Andrade-Abarca, P. S. (2024). The impact of pedagogical beliefs on the adoption of generative AI in higher education: predictive model from UTAUT2. *Front. Artif. Intell.* 7:1497705. doi: 10.3389/frai.2024.1497705

Chan, C. K. Y., and Tsi, L. H. (2024). Will generative AI replace teachers in higher education? A study of teacher and student perceptions. *Stud. Educ. Eval.* 83:101395. doi: 10.1016/j.stueduc.2024.101395

Chatterjee, D., Pati, S., Dhaigude, A. S., and Kamath, G. B. (2025). Examining the acceptance of over-the-top services among young consumers during pandemic: a multi-theory approach. *Cogent Bus Manag* 12:2439544. doi: 10.1080/23311975.2024.2439544

Chen, Z., Zhang, J., Jiang, X., Hu, Z., Han, X., Xu, M., et al. (2020). Education 4.0 using artificial intelligence for student's performance analysis. *Intelig. Artif.* 23, 124–137. doi: 10.4114/intartif.vol23iss66pp124-137

Chiu, C. M., and Wang, E. T. (2008). Understanding web-based learning continuance intention: the role of subjective task value. *Inf. Manag.* 45, 194–201. doi: 10.1016/j.im.2008.02.003

Chounta, I. A., Bardone, E., Raudsep, A., and Pedaste, M. (2022). Exploring teachers' perceptions of artificial intelligence as a tool to support their practice in Estonian K-12 education. *Int. J. Artif. Intell. Educ.* 32, 725–755. doi: 10.1007/s40593-021-00243-5

Coopamootoo, K. (2023). Usage patterns of privacy-enhancing technologies. Correlation between artificial intelligence in education and teacher self-efficacy beliefs: a review. *RumeliDE Dil. Edebiyat Araştırmaları Dergisi.* 34, 1354–1365. doi: 10.29000/rumelide.1316378

Cortez, P. M., Ong, A. K. S., Diaz, J. F. T., German, J. D., and Singh Jagdeep, S. J. S. (2024). Analyzing preceding factors affecting behavioral intention on communicational artificial intelligence as an educational tool. *Heliyon* 10:e25896. doi: 10.1016/j.heliyon.2024.e25896

Dizon, G., and Espina, S. (2023). Data ethics in digital pedagogy: safeguarding privacy and ensuring responsible data practices. *Educ. Sci.* 13:505. doi: 10.3390/educsci13040505

Durango, I., Gallud, J. A., and Penichet, V. M. (2024). Using expectancy-value theory to understand the teaching motivations of women physics lecturers. *Physical Review Physics Education Research,*20:010157. doi: 10.1103/PhysRevPhysEducRes.20.010157

Durk, J., Smith, A., Aydın, B., Julia, A., and Rabey, I. M. (2024). Analyzing preceding factors affecting behavioral intention on communicational artificial intelligence as an educational tool. *Heliyon* 10:e25896. doi: 10.1016/j.heliyon.2024.e25896

Dwivedi, Y. K., Hughes, D. L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., et al. (2021). Artificial intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int. J. Inf. Manag.* 57:101994. doi: 10.1016/j.ijinfomgt.2019.08.002

Eccles, J. S., and Wigfield, A. (2024). The development, testing, and refinement of Eccles, Wigfield, and colleagues' situated expectancy-value model of achievement performance and choice. *Educ. Psychol. Rev.* 36:51. doi: 10.1007/s10648-024-09888-9

Erdmann, A., and Toro-Dupouy, L. (2025). The influence of the institutional environment on AI adoption in universities: identifying value drivers and necessary conditions. *Eur. J. Innov. Manag.* 28, 4365–4398. doi: 10.1108/ejim-04-2024-0407

Estrellado, C. J. P., and Miranda, J. C. (2023). Artificial intelligence in the Philippine educational context: circumspection and future inquiries. *Int. J. Sci. Res. Publ.* 13, 16–22. doi: 10.29322/ijsrp.13.05.2023.p13704

Farhan, W., Razmak, J., Demers, S., and Laflamme, S. (2019). E-learning systems versus instructional communication tools: developing and testing a new e-learning user interface from the perspectives of teachers and students. *Technol. Soc.* 59:101192. doi: 10.1016/j.techsoc.2019.101192

Feng, W., and Xiaoyu, S. (2024). Understanding AI acceptance and usage in history education: an application of the UTAUT model among Malaysian higher education students. doi: 10.20944/preprints202411.1542.v1

Florendo, A., and Alvarez, M.. 2023. AI literacy among pre-service teachers. Available online at: https://philarchive.org/archive/LUMALA (Accessed November 2, 2025).

Gado, S., Kempen, R., Lingelbach, K., and Bipp, T. (2021). Artificial intelligence in psychology: How can we enable psychology students to accept and use artificial intelligence? *Psychol. Learn. Teach.* 21, 37–56. doi: 10.1177/14757257211037149

García-Sánchez, I. M., García-Sánchez, A., and García-Sánchez, F. (2023). AI-generated feedback on writing: insights into efficacy and ENL students' perceptions. *Int. J. Educ. Technol. High. Educ.* 20, 1–15. doi: 10.1186/s41239-023-00425-2

Gella, R. L. B. (2024). *Defining the legal role and liability of artificial intelligence in digital consent towards liberty and prosperity in the Philippines*. Bacolod: University of St. La Salle.

Goegan, L. D., Dueck, B. S., and Daniels, L. M. (2021). Are you feeling successful? Examining postsecondary student perceptions of success with an expectancy value theory lens. *Soc. Psychol. Educ.* 24, 985–1001. doi: 10.1007/S11218-021-09641-Y

Hair, J. F., Howard, M. C., and Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *J. Bus. Res.* 109, 101–110. doi: 10.1016/j.jbusres.2019.11.069

Hennessy, S., D'Angelo, S., McIntyre, N., Koomar, S., Kreimeia, A., Cao, L., et al. (2022). Technology use for teacher professional development in low-and middle-income countries: a systematic review. *Comput. Educ. Open* 3:100080. doi: 10.1016/j.caeo.2022.100080

Henseler, J., Ringle, C. M., and Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science,* 43, 115–135. doi: 10.1007/s11747-014-0403-8

Hojeij, Z., Kuhail, M. A., and ElSayary, A. (2024). Investigating in-service teachers' views on ChatGPT integration. *Interact. Technol. Smart Educ.* 22, 548–573. doi: 10.1108/itse-04-2024-0094

Ibrahim, A. S., and Shiring, E. J. (2022). The relationship between educators' attitudes, perceived usefulness, and perceived ease of use of instructional and web-based technologies: implications from technology acceptance model (TAM). *Int. J. Technol. Educ.* 5, 535–551. doi: 10.46328/ijte.285

Ifinedo, P. (2012). Understanding information systems security policy compliance: an integration of the theory of planned behavior and the protection motivation theory. *Comput. Secur.* 31, 83–95. doi: 10.1016/j.cose.2011.10.007

Jose, J. A. C., Bandala, A. A., Culaba, A. B., Chu, T. Scott, and Dadios, E. P., "Artificial intelligence for developing countries: Philippine context". In: *2022 IEEE 14th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)*, 2022 Boracay Island: IEEE

Julio, C. (2024). *Evaluation of speech recognition, text-to-speech, and generative text artificial intelligence for English as foreign language learning speaking practices*. [Master's Dissertation]. Tokyo: Tokyo Denki University.

Ka, C., Chan, Y., and Zhou, W. (2023). An expectancy value theory EVT based instrument for measuring student perceptions of generative AI. *Smart Learn. Environ.* 10:64. doi: 10.1186/s40561-023-00284-4

Kelly, S., Kaye, S. A., and Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telemat. Inform.* 77:101925. doi: 10.1016/j.tele.2022.101925

Kim, J., and Lee, K. S. S. (2022). Conceptual model to predict Filipino teachers' adoption of ICT-based instruction in class: using the UTAUT model. *Asia Pac. J. Educ.* 42, 699–713. doi: 10.1080/02188791.2020.1776213

Kline, R. B. (2023). *Principles and practice of structural equation modelling*. New York, NY: Guilford publications.

Konstantinova, L., Vorozhikhin, V. V., Petrov, A. M., and Shtykhno, D. (2023). Generative artificial intelligence in education: discussions and forecasts. *Open Educ.* 27, 36–48. doi: 10.21686/1818-4243-2023-2-36-48

Lan, Y. (2024). Through tensions to identity-based motivations: exploring teacher professional identity in artificial intelligence-enhanced teacher training. *Teach. Teach. Educ.* 151:104736. doi: 10.1016/j.tate.2024.104736

Lanying, H., and Chunming, L. (2023). Evaluating students' e-learning satisfaction in English studies based on UTAUT. *Asian J. Educ. Soc. Stud.* 49, 359–369. doi: 10.9734/ajess/2023/v49i41214

Leiker, D., and Cukurova, M. (2023). *Generative AI for learning: investigating the potential of learning videos with synthetic virtual instructors*. Switzerland: Springer Nature.

Lim, J., and Wang, Y. (2023). The role of interest and motivation in student self-efficacy and engagement with emerging technologies in education. *Comput. Educ.* 201:104795. doi: 10.1016/j.compedu.2023.104795

Mah, D. K., and Groß, N. (2024). Artificial intelligence in higher education: exploring faculty use, self-efficacy, distinct profiles, and professional development needs. *Int. J. Educ. Technol. High. Educ.* 21:58. doi: 10.1186/s41239-024-00490-1

Mahama, P. Y., Amankwah-Sarfo, F., and Gyedu, F. (2024). Critical issues of online learning management in higher educational institutions in a developing country context: examples from Ghana. *Int. J. Educ. Manag.* 38, 1903–1924. doi: 10.1108/ijem-01-2024-0059

Manswar, A., Said, K., Mokhtar, B., Chee-Onn, W., Al-Ahmari, D., and Al-Mawlid, A. (2024). Behavioural intention of using e-learning system: a bibliometric perspective. *J. Ecohum.* 3, 1595–1616. doi: 10.62754/joe.v3i8.4841

Marquez, L., and Austria, R. (2024). Peer mentorship in AI integration for ELT: a collaborative approach. *Teach. Engl. Technol.* 24, 45–60.

Meihami, H., and Meihami, J.. (2023). Harnessing generative AI for automated feedback in EFL writing. Available online at: https://files.eric.ed.gov/fulltext/EJ1446868.pdf (Accessed October 10, 2025).

Mittelstadt, B. D. (2019). Principles alone cannot guarantee ethical AI. *Nat. Mach. Intell.* 1, 501–507. doi: 10.1038/s42256-019-0114-4

Morris, M. G., and Venkatesh, V. (2000). Age differences in technology adoption decisions: implications for a changing workforce. *Pers. Psychol.* 53, 375–403. doi: 10.1111/j.1744-6570.2000.tb00206.x

Novak, M., and Schwan, S. (2021). Does touching real objects affect learning? *Educ. Psychol. Rev.* 33, 637–665. doi: 10.1007/s10648-020-09551-z

Ong, C. S., and Lai, J. Y. (2006). Gender differences in perceptions and relationships among dominants of e-learning acceptance. *Comput. Hum. Behav.* 22, 816–829. doi: 10.1016/j.chb.2004.03.006

Oran, B. B. (2023). Correlation between artificial intelligence in education and teacher self-efficacy beliefs: a review. *RumeliDE Dil. Edebiyat Araştırmaları Dergisi* 34, 1354–1365. doi: 10.29000/rumelide.1316378

Pedro, F., Subosa, M., Rivas, A., and Valverde, P. (2019). *Artificial intelligence in education: challenges and opportunities for sustainable development*. Paris: UNESCO.

Popenici, S. A., and Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Res. Pract. Technol. Enhanc. Learn.* 12:22. doi: 10.1186/s41039-017-0062-8

Prema, S., Raksha, D., Krishna, D., Raj, G., and Xujuan, Z. 2023. "Student perceptions of ChatGPT through an expectancy value theory." In: *2023 IEEE/WIC International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT)*. New York, NY: IEEE

Rajak, L., Chauhan, S., and Bara, S. (2024). "Transforming English pedagogy with artificial intelligence: enroute to enhanced language learning" in *Artificial intelligence: a multidisciplinary approach towards teaching and learning* (Sharjah: Bentham Science Publishers).

Ravula, P., Rupavatharam, S., Kasala, K., Kumar, K., and Singaraju, N. (2024). Training module: Gender responsive digital inclusion. Montpellier, France: CGIAR.

Rivera, M., and Mallari, J. (2024). Addressing infrastructure disparities in AI integration for ELT in the Philippines. *Educ. Technol. Soc.* 27, 88–102. doi: 10.1201/9781003486725-7

Rosales, M. A., Magsumbol, J.-A. V., Palconit, M. G. B., Culaba, A. B., and Dadios, E. P.. (2020). Artificial intelligence: the technology adoption and impact in the Philippines. In: *International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management*. New York, NY: IEEE

Salah, O. H., and Ayyash, M. M. (2025). Understanding user adoption of mobile wallet: extended TAM with knowledge sharing, perceived value, perceived privacy awareness and control, perceived security. *Vine J. Inf. Knowl. Manag. Syst.* 55, 1223–1250. doi: 10.1108/VJIKMS-03-2023-0055

Sallam, M., Al-Mahzoum, K., Alaraji, H., and Al-Adwan, A. S. (2025). Technology readiness, social influence, and anxiety as predictors of university educators' perceptions of generative AI usefulness and effectiveness. *J. Educ. Dev.* 9:1511. doi: 10.20849/jed.v9i3.1511

Sandoval, R. (2024). Institutionalizing AI literacy in ELT programs: a Philippine perspective. PhilArchive. Available online at: https://philarchive.org/archive/SANIAL (Accessed October 23, 2025).

Shao, C., Nah, S., Makady, H., and McNealy, J. (2024). Understanding user attitudes towards AI-enabled technologies: an integrated model of self-efficacy, TAM, and AI ethics. *Int. J. Hum. Comput. Interac.* 41, 3053–3065. doi: 10.1080/10447318.2024.2331858

Sharma, L., and Srivastava, M. (2020). Teachers' motivation to adopt technology in higher education. *J. Appl. Res. High. Educ.* 12, 673–692. doi: 10.1108/JARHE-07-2018-0156

Teo, T., and Noyes, J. (2014). Explaining the intention to use technology among pre-service teachers: a multi-group analysis of the unified theory of acceptance and use of technology. *Interact. Learn. Environ.* 22, 51–66. doi: 10.1080/10494820.2011.641674

Tewathia, N., Wadhwa, W., and Chatterjee, U. (2020). Gender and age as moderators in technology adoption in Indian banking sector. *Int. J. Bank Mark.* 38, 193–214.

Tuan, L. T. 2023 Using AI to support differentiated instruction in ELT. World Learning TESOL Webinar Series. Available online at: https://www.youtube.com/watch?v=5HUvxF2CBGQ (Accessed October 2, 2025).

Valbuena, M., and Tongco, J. 2024 Innovative approaches to language assessment in 2024. Ismail view. Available online at: https://ismailview.com/innovative-approaches-to-language-assessment-in-2024 (Accessed October 10, 2025).

Venkatesh, V., and Morris, M. G. (2000). Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior. *MIS Q.* 24, 115–139. doi: 10.2307/3250981

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: toward a unified view. *MIS Q.* 27, 425–478. doi: 10.2307/30036540

Wagman, K. B., Blinder, E. B., Song, K., Vignon, A., Dworkin, S., Clegg, T., et al 2023. "We picked community over privacy": privacy and security concerns emerging from remote learning sociotechnical infrastructure during COVID-19. In: *Proceedings of the ACM on Human-Computer Interaction*, New York, NY: Association for Computing Machinery

Wang, Y., Liu, C., and Tu, Y.-F. (2021). Factors affecting the adoption of AI-based applications in higher education. *Educational Technology & Society,* 24, 116–129.Available at: https://www.jstor.org/stable/27032860

Wong, W. H., and Chapman, E. (2024). Factors Affecting the Adoption of AI-Based Applications in Higher Education: An Analysis of Teachers' Perspectives Using Structural Equation Modeling. *J. Appl. Learn. Teach.* 7, 1–11. doi: 10.37074/jalt.2024.7.1.20

Wu, W., Zhang, B., Li, S., and Liu, H. (2022). Exploring factors of the willingness to accept AI-assisted learning environments: an empirical investigation based on the UTAUT model and perceived risk theory. *Front. Psychol.* 13:870777. doi: 10.3389/fpsyg.2022.870777

Xinhua, Z., and Thitinant, W. (2024). A study of the factors influencing teachers' willingness to use generative artificial intelligence based on the UTAUT model. *Int. J. Interact. Mobile Technol.* 18, 126–142. doi: 10.3991/ijim.v18i06.47991

Yue, M., Jong, M. S. Y., and Ng, D. T. K. (2024). Understanding K–12 teachers' technological pedagogical content knowledge readiness and attitudes toward artificial intelligence education. *Educ. Inf. Technol.* 29, 19505–19536. doi: 10.1007/s10639-024-12621-2

Zamiri, M., and Esmaeili, A. (2024). Methods and technologies for supporting knowledge sharing within learning communities: a systematic literature review. *Adm. Sci.* 14:17. doi: 10.3390/admsci14010017

Zhao, Y., Yin, H., and Yu, S. (2022). Exploring how enjoyment influences student engagement and learning outcomes in AI-supported environments. *Comput. Educ.* 194:104666. doi: 10.1016/j.compedu.2022.104666

Zhao, Y., Zhao, M., and Shi, F. (2024). Integrating moral education and educational information technology: a strategic approach to enhance rural teacher training in universities. *J. Knowl. Econ.* 15, 15053–15093. doi: 10.1007/s13132-023-01693-z

Zhou, T., Wang, Y., and Chen, M. (2023). Framing AI-generated feedback in EFL writing: balancing automation with human judgment. *Int. J. Educ. Technol. High. Educ.* 20, 1–15. doi: 10.1186/s41239-023-00425-2

Zimmerman, M. (2018). *Teaching AI: exploring new frontiers for learning*. Portland, OR: International society for technology in education.