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Digital learning anxiety and UTAUT predictors of university students' intention to use generative artificial intelligence in Ghana

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This study investigates the factors associated with university students' intention to use Generative Artificial Intelligence (GenAI) in Ghana, with particular attention to the role of psychological barriers in shaping technology use intention. This study extends the UTAUT model by incorporating the concept of digital learning anxiety in understanding the psychological dimension of students using generative AI. The study employed a quantitative approach using a cross-sectional survey design, with data analyzed through covariance-based structural equation modeling (CB-SEM). The sample consisted of 350 university students in Ghana. Structural equation modeling and a bias-corrected percentile bootstrapping method were conducted in AMOS (v 23) to estimate the path coefficients. The results showed that performance expectancy and effort expectancy were positively associated with students' intention to use GenAI. Additionally, a significant but small indirect association was found between effort expectancy and behavioral intention through digital learning anxiety. However, the findings indicate the insignificant influence of social influence. This study contributes to the literature by providing context-specific evidence from Ghanaian higher education on the role of Digital Learning Anxiety in students' intention to use GenAI. However, because the study used cross-sectional data, this indirect relationship should be interpreted as an association rather than evidence of a causal mechanism. The findings suggest that students' intention to use GenAI is associated with both their perceptions of the technology and their psychological responses to its use. These findings provide context-specific evidence on GenAI acceptance among the students surveyed.

KEYWORDS
affective outcomes, digital learning anxiety, generative artificial intelligence, human-AI interaction, university students, UTAUT

Introduction

Generative artificial intelligence (GenAI) has rapidly evolved from an emerging educational innovation to an increasingly integrated component of higher education (Crompton and Burke, 2023). Unlike conventional educational technologies that primarily deliver or organize learning materials, GenAI systems actively support students by generating explanations, providing feedback, assisting with writing, and engaging in interactive dialogue (Chen and Mokmin, 2024; Godwin-Jones, 2024;

Ma 2025). For university students studying in English-medium academic settings, these capabilities may offer personalized academic support that can assist with language development, writing proficiency, and independent learning (Davor et al., 2026; Zheng et al., 2024).

The emergence of ChatGPT and other large language models has accelerated the integration of Generative AI into higher education, creating new opportunities for personalized learning, intelligent tutoring, academic writing support, and interactive feedback (Asare and Boateng, 2025; Davor et al., 2026). These technologies have the potential to improve students' learning experiences, foster self-regulated learning, and support language development through adaptive human-AI interactions. At the same time, scholars have cautioned that the educational use of Generative AI presents important challenges related to academic integrity, reliability of AI-generated content, ethical decision-making, critical thinking, and responsible use. Consequently, understanding the factors that influence students' acceptance and effective use of Generative AI has become a major research priority in educational psychology and educational technology (Chiu, 2024; Kasneci et al., 2023; Tlili et al., 2023; Yan et al., 2024).

These implications are particularly evident in Sub-Saharan Africa, particularly in Ghana, where English serves as the medium of instruction throughout the university system (Al-khresheh, 2024). Recent evidence from Sub-Saharan Africa also highlights both opportunities and challenges associated with AI among university students (Boateng and Davor, 2026). For many Ghanaian university students, English is an important language of academic instruction and communication. However, the present study did not directly measure students' English proficiency or L2-related psychological characteristics (Huang et al., 2024). Despite the revolutionary potential of GenAI to act as a reliable writing instructor and cognitive partner, the quality of engagement and the success of these interactions are not guaranteed.

Access to technology alone does not guarantee its effective educational use. Rather, students' engagement depends on both their cognitive evaluations of the technology and their emotional responses during use. In order to effectively enhance such interactions, there is a need to move beyond the realm of technical access and address the psychological and behavioral aspects that impact the dynamic of interaction with such content providers. Therefore, it is crucial to understand the nature of the interaction between humans and AI and, in particular, the difficulties that undermine effective educational outcomes.

Problem statement

Generative Artificial Intelligence (GenAI) is increasingly integrated into educational environments to support learning and problem-solving. It is used for academic writing, language learning, providing feedback, and problem-solving by tools such as ChatGPT (Kasneci et al., 2023; Tlili et al., 2023). However, most studies on GenAI in education have been conducted in North America, Europe, and East Asia (Matthews, 2024; Riser, 2025; Sun and Lan, 2025; Tian and Wang, 2025). There is, however, a substantial gap in research in the developing educational environments of Sub-Saharan Africa. In these environments, the lack of digital infrastructure, changing university policies and environments regarding the use of technology for learning, as well as students' and teachers' preparedness to use AI for learning, are topics that require investigation (Davor and Boateng, 2026). While existing research has predominantly focused on the technical capabilities and educational benefits of AI technologies, considerably less attention has been devoted to understanding how students experience AI-mediated learning environments and how these experiences influence technology acceptance and learning engagement.

While previous research has been conducted on the adoption of educational technology in Ghana (Arhin et al., 2024; Boadu and Boateng, 2024), most of the research was centered on conventional digital technologies or platforms such as Moodle, Blackboard's Sakai, and other Learning Management Systems (LMS). These conventional digital educational technologies are different from Generative AI systems in that the latter are not mere platforms but rather interactive cognitive agents that support learning by generating explanations, feedback, recommendations, and learning support in real time. Thus, it is not clear whether the factors that explain the adoption of conventional digital educational technologies would be enough to explain students' engagement and interaction in AI-mediated learning environments.

The Unified Theory of Acceptance and Use of Technology (UTAUT) remains one of the most widely used frameworks for explaining technology adoption and has consistently demonstrated the importance of performance expectancy, effort expectancy, and social influence in predicting behavioral intention (Al-khresheh, 2024; Ma, 2025; Sun and Lan, 2025; Venkatesh et al., 2003). Nevertheless, the UTAUT framework was developed primarily to explain rational decision-making processes and gives limited attention to affective factors that may shape users' responses to emerging technologies. Wang and Liu (2025) extended UTAUT2 to examine psychological determinants of Generative AI adoption, highlighting the importance of considering psychological factors alongside traditional technology acceptance constructs. Recent studies have reported growing concerns among students regarding AI-related anxiety, uncertainty about academic integrity, fear of overdependence on AI systems, concerns about the reliability of AI-generated outputs, and apprehension about the implications of AI use for learning and assessment (Chen and Mokmin, 2024; Huang et al., 2024; Karahan and Bilgili, 2025). These findings suggest that students may simultaneously recognize the educational benefits of GenAI while experiencing emotional barriers that discourage its adoption.

Although Generative AI offers substantial opportunities for personalized learning, intelligent tutoring, language support, and academic writing, its successful integration into higher education is accompanied by important pedagogical and psychological challenges. Recent reviews have highlighted concerns regarding the reliability of AI-generated content, academic integrity, overdependence on AI systems, ethical decision-making, and students' emotional responses when interacting with AI-supported learning environments (Chiu, 2024; Kasneci et al., 2023; Tlili et al., 2023; Yan et al., 2024). These findings suggest that successful adoption depends not only on the technological capabilities of Generative AI but also on learners' confidence, trust, and emotional readiness to engage with AI-assisted learning, indicating the need to examine psychological

mechanisms underlying technology acceptance (Granić, 2025; Zawacki-Richter et al., 2019).

Although emerging research has incorporated anxiety into technology-acceptance models of Generative AI, evidence from Sub-Saharan African higher education remains limited. Budhathoki et al. (2024), for example, examined ChatGPT adoption and anxiety within a cross-country UTAUT framework, demonstrating the relevance of anxiety to GenAI acceptance. However, limited evidence exists on these relationships within Ghanaian higher education and on the specific indirect relationship between Effort Expectancy, Digital Learning Anxiety, and Behavioral Intention in this context. The present study therefore examines the associations among traditional UTAUT determinants, Digital Learning Anxiety, and Behavioral Intention among university students in Ghana, with particular attention to the indirect association between Effort Expectancy and Behavioral Intention through Digital Learning Anxiety. The contribution of the study lies primarily in providing context-specific evidence from an underrepresented Sub-Saharan African higher-education setting and examining this specific indirect pathway.

Literature review and hypotheses development

Performance expectancy and the nature of AI interaction

In educational settings, perceived usefulness remains a key determinant of technology adoption. In support of the argument is the work of Venkatesh et al. (2003), which proves that the performance expectancy (PE) factor affects the intention to use new technology. In using Generative AI tech among students, it is no longer just about interacting with the technology; GenAI will now act as a cognitive partner to fill the gap between students' language abilities and the complex cognitive requirements of academic tasks (Godwin-Jones, 2024). In the university students realm, the interaction will now be enhanced through instant feedback from GenAI. GenAI would now serve as a personal teaching assistant (Liu, 2025). When students perceive that the potential use is related to higher grades or time-saving benefits, this will result in the students having a positive intention to use the technology (Karahan and Bilgili, 2025). Thus, we hypothesize that:

> H1: Performance Expectancy is positively associated with students' Behavioral Intention to use GenAI.

Effort expectancy and interaction accessibility

Effort Expectancy refers to the degree to which students perceive Generative AI as easy to learn and use. A study reveals that when software is not very difficult to use, there are higher chances of its adoption. The most notable aspect of these GenAI tools is the use of natural language processing (NLP), which enables the user to engage in text conversations rather than struggle with the technical aspects (Karahan Adalı and Bilgili, 2025). This reduces the cognitive effort required to interact with the technology and encourages students to adopt it for academic purposes (Arhin et al., 2024). Based on these arguments, the following hypothesis is proposed:

> H2: Effort Expectancy is positively associated with Behavioral Intention to use GenAI.

Social influence and the quality of engagement

Social Influence represents the pressure students feel from others on how to engage with a system. In the Ghanaian educational system, institutional policies and lecturer attitudes are major determinants of how students interact with AI (Alasgarova and Rzayev, 2025). Peer pressure and the fear of being left behind also drive students toward AI adoption (Zheng et al., 2024). In addition to that, social cues, whether it is a mandatory environment or peer support, influence the individual's intention to use GenAI to improve learning outcomes (Venkatesh et al., 2003). Based on the arguments above, we suggest that:

> H3: Social Influence is positively associated with Behavioral Intention to use GenAI.

Digital learning anxiety as an interaction barrier

Anxiety associated with technology use has been examined across different generations of digital technologies, with recent research extending this examination to technology acceptance in higher education (Joshi et al., 2025). Earlier research conceptualized computer anxiety as involving cognitive, affective, and behavioral responses to computer use (Heinssen et al., 1987), while subsequent research examined anxiety associated specifically with Internet use (Joiner et al., 2007). More recently, this literature has extended to artificial intelligence. Wang and Wang (2022) developed an Artificial Intelligence Anxiety Scale that captures multiple dimensions of anxiety associated with AI, while Li and Huang (2020) further examined AI anxiety through an integrated fear acquisition perspective. In the present study, Digital Learning Anxiety is used in a more specific educational context to represent students' concerns when using GenAI for academic learning, including concerns about inappropriate academic decisions, inaccurate AI-generated information, dependence on GenAI, and possible academic penalties. DLA is therefore treated as a context-specific form of technology-related anxiety rather than as an entirely distinct anxiety construct.

Within the present study, Digital Learning Anxiety reflects students' fear, uncertainty, or discomfort associated with using Generative AI for learning, particularly concerns related to

academic integrity, dependence on AI, and the reliability of AI-generated outputs. Previous research suggests that perceived ease of interaction may be associated with lower technology-related anxiety (Sun and Lan, 2025). Consistent with this perspective, the present study examines whether Effort Expectancy is negatively associated with Digital Learning Anxiety. However, the trade-offs of AI interaction are unique. The fear of being penalized for academic misconduct creates a high level of digital anxiety, which acts as a barrier to adoption (Karal and Ozdemir, 2025). Even if a student recognizes the rational benefits of AI, this affective state can block their decision-making process (Kristandl, 2025). Accordingly, Digital Learning Anxiety is conceptualized as an affective mechanism through which students' perceptions of Generative AI influence their intention to use the technology. Based on this evidence, the following hypotheses were proposed:

> H4: Effort Expectancy is negatively associated with Digital Learning Anxiety.

> H5: Digital Learning Anxiety is negatively associated with Behavioral Intention to use GenAI.

> H6: Digital Learning Anxiety mediates the association between Effort Expectancy and Behavioral Intention.

Theoretical framework

This study is grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al. (2003), which remains one of the most influential frameworks for explaining individuals' acceptance and use of emerging technologies. UTAUT posits that users' behavioural intention is primarily determined by performance expectancy, effort expectancy, social influence, and facilitating conditions. Among these constructs, Performance Expectancy reflects the extent to which individuals believe that using a technology will enhance their task performance, whereas Effort Expectancy refers to the perceived ease associated with using the technology. Numerous studies have validated the explanatory power of UTAUT in predicting the adoption of educational technologies, including learning management systems, mobile learning platforms, and, more recently, Generative AI applications (Al-khresheh, 2024; Ma, 2025; Sun and Lan, 2025; Venkatesh et al., 2003).

Although UTAUT has demonstrated strong predictive ability across diverse technological contexts, recent evidence suggests that cognitive evaluations alone may not fully explain students' acceptance of Generative AI. Unlike conventional educational technologies, Generative AI introduces unique psychological concerns, including uncertainty regarding the accuracy of AI-generated responses, fear of academic misconduct allegations, overdependence on AI-generated content, and ethical concerns surrounding responsible AI use (Chen and Mokmin, 2024; Huang et al., 2024; Karahan and Bilgili, 2025; Karal and Özdemir, 2025). These findings indicate that students often evaluate Generative AI not only in terms of its usefulness and ease of use but also through emotional responses that influence their willingness to engage with the technology.

Emerging empirical studies have further demonstrated that anxiety associated with Generative AI negatively influences technology acceptance and learning engagement. For example, Karal and Özdemir (2025) reported that AI anxiety significantly reduced undergraduate students' acceptance of Generative AI, whereas Kristandl (2025) argued that AI-related anxiety represents a critical psychological barrier that should be incorporated into technology acceptance models. Similarly, Huang et al. (2024) found that students' emotional responses toward AI significantly influenced their learning experiences and willingness to adopt AI-supported educational tools. Collectively, these studies suggest that affective factors operate alongside traditional UTAUT constructs in explaining students' behavioural intention toward Generative AI.

Drawing upon this emerging evidence, the present study extends UTAUT by incorporating digital learning anxiety as a mediating construct linking Effort Expectancy and Behavioural Intention. The proposed model examines whether greater perceived ease of GenAI use is associated with lower Digital Learning Anxiety and whether lower anxiety, in turn, is associated with stronger Behavioral Intention. Including Digital Learning Anxiety alongside the UTAUT constructs therefore allows the model to consider both cognitive evaluations and affective responses associated with Generative AI acceptance.

The original UTAUT rather than UTAUT2 was adopted because the present study focuses on educational technology acceptance within an institutional learning context rather than consumer technology use. UTAUT2 was developed primarily to extend UTAUT to consumer technology use (Venkatesh et al., 2012), whereas the present study examines Generative AI within a higher-education setting. The model therefore concentrates on the UTAUT predictors most directly related to the study objectives: Performance Expectancy, Effort Expectancy, and Social Influence. Nevertheless, the omission of Facilitating Conditions means that the model does not directly account for differences in technological resources, institutional support, or access conditions, and this should be considered when interpreting the findings.

Conceptual framework

The study consists of five core constructs: Performance Expectancy, Effort Expectancy, Social Influence, Digital Learning Anxiety, and Behavioral Intention. As suggested in Figure 1, PE, EE, and SI are the independent drivers of Behavioral Intention to use GenAI.

Digital Learning Anxiety (DLA) is positioned as a mediating variable representing the affective dimension of the interaction process. While PE and SI are hypothesized to be positively associated with Behavioral Intention, Effort Expectancy (EE) is examined in relation to both Behavioral Intention and Digital Learning Anxiety. DLA is also examined in relation to students' intention to use the technology. The framework proposes that students' intention to use Generative AI is associated with both cognitive evaluations and affective responses, thereby providing a broader explanation of GenAI use intention in higher education. Control variables such as gender, academic level, prior Generative AI experience, device access, and English

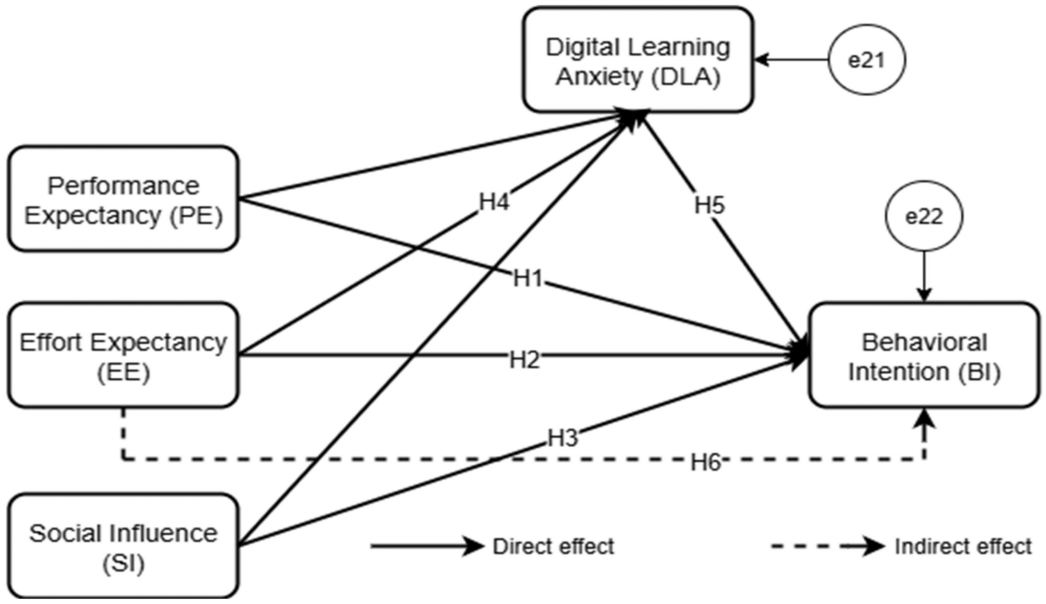

FIGURE 1
Conceptual framework (source: Authors' creation, 2025).

proficiency were not included in the structural model because the study was designed to test the theoretically specified UTAUT-Digital Learning Anxiety relationships rather than develop an adjusted explanatory model incorporating demographic and background characteristics. Nevertheless, these factors may be associated with the study constructs, and their omission means that potential unmeasured confounding cannot be ruled out. The reported relationships should therefore be interpreted as associations within the specified model rather than as effects independent of all possible background factors.

Methodology

Design

The study employed a quantitative approach using a cross-sectional survey design, with data analyzed through covariance-based structural equation modeling (CB-SEM). According to Creswell and Creswell (2018), a cross-sectional survey examines the relationship between constructs within a population at a precise time. Data were collected at a single point in time to examine the relationships among the study variables.

Population, sample size, and sampling techniques

The study targeted undergraduate students from the College of Humanities at the public university in Ghana, encompassing departments such as English, Linguistics, and Communication Studies, with a total population of 3,200. These students were selected because their academic coursework is conducted substantially in English and involves language-intensive academic activities. A total of 350 undergraduate students participated in the study. The sample size of 350 was considered adequate for the specified CB-SEM model, given the model's complexity and the number of observed indicators. SEM sample-size adequacy depends on factors such as model complexity, factor loadings, and estimation conditions rather than on a single universal sample-size rule (Wolf et al., 2013). With this approach, respondents who were available and willing to respond to the questionnaire were finally selected for the study (Sterner et al., 2024).

The questionnaire was administered in paper format during scheduled lecture sessions to maximize participation. A cover letter accompanied the questionnaire, detailing the objectives of the study, the criteria for qualification (university students using digital tools), and an assurance of anonymity and confidentiality. The data collection began on November 10, 2025, and ended on December 2, 2025. After 3 weeks of the data collection process, 350 questionnaires were appropriately filled out and used for the analysis. From Table 1, it was clear that Level 300 students dominated the study, constituting 41.1%, followed by Level 400 students with a percentage of 32.6%, and Level 200 students, who constituted 26.3%. Regarding gender, males constituted 54.3%, while females constituted 45.7%.

Questionnaire development

A structured questionnaire was utilized to collect the data. Although the measurement items were adapted from prior studies, we piloted the questionnaire to determine the necessity of clarifying any ambiguous statements, particularly regarding technical AI terminology. The study was pilot-tested on a sample of 30 students, of whom 10 students were randomly selected from different lecture groups. With their comments and suggestions, the questionnaire was amended and subsequently used for the main data collection.

TABLE 1 Demographics of university students.

Student background	Frequency (*N*)	Percentages (%)
Gender		
Male	190	54.3
Female	160	45.7
Level of University Students		
Level 200	92	26.3
Level 300	144	41.1
Level 400	114	32.6

TABLE 2 The reliability analysis.

Variables	Number of items	McDonald's Omega (ω)
Performance Expectancy (PE)	5	.964
Effort Expectancy (EE)	5	.969
Social Influence (SI)	5	.884
Digital Learning Anxiety (DLA)	5	.966
Behavioral Intention (BI)	5	.957

The questionnaire had three sections. Part A consisted of the basic demographics: gender, age, and university level. Part B contained items measuring the UTAUT constructs of Performance Expectancy, Effort Expectancy, and Social Influence. Items measuring these constructs were adapted from Venkatesh et al. (2003) and contextualized to GenAI-supported learning. The third part, Part C, contained items measuring Digital Learning Anxiety (DLA) and Behavioral Intention (BI). The DLA items were adapted from the identified literature on technology- and AI-related anxiety and contextualized to Generative AI-supported learning, while the BI items were adapted from Venkatesh et al. (2003). All items were measured on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The measurement items and their corresponding sources are presented in Appendix A.

Data validity and reliability

Content validity was first established through expert review. The suitability of the draft instrument was assessed by three senior researchers and two lecturers in the Department of English and Linguistics. This assessment was done to check whether the items of measurement sounded ambiguous, were appropriate for the research objectives with regard to Generative AI, and whether the statements were clear to university students. From their suggestions, minor adjustments in wording were made in the items measuring Digital Learning Anxiety to make them even clearer.

Following the assessment of content validity, statistical analysis through SPSS (v.23) was used to check the internal consistency of the constructs. Although Cronbach's alpha is widely reported, McDonald's Omega was adopted as the principal reliability coefficient because it provides a more robust estimate of internal consistency for latent variable models. As shown in Table 2, the reliability analysis was conducted for the five core constructs: performance expectancy (PE), effort expectancy (EE), social influence (SI), digital learning anxiety (DLA), and behavioral intention (BI). It can be observed that all constructs demonstrated high internal consistency, with values above the commonly recommended threshold of 0.70 (Hair et al., 2012). Effort Expectancy (EE) obtained the highest reliability ($\omega = .969$), followed by Digital Learning Anxiety ($\omega = .966$), Behavioral Intention ($\omega = .957$), and Performance Expectancy ($\omega = .964$). The lowest value, for Social Influence (SI), was still satisfactory at $\omega = .884$. These results indicate satisfactory internal consistency among the items measuring the five constructs.

Common method bias (CMB)

To minimize common method bias, procedural and statistical actions were taken (Podsakoff et al., 2003). Participants were assured of their anonymity and that their answers would be treated on a confidential basis to avoid social desirability bias. In addition, the questionnaire items were separated into different sections to reduce response pattern tendencies. The single questionnaire was divided into several sections, each consisting of the corresponding items. The first unrotated factor accounted for 43.24% of the total variance. However, because Harman's single-factor test provides only a limited diagnostic of common method bias, this result was not treated as conclusive evidence that common method bias was absent (Podsakoff et al., 2003). Although procedural remedies and Harman's single-factor assessment were used to assess the possibility of common method bias, Harman's test alone cannot conclusively establish the absence of such bias. Therefore, the results should not be interpreted as demonstrating that common method bias has been completely eliminated.

Exploratory factor analysis (EFA) and KMO and Bartlett's test

Exploratory Factor Analysis was conducted using the SPSS statistical package version 23. EFA was conducted to examine the underlying factor structure of the measurement items and to assess whether the observed variables loaded onto their intended latent constructs. EFA helps to uncover the possible link between the variables; it identifies the underlying dimensions that may not be clear. In EFA, it is recommended that the acceptable factor loading should be above the minimum of 0.5, as recommended by Marsh et al. (2020). In the study, Table 3 shows the Exploratory Factor Analysis, KMO, and Bartlett's Test.

From Table 3 above, the value of the Total Variance Explained at 83.853% indicates the percentage of variance in the data sets explained by the factors evident in the results of the factor analysis. It is very high and indicates a considerable amount of variance in the data sets being explained by the factors. A value of 0.936 (as in Table 3) presented by the KMO indicates the data are excellent for conducting a factor analysis. Additionally, Bartlett's Test of Sphericity was significant,

χ^2 (300) = 9897.785, $p < .001$, indicating that the correlation matrix differed significantly from an identity matrix and was therefore suitable for factor analysis. The KMO value of.936 further indicated excellent sampling adequacy for factor analysis. The EFA was conducted on the complete set of 25 measurement items, and the results supported a five-factor structure corresponding to the theoretical constructs of performance expectancy, effort expectancy, social influence, digital learning anxiety, and behavioral intention.

Confirmatory factor analysis (CFA)

Confirmatory Factor Analysis (CFA) was run in AMOS (v. 23) after EFA analysis. The measurement items that loaded onto their respective constructs were used to perform CFA analysis. After performing the CFA, we noticed that all the measurement items' loadings were above the minimum threshold of 0.5, as Hair et al. (2012) advised. Hair et al. (2019) Model fit criteria were taken into account to consider whether the measurement items used fit the model. Confirmatory Factor Analysis (CFA) is reported in Table 4. Figure 2 presents the confirmatory factor analysis model, illustrating the relationships between the latent constructs and their observed indicators.

Model fit measures

The chi-square test compares the observed covariance matrix with the covariance matrix implied by the specified model. Because the chi-square statistic is sensitive to sample size, it was interpreted alongside other model-fit indices. The CMIN/DF ratio was 1.729, which falls within the commonly reported favourable range of approximately 1–3. The Comparative Fit Index (CFI = .980) and Tucker–Lewis Index (TLI = .978) exceeded.95, indicating good comparative fit. The Standardized Root Mean Square Residual (SRMR = .019) was below.08, while the Root Mean Square Error of Approximation (RMSEA = .046) was below.08, indicating close model fit. The GFI (.901) and NFI (.955) also met their respective reported thresholds. Finally, the PClose value of.841 provides no evidence against close fit. Taken together, these indices indicate that the measurement model demonstrated good overall fit.

The results of the confirmatory factor analysis, including factor loadings, composite reliability (CR), and average variance extracted (AVE), are presented in Table 5. As shown in Table 5, all factor loadings exceeded the minimum acceptable threshold of 0.50, with the majority exceeding 0.70. The CR and AVE values further indicate satisfactory reliability and convergent validity. Although SI1 had a standardized loading of.654 in the CFA, it was retained because the loading exceeded the minimum acceptable threshold of.50 and the Social Influence construct demonstrated satisfactory composite reliability (CR = .887) and average variance extracted (AVE = .612). Its retention was therefore considered theoretically and psychometrically defensible.

Although the standardized CFA loading of SI1 (.654) was lower than those of the other Social Influence items, it exceeded the minimum acceptable loading of.50 and was therefore retained. Its retention was also supported by the satisfactory composite reliability (CR = .887) and average variance extracted (AVE = .612) of the Social Influence construct.

TABLE 3 Exploratory Factor Analysis (EFA) and KMO and Bartlett's Test

Rotated component matrix					
Measurement items	Component				
	1	2	3	4	5
PE1			.844		
PE2			.837		
PE3			.858		
PE4			.838		
PE5			.829		
EE1		.904			
EE2		.880			
EE3		.898			
EE4		.896			
EE5		.891			
DLA1	.903				
DLA2	.925				
DLA3	.889				
DLA4	.921				
DLA5	.893				
BI1				.854	
BI2				.835	
BI3				.865	
BI4				.838	
BI5				.837	
SI1					.710
SI2					.824
SI3					.784
SI4					.845
SI5					.801
KMO and Bartlett's Test					
Total variance explained					83.853
Kaiser-Meyer-Olkin measure of sampling Adequacy					.936
Bartlett's Test of Sphericity	Approx. Chi-Square				9897.785
	df				300
	Sig.				<.001
Determinant					2.244E-13

Discriminant validity analysis

Discriminant validity was initially assessed using the Fornell–Larcker criterion by comparing the square root of the AVE for each construct with its correlations with the other constructs

TABLE 4 The model fit indices.

Measures	Estimates	Standard	Interpretation	Source
CMIN	458.125	The smaller, the better	——	—
DF	265	The smaller the better	——	—
CMIN/DF	1.729	Between 1 and 3	Close fit	Xia and Yang (2019)
TLI	.978	> 0.95	Close fit	Hu et al. (1999)
CFI	.980	> 0.95	Close fit	Marsh et al. (2020)
NFI	.955	> 0.90	Close fit	Hair et al. (2019)
GFI	.901	> 0.90	Acceptable fit	Hair et al. (2012)
RMSEA	.046	< 0.08	Close fit	Hu et al. (1999)
PClose	.841	> 0.05	Close fit	Hu et al. (1999)
SRMR	.019	< 0.08	Good fit	Marsh et al. (2025)

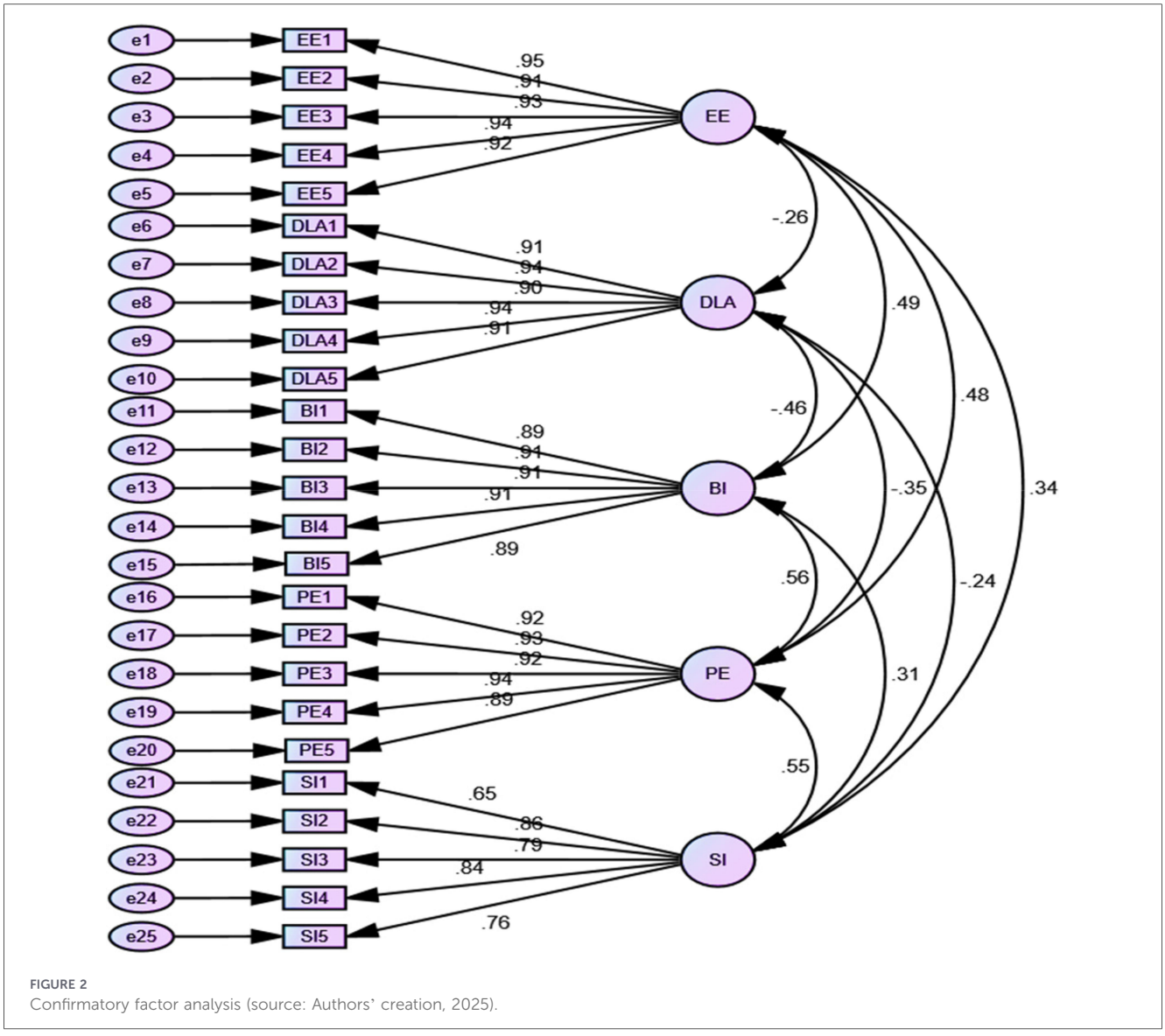

FIGURE 2
Confirmatory factor analysis (source: Authors' creation, 2025).

TABLE 5 Confirmatory factor analysis (CFA).

Items	Loadings
Performance Expectancy (PE); CR = .964; AVE = .844	
PE1: I find GenAI useful in my language learning studies.	.923
PE2: Using GenAI improves the quality of my language learning outcomes.	.926
PE3: Using GenAI enables me to accomplish language tasks more quickly.	.920
PE4: Using GenAI increases my productivity in writing academic essays.	.936
PE5: If I use GenAI, I will increase my chances of getting a better grade.	.887
Effort Expectancy (EE): CR = .969; AVE = .861	
EE1: My interaction with GenAI is clear and understandable.	.948
EE2: It is easy for me to become skillful at using GenAI tools.	.905
EE3: I find GenAI tools flexible to interact with during my learning tasks.	.927
EE4: I find GenAI tools easy to use.	.936
EE5: Learning to operate GenAI is easy for me.	.924
Social Influence (SI): CR = .887; AVE = .612	
SI1: People who are important to me expect me to use GenAI in my studies.	.654
SI2: People who influence my behavior think that I should use GenAI.	.858
SI3: My lecturers have been helpful in the use of GenAI.	.789
SI4: In general, the university has supported the use of GenAI.	.835
SI5: My peers think it is a good idea to use GenAI for studies.	.760
Digital Learning Anxiety (DLA); CR = .966; AVE = .849	
DLA1: I am afraid of being penalized or labeled a cheat for using GenAI.	.911
DLA2: I feel anxious about making inappropriate academic decisions when using GenAI.	.938
DLA3: I feel uneasy relying on GenAI because it may provide incorrect or misleading information	.904
DLA4: I worry that my results might be held back due to suspicions of AI use.	.943
DLA5: I feel stressed when I have to depend on GenAI for important academic tasks.	.912
Behavioral Intention (BI): CR = .957; AVE = .816	
BI1: I intend to use GenAI in my language learning tasks in the future.	.892
BI2: I predict I will use GenAI frequently in my academic work.	.909
BI3: I plan to use GenAI tools for my studies as much as possible.	.912
BI4: I am willing to integrate GenAI into my daily study routine.	.914
BI5: I will use GenAI to help bridge the gap in my language proficiency.	.891

(Fornell and Larcker, 1981). As shown in Table 6, the square root of each construct's AVE exceeded its correlations with the other constructs. The largest inter-construct correlation was.557 between Performance Expectancy and Behavioral Intention, whereas the smallest square root of AVE was.783 for Social Influence. These results provide evidence of discriminant validity among the constructs.

Discriminant validity was further assessed using the heterotrait–monotrait ratio (HTMT). As shown in Table 7, the HTMT values ranged from .239 to.554, with all values below the conservative threshold of.85. The highest HTMT values were observed between PE and BI (.554) and between PE and SI (.554). These results provide further evidence of adequate discriminant validity among the five constructs (Henseler et al., 2015).

Path results

A covariance-based structural equation modeling (CB-SEM) run in AMOS (v. 23) was used to estimate the various hypothesized paths. CB-SEM is particularly useful for testing theoretical models that allow researchers to specify and test the complex bond between observed and latent variables, ensuring its suitability for hypothesis testing. The estimate was performed using the Bias-Corrected (BC) percentile technique of bootstrapping, using 5,000 bootstrap samples with a 95% confidence interval. The hypothesized results are presented in Table 8 and Figure 3.

Research results

> H1: Performance Expectancy is positively associated with students' Behavioral Intention to use GenAI

Hypothesis 1 (H1) suggested that performance expectancy (PE) will positively influence students' behavioral intention (BI) to use Generative AI. This shows that the more students perceive GenAI as a means to enhance their academic performance, the more likely they are to use it. The results showed a significant positive association between Performance Expectancy and Behavioral Intention (B = .343, SE = .044, β = .377, CR = 7.772, $p < .001$), providing support for H1.

> H2: Effort Expectancy has a positive influence on Behavioral Intention towards the use of GenAI.

Hypothesis two (H2) suggested that the greater the perceived ease of use (Effort Expectancy), the higher the behavioral intention. The results showed a significant positive association between Effort Expectancy and Behavioral Intention (B = .225, SE = .037, β = .281, CR = 6.087, $p < .001$), providing support for H2.

> H3: Social Influence has a direct positive influence on Behavioral Intention to use GenAI.

TABLE 6 Discriminant validity.

Variables	CR	AVE	EE	DLA	BI	PE	SI
EE	0.969	0.861	***0.928***				
DLA	0.966	0.849	−0.261***	***0.922***			
BI	0.957	0.816	0.491***	−0.455***	***0.903***		
PE	0.964	0.844	0.477***	−0.345***	0.557***	***0.919***	
SI	0.887	0.612	0.340***	−0.240***	0.306***	0.548***	***0.783***

***Denotes a p-value less than the 1% significance level; $\sqrt{AVE}$ Values are in bold and italic.

TABLE 7 HTMT discriminant validity.

Construct	PE	EE	DLA	BI	SI
PE	—				
EE	.475	—			
DLA	.351	.261	—		
BI	.554	.491	.459	—	
SI	.554	.342	.239	.307	—

TABLE 8 Path summary.

Direct effect	B	S.E.	β	C.R.	p-value
PE → BI	.343	.044	.377	7.772	<.001
EE → BI	.225	.037	.281	6.087	<.001
SI → BI	−.037	.046	−.038	−.818	.413
EE → DLA	−.108	.045	−.126	−2.379	.017
DLA → BI	−.263	.045	−.281	−5.801	<.001
Indirect effect	β		L.B	U.B	p-value
EE→DLA→BI	.035		0.030	.099	<.001

Hypothesis three (H3) proposed that Social Influence would be positively associated with Behavioral Intention. The structural model showed that Social Influence was not significantly associated with Behavioral Intention (B = −.037, SE = .046, β = −.038, CR = −.818, p = .413). Therefore, H3 was not supported. The non-significant association indicates that Social Influence did not explain additional variation in Behavioral Intention within the specified structural model. Further research is needed to determine why Social Influence was not significantly associated with Behavioral Intention in this sample.

> H4: Effort Expectancy is negatively associated with Digital Learning Anxiety.

The study also examined the affective dimensions of the interaction. Hypothesis four (H4) suggests that Effort Expectancy would have a direct negative impact on Digital Learning Anxiety (DLA). The results showed a significant negative association between Effort Expectancy and Digital Learning Anxiety (B = −.108, SE = .045, β = −.126, CR = −2.379, p = .017), providing support for H4.

> H5: Digital Learning Anxiety is negatively associated with Behavioral Intention to use GenAI.

Furthermore, Hypothesis five (H5) stated that Digital Learning Anxiety negatively affects Behavioral Intention. The results showed a significant negative association between Digital Learning Anxiety and Behavioral Intention (B = −.263, SE = .045, β = −.281, CR = −5.801, p < .001), providing support for H5.

> H6: Digital Learning Anxiety mediates the relationship between Effort Expectancy and Behavioral Intention.

Using bootstrapping, the indirect association was statistically significant [95% CI (.030, .099), p < .001]. This indicates a significant indirect association between Effort Expectancy and Behavioral Intention through Digital Learning Anxiety. However, because the data were collected at a single point in time, this indirect relationship should be interpreted as an indirect statistical association consistent with the hypothesized mediation model rather than evidence of a causal process. The magnitude of the indirect association was small relative to the direct association between Effort Expectancy and Behavioral Intention. The indirect association accounted for approximately 11.1% of the total association (VAF = 11.1%), indicating that most of the modeled Effort Expectancy-Behavioral Intention association was represented by the direct path rather than the indirect pathway through Digital Learning Anxiety.

Discussion

This study examined the associations of traditional UTAUT constructs and Digital Learning Anxiety with university students' intention to use Generative AI. The findings showed that Performance Expectancy and Effort Expectancy were positively associated with Behavioral Intention, whereas Digital Learning Anxiety was negatively associated with Behavioral Intention. Social Influence was not significantly associated with Behavioral Intention. These findings provide context-specific evidence that both cognitive evaluations and affective responses are relevant to understanding students' intention to use GenAI. Among the predictors examined, Performance Expectancy had the largest positive standardized association with Behavioral Intention. This finding indicates that students primarily evaluate Generative AI based on its perceived ability to improve their academic performance. This finding is consistent with the original UTAUT model, which identifies performance

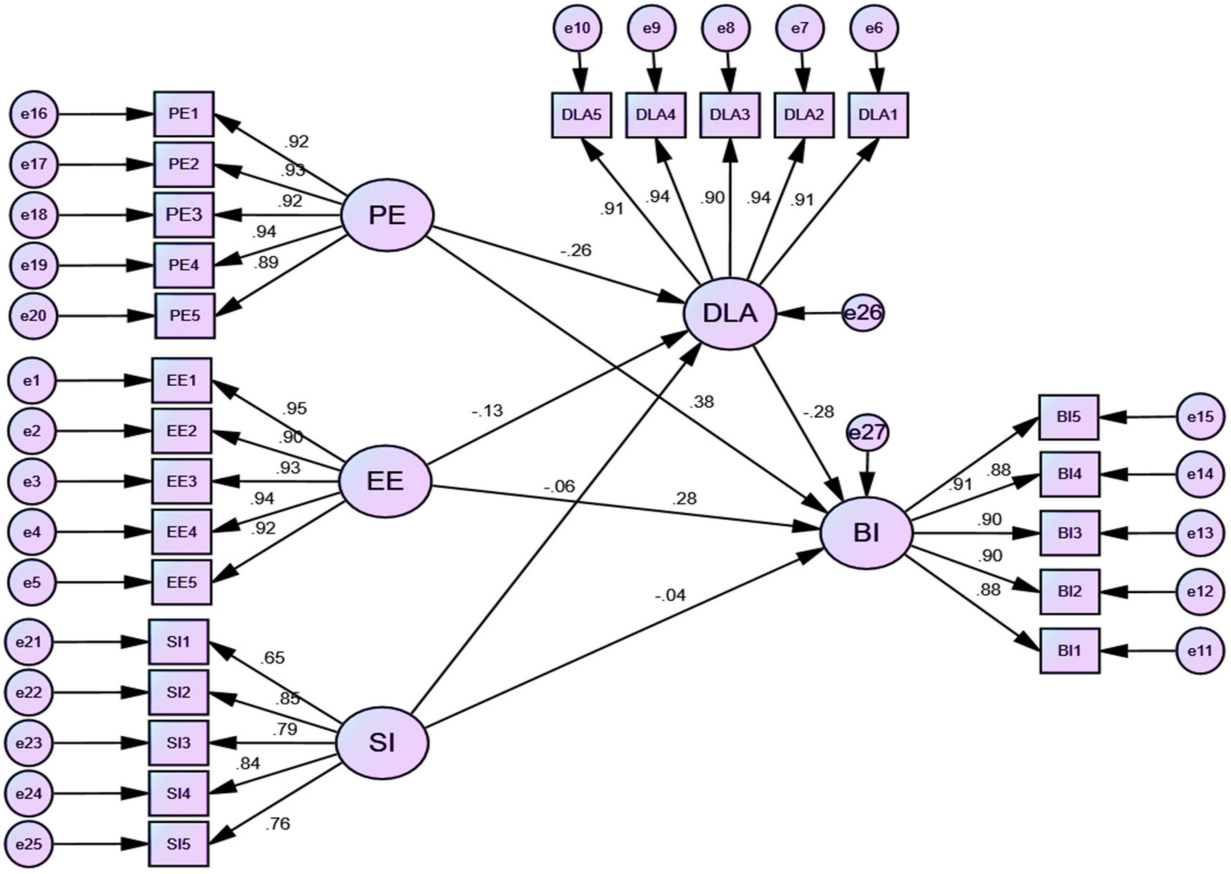

FIGURE 3
Path analysis (source: Authors' creation, 2025).

expectancy as the strongest determinant of technology adoption (Venkatesh et al., 2003). The present study extends this evidence to Generative AI within a Ghanaian higher-education context, suggesting that students primarily consider the perceived educational value of GenAI when forming their intention to use it. This reinforces the argument that students evaluate AI according to its educational value and contribution to learning outcomes. Regarding language learning, Matthews (2024) argued that interaction becomes more fluid for students who view AI as a cognitive partner that assists with outlines or syntax.

Furthermore, the significant positive association of Effort Expectancy suggests that the nature of the interaction is defined by its accessibility. The natural language processing (NLP) abilities of large language models allow for a plug-and-play experience that is far simpler than traditional Learning Management Systems (LMS), which often require technical training (Karahan and Bilgili, 2025). Furthermore, the significant positive association between Effort Expectancy and Behavioral Intention suggests that perceived ease of interaction is relevant to students' intention to use GenAI. The natural-language interface of many GenAI systems may make interaction more accessible than technologies requiring greater technical familiarity. However, the present study did not directly compare GenAI with other educational technologies.

Contrary to the original UTAUT model, Social Influence was not significantly associated with Behavioral Intention. This finding suggests that Social Influence did not explain additional variation in students' intention to use GenAI after the other predictors in the model were considered. The finding differs from the traditional UTAUT proposition that social influence contributes to technology acceptance (Venkatesh et al., 2003). However, the present study did not examine the specific social circumstances surrounding students' GenAI use. Therefore, the reason for the non-significant relationship cannot be established from the present data. Future research could examine how lecturer expectations, peer influence, institutional norms, and students' patterns of GenAI use may help explain the role of Social Influence in GenAI acceptance.

A key finding of this study was the significant negative association between Digital Learning Anxiety and students' intention to use Generative AI (H5). Effort Expectancy was also negatively associated with Digital Learning Anxiety (H4), indicating that students who perceived GenAI as easier to use tended to report lower levels of anxiety. These findings are consistent with Karal and Özdemir (2025) and Kristandl (2025), who identified AI-related anxiety as relevant to students' engagement with Generative AI. However, the cross-sectional nature of the present data does not establish the direction or causal nature of these relationships. The mediation analysis showed that lower Effort Expectancy was associated with higher Digital Learning Anxiety, while higher Digital Learning Anxiety was associated with lower Behavioral Intention. The indirect

association was statistically significant but small; however, the cross-sectional design does not establish temporal ordering or causality among these variables.

Theoretical implications

The findings contribute to research on GenAI acceptance by showing that affective responses may be considered alongside traditional UTAUT constructs. Performance Expectancy and Effort Expectancy were positively associated with Behavioral Intention, whereas Digital Learning Anxiety was negatively associated with Behavioral Intention. Social Influence, however, did not explain additional variation in Behavioral Intention within the specified structural model. These findings suggest that models of GenAI acceptance may benefit from considering students' affective responses alongside their evaluations of usefulness and ease of use.

The significant indirect association between Effort Expectancy and Behavioral Intention through Digital Learning Anxiety also provides evidence for examining affective processes alongside UTAUT predictors. However, this indirect association was small, accounting for approximately 11% of the total association between Effort Expectancy and Behavioral Intention. Most of the association was therefore direct. Moreover, because the variables were measured at the same point in time, the indirect association should not be interpreted as evidence that Effort Expectancy causes changes in Digital Learning Anxiety or that anxiety subsequently causes changes in Behavioral Intention.

Practical implication

The findings suggest some practical considerations that may be examined further in the design of GenAI-supported learning environments. Given the positive association between Performance Expectancy and Behavioral Intention, universities may consider helping students understand the potential academic uses and limitations of GenAI. Similarly, the associations involving Effort Expectancy and Digital Learning Anxiety suggest that accessible guidance and opportunities to become familiar with GenAI may be worth investigating as possible ways of supporting students' engagement with these technologies. Universities may also consider providing low-stakes opportunities in which students can explore appropriate uses of GenAI and receive guidance on academic integrity and responsible use. However, the present cross-sectional findings do not demonstrate that such interventions will increase GenAI adoption or reduce anxiety. These suggestions should therefore be treated as design hypotheses that require evaluation through experimental, longitudinal, or intervention-based research.

Conclusion

This study examined the cognitive and affective factors associated with university students' intention to use Generative AI by extending the UTAUT framework with Digital Learning Anxiety. The data are quantitative, cross-sectional in design, and come from structured questionnaires administered to 350 undergraduate students from Ghana. In testing the set of proposed pathways and nuanced links that exist between cognitive and emotional factors, Covariance-Based Structural Equation Modeling was employed. This study contributes to AI in education by providing an empirically supported model that integrates both cognitive and affective factors associated with students' intention to use Generative AI. The findings showed that perceived usefulness and ease of use were positively associated with Behavioral Intention, whereas Digital Learning Anxiety was negatively associated with Behavioral Intention. The findings indicate that students' intention to use Generative AI is associated with both their evaluations of the technology and their psychological responses to its use. Although Digital Learning Anxiety was significantly associated with Behavioral Intention, the indirect association between Effort Expectancy and Behavioral Intention through Digital Learning Anxiety was comparatively small. The findings therefore suggest that Effort Expectancy was associated with Behavioral Intention primarily through its direct relationship, with a smaller indirect association through Digital Learning Anxiety. This study offers a context-specific contribution to understanding human-AI interaction in developing educational systems and provides a foundation for further research on GenAI acceptance in Ghanaian higher education.

Limitations

Despite its contributions, this study has several limitations. First, the cross-sectional design does not permit the establishment of long-term causal relationships. Because Effort Expectancy, Digital Learning Anxiety, and Behavioral Intention were measured at the same point in time, the indirect relationship identified in the model does not establish temporal or causal mediation. Reverse relationships and unmeasured factors that may influence these constructs cannot be ruled out. Accordingly, the observed indirect association may also reflect alternative directional relationships or common causes that were not included in the model. Additionally, because all measures were collected using self-reported responses, the findings may be influenced by respondents' subjective perceptions. Although statistical procedures were employed to assess the validity and reliability of the measurement model, future studies may benefit from combining survey data with behavioral or observational measures of AI usage. The use of convenience sampling also limits the representativeness of the sample. Because participants were recruited during scheduled lecture sessions, students who were absent during data collection were less likely to be represented. The findings should therefore not be generalized to all university students in Ghana without caution. The structural model did not include potential control variables such as gender, university level, prior GenAI experience, device access, or English proficiency. Some of these factors may be associated with students' perceptions of GenAI, Digital Learning Anxiety, and Behavioral Intention. Consequently, the observed relationships may partly reflect unmeasured confounding, and future studies should examine the robustness of these associations after accounting for relevant demographic, technological, and language-related characteristics.

Although the study was conducted among university students in an English-medium academic setting and the questionnaire included items contextualized to language-related academic activities, English proficiency and L2-specific psychological constructs were not directly measured. The findings should therefore not be interpreted as evidence that the observed relationships are specifically attributable to students' English proficiency or L2-related anxiety. Again, the rapidly evolving nature of generative AI limits the temporal stability of the findings. By targeting humanities students in one academic setting, it becomes difficult to establish the effectiveness in other disciplines, such as STEM. Moreover, the convenience sampling approach may have introduced selection bias because participation depended on students' availability and willingness to respond. Finally, the quantitative design did not permit an in-depth exploration of students' lived experiences when interacting with Generative AI. Future qualitative studies could provide richer insights into these experiences.

Suggestions for further research

Future studies could extend the framework by examining additional factors such as Academic Integrity Awareness and investigating whether the observed relationships differ across academic disciplines. Longitudinal research could examine how students' AI-related anxiety and acceptance change as their experience with GenAI develops over time. Qualitative research may also provide deeper insight into the social and institutional factors associated with students' decisions to use GenAI. Finally, empirical studies examining the effects of GenAI-supported learning on students' actual academic performance and AI-use behaviour would provide a more balanced understanding of its educational implications.

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 University of Skills Training and Entrepreneurial Development (USTED). 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. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

ID: Writing – original draft, Methodology, Conceptualization. BA: Writing – review & editing, Supervision, Validation, Formal analysis. FB: Conceptualization, Writing – review & editing, Methodology. EB: Formal analysis, Methodology, Writing – original draft, Conceptualization.

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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 not used in the creation of this manuscript.

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Appendix A

Instrument items and sources.

Item	Measurement item	Source
Performance Expectancy (PE): Confirmatory factor analysis: CR = .964; AVE = .844.		
PE1	I find GenAI useful in my language learning studies.	Venkatesh et al. (2003)
PE2	Using GenAI improves the quality of my language learning outcomes.	Venkatesh et al. (2003)
PE3	Using GenAI enables me to accomplish language tasks more quickly.	Venkatesh et al. (2003)
PE4	Using GenAI increases my productivity in writing academic essays.	Venkatesh et al. (2003)
PE5	If I use GenAI, I will increase my chances of getting a better grade.	Venkatesh et al. (2003)
Effort Expectancy (EE): Confirmatory factor analysis: CR = .969; AVE = .861.		
EE1	My interaction with GenAI is clear and understandable.	Venkatesh et al. (2003)
EE2	It is easy for me to become skillful at using GenAI tools.	Venkatesh et al. (2003)
EE3	I find GenAI tools flexible to interact with during my learning tasks.	Venkatesh et al. (2003)
EE4	I find GenAI tools easy to use.	Venkatesh et al. (2003)
EE5	Learning to operate GenAI is easy for me.	Venkatesh et al. (2003)
Social Influence (SI); Confirmatory factor analysis: CR = .887; AVE = .612.		
SI1	People who are important to me expect me to use GenAI in my studies.	Venkatesh et al. (2003)
SI2	People who influence my behavior think that I should use GenAI.	Venkatesh et al. (2003)
SI3	My lecturers have been helpful in the use of GenAI.	Venkatesh et al. (2003)
SI4	In general, the university has supported the use of GenAI.	Venkatesh et al. (2003)
SI5	My peers think it is a good idea to use GenAI for studies.	Venkatesh et al. (2003)
Digital Learning Anxiety (DLA); Confirmatory factor analysis: CR = .966; AVE = .849.		
DLA1	I am afraid of being penalized or labeled a cheat for using GenAI.	Ding and Xue (2025)
DLA2	I feel anxious about making inappropriate academic decisions when using GenAI.	Ding and Xue (2025)
DLA3	I feel uneasy relying on GenAI because it may provide incorrect or misleading information.	Ding and Xue (2025)
DLA4	I worry that my results might be held back due to suspicions of AI use.	Ding and Xue (2025)
DLA5	I feel stressed when I have to depend on GenAI for important academic tasks.	Ding and Xue (2025)
Behavioral Intention (BI); Confirmatory factor analysis: CR = .957; AVE = .816.		
BI1	I intend to use GenAI in my language learning tasks in the future.	Venkatesh et al. (2003)
BI2	I predict I will use GenAI frequently in my academic work.	Venkatesh et al. (2003)
BI3	I plan to use GenAI tools for my studies as much as possible.	Venkatesh et al. (2003)
BI4	I am willing to integrate GenAI into my daily study routine.	Venkatesh et al. (2003)
BI5	I will use GenAI to help bridge the gap in my language proficiency.	Venkatesh et al. (200 3)