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Generative AI Competence and Student Engagement in Higher Education: Mediating Roles of Utilization, Autonomy, and Formal Learning

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ABSTRACT

Purpose *- This study investigates university students' competence in and engagement with Generative AI applications by analyzing usage, perceived autonomy, and AI formal learning as predictive mediators. An integrated theoretical model is developed to clarify the drivers of engagement in AI-enhanced learning environments.*
Design/methodology/approach *– The study used a cross-sectional survey design conducted in July 2024 to collect data from 262 students across various disciplines. An online survey collected data from a convenience sample of undergraduate students.*
Findings: *Analysis conducted using PLS-SEM revealed that GenAI competence is*

a powerful, direct driver of students' engagement ($\beta = 0.255$, $p < 0.001$), accounting for 64.5% of its variance ($R^2 = 0.645$), with a small to medium effect size ($f^2 = 0.117$). This relationship is significantly mediated through three distinct pathways: GenAI utilization ($\beta = 0.155$, $p < 0.001$), perceived autonomy ($\beta = 0.121$, $p = 0.005$), and AI formal learning ($\beta = 0.092$, $p = 0.005$). The model's strong predictive relevance ($Q^2 = 0.436$) confirms its utility for forecasting outcomes. These results validate the integrated theoretical model, demonstrating that engagement is driven by an interconnected system of competence, behaviour, autonomy, and institutional training rather than skill alone.
Practical implications *- This study offers insightful insights on factors impacting the uptake of Generative AI conversational bots. To ensure effective Generative AI adoption, institutions must integrate competencies such as prompt engineering and ethical AI assessment into educational curricula to enhance learning outcomes.*
Originality/value *– This study introduces the first integrated mediation model of GenAI competence and student engagement in a Ghanaian context, moving beyond adoption-focused research to explain engagement through psychological, behavioural, and institutional mechanisms. This contributes to theory by extending SDT, UTAUT/TAM, and UGT into a unified explanatory framework for AI-enabled learning engagement.*

Keywords: AI formal learning; Educational implications; GenAI competence; GenAI utilization; Perceived autonomy; Students' engagement

INTRODUCTION

The latter half of 2022 and early 2023 have seen the emergence of teaching and learning using Generative Artificial Intelligence (GenAI) tools (Law, 2024; Chugh et al., 2025; Al-Zahrani, 2024; Hsu & Ching, 2023; Kalota, 2024). The intention of improving learning outcomes and student engagement (Rudolph et al., 2024; Dhamija & Dhamija, 2024) has propelled the widespread adoption of artificial intelligence (AI) and chatbots in educational contexts (Kelly et al., 2023). A specific area of interest in this sphere is the concept of GenAI competence, which concerns the effective use of AI tools in formal learning environments (Ghimire, 2024). ChatGPT, and similar GenAI tools like Google Bard, Midjourney, Copilot, Perplexity AI, YouChat, Bing AI, Claude 3, Google Gemini, Inflection Pi, Quill

Bot, and Fireflies.ai, are among the GenAI tools commonly used by students. Despite the growing use of AI in education, a significant knowledge gap persists regarding how GenAI competence influences student engagement (de la Torre & Baldeon-Calisto, 2024). Additionally, the role of perceived autonomy and AI-based formal learning as mediators in this relationship remains underexplored.

This study seeks to fill these critical gaps by developing and testing an integrated theoretical model. A key contribution lies in simultaneously examining the mediating roles of GenAI utilization, perceived autonomy, and AI formal learning in the relationship between GenAI competence and student engagement. While previous research has often examined these variables in isolation, e.g., Ghimire (2024) on competence, Chiu (2021) on autonomy, and Rudolph et al. (2024) on engagement, the model provides a more holistic understanding of their interdependencies. Furthermore, a contextual contribution is made by focusing on the under-researched population of university students, offering valuable insights from a non-Western educational setting. The findings are expected to provide educators and policymakers with an evidence-based framework for effectively integrating GenAI into teaching and learning practices.

There is a growing curiosity about the effects of GenAI on schooling and assessment design. Diverse reactions to the emergence of GenAI have been expressed by academic professionals worldwide. According to Sullivan et al. (2023) and Caling et al. (2025), these responses range from outright prohibitions on GenAI tool usage to permitting their utilization with proper attribution. Recent scholarship continues to highlight the evolving role of GenAI in higher education. For instance, Peterson (2025) examined integrity frameworks for managing student use of GenAI, while Sozon et al. (2025) evaluated both benefits and challenges of adoption, emphasizing implications for engagement and autonomy.

Since the advent of generative AI, researchers have been developing conversational AI interfaces using large language models (LLMs), machine learning, and natural language processing (NLP). Higher education now has a new area of study as a result of this (Essel et al., 2022; 2024). Most tertiary educational institutions now focus on improving their students' digital competencies to better equip them for the industry. Students who possess these competencies are better prepared to manage daily work tasks. The extensive development of digital competencies among higher-education students has intrinsic value, benefiting them throughout their academic journey and beyond, as they enter the workforce. Eke (2023) defines GenAI as systems that are 'designed to generate content or output such as text, images, audio, simulations, video, and code from the data the system is trained on'. Olga et al. (2023) added that the output of GenAI is deemed to be coherent and well-formed text, images, and sound generated in new designs. In the context of this research, GenAI tools refer to a diverse array of AI technologies and techniques used to generate new knowledge and insights. Digital literacy empowers students to leverage digital tools, including Massive Open

Online Courses (MOOCs), social networking platforms, video streaming services, and Internet of Things (IoT) devices, to enhance their learning experience (Bennett & McWhorter, 2023). It can be suggested that students feel more engaged and motivated because the digital environment encourages and fosters autonomous learning (Chiu, 2021). Autonomous learning can enhance students' motivation and encourage them to participate in more learning activities (Masouleh & Jooneghani, 2012). Learner autonomy is a trend in education that emphasizes students' engagement in their own learning. Holec (1981), regarded as the founder of autonomous learning, was quoted by Uslu and Durak (2022) as saying that it is "the ability to take charge of one's learning". This asserts that a person has control over their learning plan, timetable, and other aspects of learning, hence encouraging self-motivation, self-awareness, self-control, independence, and active learning strategies.

This study aims to explore the relationships among student engagement, GenAI competence, AI formal learning, perceived autonomy, and mechanisms of GenAI use. The study model investigates how GenAI competence affects its utilization, perceived autonomy, and AI formal learning. It also explores how the mediating role of GenAI utilization, perceived autonomy, and AI formal learning affects students' engagement. Furthermore, the model distinguishes between different types of outcomes, i.e., utilization, autonomy, and AI formal learning. By putting this integrated model into practice, the study aims to clarify the interactions among variables that influence the uptake and use of GenAI in learning environments. Moreover, by offering well-informed, evidence-based guidance for its successful integration into academic contexts, the study hopes to contribute to the growing body of knowledge on GenAI's educational implications.

LITERATURE REVIEW

Globally, research on Generative AI in education has coalesced around several key themes. A prominent strand of literature investigates predictors of adoption and behavioral intentions. Studies frequently employ the established technology acceptance model to understand user motivation (Venkatesh et al., 2003; Davis, 1989). Furthermore, a significant body of work examines GenAI's impact on learning processes, demonstrating its efficacy in enhancing student engagement and achievement (Liang et al., 2023; Yang et al., 2024). For instance, while Liang et al. (2023) identify self-efficacy and cognitive engagements as critical mediators, Yang et al. (2024) highlight the fundamental role of student autonomy in maximizing GenAI's utility. Complementing these findings, Batista et al. (2024) conducted a systematic literature review that mapped trends, challenges, and future directions of GenAI in higher education, reinforcing the importance of competence, autonomy, and institutional support in shaping engagement outcomes. Beyond student-focused outcomes, research has also examined institutional and educator perspectives. Collie (2024) and Dhamija & Dhamija (2024), for example, elaborated on the significance of contextual and leadership factors in predicting educators' engagement with GenAI for professional development. These findings suggest that GenAI's effectiveness is shaped not only by technological capabilities but also by psychological factors such as self-efficacy and autonomy, behavioral intentions, and the presence of supportive contextual systems.

These global conversations are complemented by a growing body of research within the Ghanaian higher educational context. Recent seminal work has begun to rigorously model the factors influencing AI adoption among Ghanaian students and educators. For example, studies have successfully applied hybrid modeling techniques to understand economics students' behavioral intention and usage of ChatGPT (Salifu et al., 2024) and to model the relationship between ChatGPT use and academic performance through the lens of Self-Determination Theory (Acquah et al., 2025). Further research has identified key predictors of behavioral intention, including the moderating role of demographic factors such as age and gender (Arthur et al., 2025), and has extended this inquiry to pre-service teachers' intentions to use AI in lesson planning (Acquah et al., 2024). These Ghanaian studies provide a strong foundation confirming that international models of technology acceptance hold true in this specific context and offering critical insights into user profiles most likely to adopt GenAI tools.

Despite these significant contributions, a critical gap remains. The existing literature, both global and within Ghana, has primarily focused on direct relationships, predicting user intention or correlating usage with performance. However, the interrelationships among learner competence, GenAI utilization, perceived autonomy in the learning process, engagement in formal AI learning, and overall engagement remain largely unexplored, particularly in the Ghanaian context. While Hidayat-Ur-Rehman (2024) touches on similar variables, a comprehensive, model-driven integration of these constructs into a single system is absent. The question of how GenAI competence translates into heightened engagement through the mediating mechanisms of utilization, autonomy, and formal learning remains to be empirically answered. The study aims to fill this gap by developing and testing an integrated model linking these constructs. By applying the PLS-SEM analysis to data from a university context, this study provides a comprehensive understanding of the psychological and behavioural mechanisms that drive successful GenAI integration. It moves beyond the question of "if" students use AI to explore "how" their use leads to deeper engagement, thereby offering educators and policymakers a framework for implementation.

GenAI Competence and Students' Engagement

This investigation aims to explore the relationship between students' ability to effectively use generative AI tools and their involvement in the learning process. GenAI competence refers to a student's knowledge, skill, and efficacy in leveraging GenAI applications to achieve academic goals. It goes beyond familiarity and access to include the ability to craft effective prompts, critically evaluate AI-generated outputs, and meaningfully incorporate these outputs into learning tasks (Ghimire, 2024; Essel et al., 2024). In the context of Self-Determination Theory (SDT), GenAI competence directly fulfills an essential psychological need: the desire to feel effective and to master challenging tasks (Deci & Ryan, 1985). A student high in GenAI competence is not just a user but an adept strategist, capable of harnessing AI to enhance their learning. The intended outcome of this competence is improved engagement, a complex construct that describes the energy, effort, and connection invested in educational activities (Fredricks et al., 2004; Fredricks & McColskey, 2012). It includes behavioural engagement, which involves participation and effort in academic tasks, such as using GenAI to complete assignments and engage with content; emotional engagement, which refers to the emotional response to learning and the university environment, fostering feelings of interest, motivation, and reduced anxiety through AI support; and cognitive engagement, which involves investing in deep learning and mastering complex ideas, such as using GenAI to explore topics beyond the curriculum, critique arguments, and synthesize information.

Emerging empirical evidence indicates a strong positive link between AI literacy and student engagement. Studies show that students proficient with AI tools report higher motivation levels and are more actively involved in their learning (Liang et al., 2023; Yang, 2024). For example, GenAI Competence can motivate students by making learning more interactive and accessible, thus boosting behavioural engagement. It can also enhance cognitive engagement by offering instant feedback and scaffolding for complex problems, enabling students to approach more challenging material with confidence (Kasneci et al., 2023). However, the mechanism through which competence translates into engagement is not automatic. It is unlikely that competence alone directly causes engagement; rather, its effect is probably mediated by key psychological and behavioural processes. A student may be highly competent in using GenAI; however, without a sense of desire, such as autonomy, practical opportunities to use it, or a supportive learning structure, that competence may not lead to deeper engagement. Building on this, Deroncele-Acosta et al. (2026) highlighted how GenAI fosters transversal competencies such as critical thinking, autonomy, and collaboration, reinforcing the mediating role of competence in student engagement.

This led to the proposal of the first direct hypothesis:

H1: GenAI competence has a positive direct effect on student engagement.

Mediating Role of GenAI Utilization

As far as education is concerned, GenAI utilization refers to the level of GenAI support provided for learning by students. It has been found that student-GenAI interaction positively impacts learning achievement, a relationship mediated by self-efficacy and cognitive activity (Liang et al., 2023). GenAI's ability to tailor proposals through real-time analysis of a learner's profile translates to personalized education (Borah et al., 2024). Therefore, it is hypothesized that:

H5: GenAI utilization mediates the relationship between GenAI competence and student engagement.

Mediating Role of Perceived Autonomy

Perceived autonomy emphasizes the students' sense of control and agency in their learning experiences. While interaction with GenAI can enhance learning autonomy through social presence for some students, it may negatively affect those who focus on knowledge acquisition (Xie et al., 2024). Students' perceptions of GenAI in higher education are shaped by perceived value and cost, with perceived value strongly correlating with intention to use (Chan & Zhou, 2023). However, perceived unfairness and detection possibility can decrease acceptance of GenAI in college assignments (Choi, 2024). Despite generally positive attitudes, students recognize potential side effects and the need for academic regulations (Choi, 2024). Based on this, the study hypothesizes that:

H6: Perceived autonomy mediates the relationship between GenAI competence and student engagement.

Mediating role of AI formal learning

AI Formal Learning is the application of AI-based teaching resources and technologies in formal learning environments. Through the mediation of self-competence, AI and mobile learning have demonstrated beneficial effects on student learning outcomes (Priamono et al., 2024). Academic results can be improved by integrating AI into educational systems through smart learning (Akour et al., 2023). In language learning, AI-supported technologies have shown promise but require further improvement for collaborative design and communication (Yang & Kyun, 2022). To optimize AI's benefits for education, there is a need for pedagogical design and teacher interventions. These findings highlight the importance of teachers having ongoing technology training and how AI may be used to develop more individualized and flexible educational settings (Akour et al., 2023; Priamono et al., 2024). This leads to the final mediating hypothesis:

H7: AI formal learning mediates the relationship between GenAI competence and student engagement.

THEORETICAL INTEGRATION AND HYPOTHESIS DEVELOPMENT

This study integrates Self-Determination Theory (SDT) (Deci & Ryan, 1985), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), the Technology Acceptance Model (TAM) (Davis, 1989), and Uses and Gratifications Theory (UGT) (Katz et al., 1973) to explain how GenAI competence translates into student engagement. While each theory offers unique insights, their integration captures the cognitive, behavioural, and motivational mechanisms underlying students' interaction with GenAI technologies. Recent syntheses confirm that such multi-theoretical approaches are essential for understanding the complex effects of GenAI in education (Li & Awang, 2026).

Generative AI Competence (GC) is conceptualized as a foundational capability for effective interaction with AI systems. From a TAM perspective, competence enhances perceived ease of use and usefulness, encouraging actual system use and is captured, e.g., as GenAI utilization (GU). UTAUT reinforces this pathway: higher competence increases behavioural intention and usage by improving performance expectancy and reducing effort expectancy barriers (Sahar & Munawaroh, 2025). Hence, GC is linked to GU through both TAM and UTAUT, positioning utilization as a key behavioural mediator. From the SDT standpoint, competence is a critical psychological need that fosters intrinsic motivation and agency. In this study, this mechanism is captured through Perceived Autonomy (PA). Students who feel competent in using GenAI tools experience greater control over their learning, enhancing autonomous motivation. Autonomy, in turn, has been consistently associated with deeper engagement and self-directed learning (Chiu & Hew, 2018). Thus, PA represents the psychological pathway through which GC influences student engagement. This motivational logic is reinforced by Luo and Day (2026), who find that SDT-based psychological needs, particularly autonomy and competence, are stronger predictors of GenAI adoption than traditional technology acceptance constructs. Similarly, Alqurni (2026) highlights that agentic AI environments can foster autonomy support and self-learning motivation, underscoring the value of the psychological pathway.

AI Formal Learning (AIFL) is grounded in both UTAUT and SDT. From a UTAUT lens, institutional support and facilitating conditions enable effective technology use. From an SDT perspective, structured learning environments scaffold competence development and reinforce autonomous functioning. AIFL therefore serves as an instructional pathway that translates individual competence into sustained engagement (Sahar & Munawaroh, 2025; Castillo-Martínez et al., 2024). The importance of formal learning contexts is echoed by Webb et al. (2026), who demonstrate that structured exposure to GenAI, combined with perceived competence, significantly influences academic performance and language proficiency.

UGT (Katz et al., 1973) complements these perspectives by explaining why students actively engage with GenAI technologies. UGT posits that individuals use media to satisfy specific needs, i.e., efficiency, curiosity, and academic productivity. Students with higher GenAI competence are better positioned to derive meaningful gratifications from usage, which reinforces both utilization and engagement (SE). This perspective strengthens the model's behavioural and motivational links by emphasizing user-driven value realization.

Collectively, these theories support a parallel mediation framework in which GenAI competence influences student engagement through three distinct but complementary pathways: (1) a behavioural pathway through GenAI utilization (TAM/UTAUT); (2) a psychological pathway through perceived autonomy (SDT); and (3) an instructional pathway through AI formal learning (UTAUT/SDT). This multi-theoretical synthesis clarifies the mechanisms underlying the competence–engagement relationship and advances the literature by showing that the impact of GenAI competence is distributed across interconnected behavioural, motivational, and institutional processes, a conclusion further supported by emerging evidence that GenAI interventions influence student outcomes through integrated pedagogical, motivational, and regulatory mechanisms (Li & Awang, 2026).

Conceptual Framework & Hypothesis

Guided by the integrated theoretical foundation, we propose the following conceptual framework (Figure 1) to examine the relationship between the constructs.

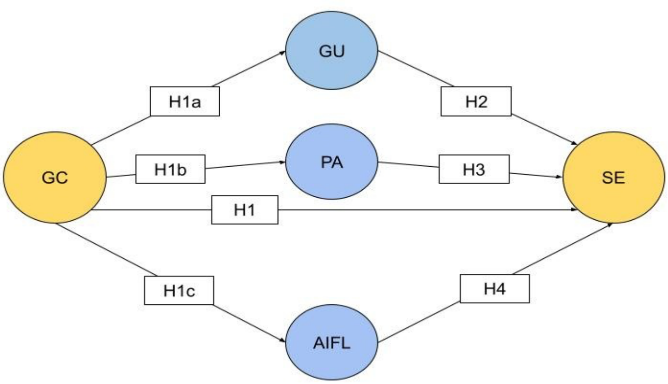

Figure 1. Conceptual model showing relationships among GenAI competence, mediating variables, and student engagement.

Note. GC = Generative AI Competence; GU = GenAI Utilization; PA = Perceived Autonomy; AIFL = AI Formal Learning; SE = Student Engagement. H1 represents the direct effect of GC on SE. H1a–H1c represent the effects of GC on GU, PA, and AIFL, respectively. H2–H4 represent the effects of GU, PA, and AIFL on SE

Source(s): Authors' constructs (2024)

Based on this framework and the theories discussed, the following hypotheses were proposed:

H_1: GenAI competence has a positive direct effect on (a) GenAI utilization, (b) perceived autonomy, and (c) AI formal learning.

H_2: GenAI utilization has a positive direct effect on student engagement.

H_3: Perceived autonomy has a positive direct effect on student engagement.

H_4: AI formal learning has a positive direct effect on student engagement.

H_5: GenAI utilization mediates the relationship between GenAI competence and student engagement.

H_6: Perceived autonomy mediates the relationship between GenAI competence and student engagement.

H_7: AI formal learning mediates the relationship between GenAI competence and student engagement.

RESEARCH METHOD

The study employed a cross-sectional survey of undergraduate students with prior exposure to generative AI tools, using purposive and convenience sampling to capture authentic user experiences in an emerging domain where populations are difficult to enumerate. This approach is appropriate for exploratory and theory-testing studies, enabling the efficient and economical collection of data from a relatively large sample, well-suited for testing complex interrelationships between multiple constructs, i.e., GC, GU, PA, AIFL, and SE, using Structural Equation Modeling (SEM). The study was conducted among university students in a science and technology institution, selected for two key reasons: (1) As a leading science and technology institution, its students are more likely to be early adopters and active users of emerging technologies such as generative AI, making it an information-rich context. (2) Its large and diverse student population enhances the robustness and variability of the sample. A non-probability convenience sampling technique was employed, which is appropriate for exploratory and theory-testing research in emerging domains where a complete sampling frame is unavailable (Etikan et al., 2016). Participants were eligible if they were undergraduate or postgraduate students with prior experience using generative AI tools (e.g., ChatGPT, Gemini, Microsoft Copilot) for academic purposes.

Sample size adequacy was determined using Daniel Soper's a priori sample size calculator (Soper, 2023), based on five (5) latent variables, twenty-one (21) observed indicators, an anticipated effect size of 0.30, statistical power of 0.90, and a significance level of $p < .05$ (Cohen, 1987). The minimum recommended sample size was 223. To enhance robustness and account for potential non-response, a 10% buffer was added (Das & Datta, 2024), resulting in a target sample of 245. The final sample (N = 262) exceeded this requirement, ensuring sufficient statistical power for PLS-SEM analysis.

Measures, Research Instrument, and Operational Definitions

Data were collected using a self-administered online questionnaire, with measurement items adapted from previously validated scales in the literature to ensure content and construct validity. The instrument consisted of two sections: (1) demographic information (e.g., age, gender, level of study), and (2) measurement items assessing the study constructs. All constructs were operationalized as reflective latent variables, measured using multiple indicators. Specifically, Generative AI Competence (GC) (5 items, $\alpha = 0.940$), Student Engagement (SE) (6 items, $\alpha = 0.970$), GenAI Utilization (GU) (3 items, $\alpha = 0.927$), Perceived Autonomy (PA) (3 items, $\alpha = 0.916$), and AI Formal Learning (AIFL) (3 items, $\alpha = 0.952$). Items were adapted from prior studies (Chiu et al., 2021; Heidari et al., 2021) and modified to fit the GenAI learning context (see Table 1). The measurement indicators and their corresponding operational definitions are presented in Table 2. All items were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with 3 representing a neutral response. A pilot test with students (n = 25) was conducted to ensure clarity, reliability, and appropriate completion time (5–7 minutes), resulting in minor wording refinements. The instrument was further validated through review by subject-matter experts.

Table 1:
Summary of constructs and their sources

SN	Construct	Indicators	Sources
1	GenAI Competence (GC)	5	Heidari et al. (2021); Chiu et al. (2021)
2	GenAI Utilization (GU)	3	Heidari et al. (2021)
3	Perceived Autonomy (PA)	3	Heidari et al. (2021)
4	AI Formal Learning (AIFL)	3	Heidari et al. (2021)
5	Student Engagement (SE)	6	Heidari et al. (2021); Chiu et al. (2021)
		20	

Table 2:
Measurement indicators and operational definition

Construct	Operational definition	Measuring indicator	
GenAI Competence	The ability to use various Generative Artificial Intelligence tools to execute tasks, especially academic ones, without any difficulty.	GC1	I have general knowledge about how GenAI is used.
		GC2	I have general knowledge about GenAI capabilities.
		GC3	I can use GenAI well.
		GC4	I can use a variety of GenAI tools.
		GC5	I can use at least one (1) GenAI tool skillfully (e.g., ChatGPT, AskAI, Claude, Copilot, etc.).
Student Engagement	The interactions that students have with digital tools, especially GenAI tools in performing various tasks based on their passions, interests, and curiosity.	SE1	I am happy about GenAI in my field of study.
		SE2	I am proud of the academic activities that I am able to do with GenAI.
		SE3	It is difficult to detach myself from my GenAI usage.
		SE4	When I am using GenAI, I forget everything else around me.
		SE5	I feel extremely happy in my studies when using GenAI.
		SE6	I get carried away when I am using GenAI to do an academic activity.
GenAI Utilization	This refers to the rate or how frequently one uses Generative Artificial Intelligence tools in performing certain tasks or activities in educational settings.	GU1	I often use GenAI to sustain motivation in learning.
		GU2	I often use GenAI to elicit support and help in my studies.
		GU3	I often use GenAI technologies to engage in constructive activities as far as my studies is concerned.

Perceived Autonomy	This refers to students' sense of control and agency in their learning experiences.	PA1	I often use GenAI to expand learning opportunities.
		PA2	I often use GenAI to seek engaging learning experiences.
		PA3	I often use GenAI technologies to seek learning strategies and tips.
AI Formal Learning	This refers to the use of AI based educational tools and resources in formal learning settings.	AIFL1	I often use GenAI technologies to keep informed of the development in my academic discipline.
		AIFL2	I often use GenAI technologies to expand. knowledge of my courses.
		AIFL3	I often use GenAI technologies to engage in self-expression.

Data Analysis Procedure

Microsoft Excel 365 was utilized for data estimation, with the dataset analyzed using Jamovi 2.5.6 (The Jamovi project, 2024; R Core Team, 2023; Widaman & Revelle, 2022; Rosseel & Loh, 2024) and SmartPLS3 software (Ringle et al., 2022). The data analysis followed a two-step process recommended by Anderson & Gerbing (1988) and Nordhoff et al. (2021) for SEM. PLS-SEM was selected due to its suitability for prediction-oriented research, its robustness to non-normal data, and its effectiveness in handling complex models with multiple mediators. The variables of interest (GenAI competency and student engagement) were summarized using descriptive statistics.

Step 1: Assessment of the Measurement Model

This step assessed reliability and validity based on internal consistency. Reliability was measured using Composite Reliability (ρ_0) and Cronbach's Alpha (α), with a threshold > 0.7; Convergent validity was assessed using Average Variance Extracted (AVE > 0.5) and indicator loadings (> 0.7) (Benitez et al., 2019; Hair et al., 2019). Discriminant validity was assessed using the Fornell-Larcker criterion (Fornell & Larcker, 1981) and the Heterotrait-Monotrait (HTMT) ratio (< 0.9) (Hair et al., 2019), supplemented with cross-loadings. Results are presented in Tables 4 & 5.

Step 2: Assessment of the Structural Model

The structural model was evaluated by examining the hypothesized relationships among the constructs. Path coefficients (β), their statistical significance (p-values), and coefficients of determination (R^2) for endogenous constructs were assessed to determine the strength and explanatory power of the model (Briones-Peñalver et al., 2018). Before the analysis, multivariate normality was assessed using Mardia's coefficient (skewness = β; kurtosis = γ:225.3), which indicated non-normality ($p < 0.05$), further justifying the use of PLS-SEM and bootstrapping. Path coefficients and mediation effects were tested using bootstrapping with 5,000 resamples, a non-parametric procedure that generates empirical sampling distributions to estimate standard errors, t-values, p-values, and confidence intervals, providing robust inference for indirect (mediating) effects.

The model was evaluated based on the standard criteria for variance-based PLS-SEM. Given that PLS-SEM is a variance-based method, traditional CB-SEM fit indices like CFI, TLI, and RMSEA are not applicable (Hair et al., 2019). Instead, model fit was assessed using the Standardized Root Mean Square Residual (SRMR), which represents the difference between observed and model-implied correlation. The obtained SRMR value (SRMR = 0.063) falls below the recommended threshold of 0.08, indicating a good fit (Hensler et al., 2014). Although PLS-SEM does not prioritize global fit indices to the same extent as covariance-based SEM, SRMR provides a useful approximate measure of model adequacy. In addition, the predictive relevance was evaluated using the Stone–Geisser Q^2 statistic (> 0 suggests predictive relevance), where values greater than zero indicate that the model has predictive relevance for the endogenous constructs.

Ethical Considerations

Ethical approval was granted by the Ethics Committee of the Department of Educational Innovations in Science and Technology (EC-EIST-0172024, approved: July 1, 2024) at KNUST. The study adhered to the Helsinki Declaration (2013) and maintained the anonymity and confidentiality of the respondents. Data collection commenced after the study met all ethical requirements. The study description and consent statement were the first items respondents had to complete before proceeding to other items in the survey.

RESULTS

Respondents – Demographic Analysis

The sociodemographic characteristics of 262 participants are presented in Table 3. The sample was predominantly male (69.5%, n = 182) and female (30.5%, n = 80). This gender distribution is not representative of the general population but reflects the enrollment patterns typical of STEM-focused programs at KNUST, where male students often outnumber female students, particularly in technology and engineering disciplines (Quarshie et al., 2023). While this limits the generalizability of the findings across genders, it provides an accurate picture of the current student population in a technology- dominated environment. The majority of participants (90.45%, n = 237) were between 18 and 25 years old, with a mean age of 22. Year 1 students constitute the largest group (42.4%, n = 111). Regarding self-reported digital competencies, the largest group of students rated themselves as advanced (43.6%, n = 114). The concentration of young, digitally competent individuals in the sample suggests a population highly likely to interact with generative AI tools, presenting a vital opportunity for a targeted generative AI strategy in educational settings.

Table 3: Sociodemographic characteristics of participants (*N = 262*)

Variables	Category	f (%)
Gender	Male	182 (69.5)
	Female	80 (30.5)
Age Group	18 - 25	237 (90.45)
	25 years and above	25 (9.55)
Academic level	Year 1	111 (42.4)
	Year 2	75 (28.6)
	Year 3	50 (19.1)
	Year 4	26 (9.9)
Digital Competence level	Beginners	25 (9.5)
	Intermediate	85 (32.4)
	Advanced	114 (43.6)
	Experts	38 (14.5)

Measurement model assessment

The outer loadings of the constructs are displayed in Table 4. Hair et al. (2019) state that loadings above 0.70 are considered indicative of a well-defined structure. This is confirmed in Table 4 since all the loadings are greater than 0.7.

The model's validity and reliability were assessed using Cronbach's alpha coefficient (CA), average variance extracted (AVE), composite reliability (CR), Fornell-Larcker criteria, and the Heterotrait-Monotrait (HTMT) ratio. The measurement model's reliability was evaluated using AVE, CR, and CA. Ursachi et al. (2015) define acceptable CA values as those ranging from 0.6 to 0.7. CR values of 0.70 or above could be considered acceptable (Hair et al., 2021). Table 4 demonstrates that the CA and CR values exceed 0.8. The suggested model is reliable as a result. AVE was used to validate the measurement model. Hair et al. (2019) define an adequate AVE value as 0.50 or higher. Each AVE value in Table 4 is greater than 0.50. As a result, the convergent validity of the proposed model is demonstrated.

The assessment of discriminant validity using the heterotrait–monotrait ratio (HTMT), as presented in Table 5, reveals that several construct pairs fall within acceptable thresholds, particularly GC–AIFL (0.543), GC–GU (0.640), GC–PA (0.651), GC–SE (0.724), and PA–SE (0.864), indicating adequate discriminant validity for these relationships.

However, some construct pairs slightly exceed the recommended threshold of 0.85 (Hensler et al., 2014), including GU–AIFL (0.859, approaching threshold), PA–AIFL (0.915), PA–GU (0.914), and GU–SE (0.900). These elevated HTMT values reflect the conceptual relatedness among the constructs rather than a lack of distinctiveness. Specifically, the higher HTMT values involving GenAI Utilization (GU), Perceived Autonomy (PA), and AI Formal Learning (AIFL) are theoretically expected, as these constructs collectively capture closely linked dimensions of students' interaction with GenAI technologies, namely, behavioural engagement (GU), psychological experience (PA), and institutional learning support (AIFL). Similarly, the association between GU and Student Engagement (SE) (HTMT = 0.900) reflects the shared behavioural component between technology use and engagement outcomes. Importantly, despite this empirical proximity, the constructs remain conceptually distinct. GU represents the actual use of GenAI tools, PA captures students' perceived control and autonomy, and AIFL reflects structured institutional learning support, while SE constitutes a broader multidimensional outcome encompassing behavioural, cognitive, and emotional engagement (Ryan & Deci, 2000).

Consistent with the recommendations of Franke and Sarstedt (2019), discriminant validity should not be assessed solely based on rigid statistical thresholds but rather in conjunction with theoretical justification, particularly in models where constructs are inherently related. In such contexts, moderately high HTMT values may reflect meaningful conceptual overlap rather than a lack of construct distinctiveness. Accordingly, where HTMT values exceeded the recommended threshold, further diagnostic evaluation was conducted by examining indicator loadings and cross-loadings. As reported in Table 4, all indicators loaded highest on their respective constructs, thereby confirming their empirical distinctiveness despite the observed inter-construct correlations.

Furthermore, the structural model provides strong support for construct distinctiveness. Each construct demonstrates significant and theoretically consistent relationships within the model (e.g., GU → SE, $\beta = 0.286$; PA → SE, $\beta = 0.211$; AIFL → SE, $\beta = 0.196$), confirming their unique explanatory roles. This pattern reinforces the nomological validity of the model, indicating that the constructs operate as distinct yet complementary components within the broader theoretical framework. Therefore, we retain the constructs for analysis but acknowledge this limitation and interpret the relationships between these specific constructs with caution.

Table 4: Factor Loadings, validity, and reliability of latent constructs

Construct and Items	Loadings	CR	CA	AVE
AI Formal learning **(AIFL)**		0.892	0.819	0.734
$AIFL_1$	0.874			
$AIFL_2$	0.868			
$AIFL_3$	0.828			
Generative AI Competence **(GC)**		0.938	0.911	0.79
GC_1	0.887			
GC_2	0.884			
GC_3	0.899			
GC_4	0.885			
GenAI Utilization **(GU)**		0.867	0.769	0.685
GU_1	0.747			
GU_2	0.861			
GU_3	0.870			
Perceived Autonomy **(PA)**		0.905	0.843	0.761
PA_1	0.853			
PA_2	0.906			
PA_3	0.857			
Student Engagement **(SE)**		0.889	0.811	0.727
SE_1	0.871			
SE_2	0.876			
SE_5	0.809			

Table 5: Discriminant Validity using the criterion by Fornell & Larcker & HTMT

Construct	AIFL	GC	GU	PA	SE
AI Formal Learning (**AIFL**)	**0.857**				
GenAI Competence (**GC**)	0.473	**0.889**			
GenAI Utilization (**GU**)	0.68	0.543	**0.828**		
Perceived Autonomy (**PA**)	0.762	0.573	0.735	**0.872**	
Student Engagement **(SE)**	0.672	0.624	0.713	0.717	**0.853**
Heterotrait-Monotrait criterion (HTMT)					
AI Formal Learning **(AIFL)**					
GenAI Competence **(GC)**	**0.543**				

GenAI Utilization **(GU)**	0.859	**0.640**		
Perceived Autonomy **(PA)**	0.915	0.651	**0.914**	
Student Engagement **(SE)**	0.817	0.724	0.900	**0.864**

Analysis of Structural Model

After assessing the convergent and discriminant validity of the model, a structural equation model (SEM) was constructed to validate the hypotheses as shown in Figure 2 below.

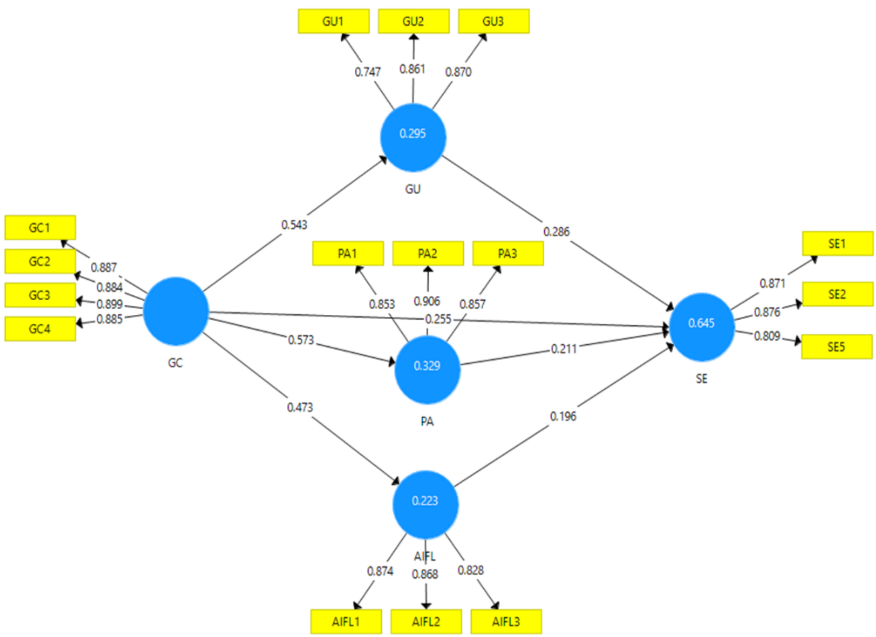

Figure 2. Estimated structural and measurement model with mediating effects of GU, PA, and AIFL.

Note. Standardized path coefficients (β) are shown along structural paths, and outer loadings are reported for reflective indicators. R² values indicate the proportion of variance explained in endogenous constructs (GU = 0.295, PA = 0.329, AIFL = 0.223, SE = 0.645).

Model Fit Analysis

The standardized root mean residual (SRMR) is the square root of the mean residual between the implied correlations predicted by the model and the observed correlations. It allows us to consider the average size of the discrepancies between empirical and predicted correlations as model fit indices (Hair et al., 2019). A value ≥ 0.08 indicates a good fit (Hu & Bentler, 1999). The proposed structural model in Figure 2 has an SRMR index of 0.063, which is below the threshold of 0.08, indicating a good fit between the model and the observed data. The Normed Fit Index (NFI) was 0.818, which is below the recommended value of 0.90. These indices suggest that the proposed model is a good representation of the underlying data structure.

Analysis of the Structural Model

The structural model was evaluated, and the connections among the constructs in the proposed research model were examined after validation of the measurement model. Figure 2 and Table 6 display the structural model test results. All seven (7) hypotheses were supported.

Table 6: Results of Structural Model Analysis

Hypothesis	Path	Path Coeff. (β)	T Statistics	P Values	Supported?	Interpretation
H1a	GC → GU	0.543	9.383	<0.001	Yes	A strong, significant positive effect.
H1b	GC → PA	0.573	10.451	<0.001	Yes	A strong, significant positive effect.
H1c	GC → AIFL	0.473	8.064	<0.001	Yes	A significant positive effect.
H2	GU → SE	0.286	4.624	<0.001	Yes	A significant positive effect.
H3	PA → SE	0.211	2.895	0.004	Yes	A significant positive effect.
H4	AIFL → SE	0.195	2.999	0.003	Yes	A significant positive effect.
H1	GC → SE	0.255	5.604	<0.001	Yes	A significant positive direct effect.

In addition to the mediated paths, the direct effect of GenAI Competence on Student Engagement (H1) was tested. The analysis revealed that GenAI

Competence is a powerful driver as it has a strong, significant direct effect on Student Engagement (H1: $\beta = 0.255$, $p < 0.001$). Competence significantly enhanced all three proposed mediators, i.e., GenAI Utilization (H1a), Perceived Autonomy (H1b), and AI Formal Learning (H1c). The presence of both significant direct and indirect pathways indicates a model of complementary partial mediation. This indicates that GenAI Competence boosts Student Engagement both directly and indirectly by improving students' ability to use the tools, their feeling of freedom in using them, and their access to formal training.

Table 7: Mediation Analysis Output

Pathway	Sample (O)	Mean (M)	Deviation (SD)	T Statistics	P Values
GC → AIFL → SE	0.092	0.094	0.032	2.843	0.005
GC → GU → SE	0.155	0.158	0.038	4.094	<0.001
GC → PA → SE	0.121	0.119	0.043	2.842	0.005

Analysis of the Mediating Effects

The mediation analysis was conducted to determine the indirect pathways through which Generative AI Competence (GC) influences Student Engagement (SE). As presented in Table 7, the results confirm the presence of significant specific indirect effects for all three hypothesized mediators, demonstrating that the relationship operates through multiple distinct channels. The analysis reveals that GenAI Utilization (GU) serves as the most substantial mediating mechanism in the model ($\beta = 0.155$, $p < 0.001$). This indicates that a primary reason competent students are more engaged is their increased propensity to actively and frequently use GenAI tools as part of their academic routines. The pathway through Perceived Autonomy (PA) also represents a significant and meaningful mediator ($\beta = 0.121$, $p = 0.005$). This finding indicates that GenAI competence contributes to higher engagement by fostering a stronger sense of choice and control in students' learning processes.

The pathway through AI Formal Learning (AIFL) was confirmed as a significant, though comparatively smaller, mediator ($\beta = 0.092$, $p = 0.005$). This demonstrates that structured institutional training and support play a credible, yet more modest, role in translating competence into tangible gains in engagement.

The empirical evidence solidly supports a model of parallel mediation (See Table 7). The influence of GenAI competence on student engagement is not monolithic but rather transmitted through three statistically significant and conceptually distinct intermediaries: the behavioural channel of utilization, the psychological channel of autonomy, and the instructional channel of formal learning support

4.7 R^2, Q^2, and Path Coefficient Results

The model's explanatory power was assessed using the coefficient of determination (R^2) for the endogenous constructs. As illustrated in Table 8, the model explains 32.9% of the variance in Perceived Autonomy (PA), 29.5% in GenAI Utilization (GU), and 22.3% in AI Formal Learning (AIFL). Most importantly, the model explains a substantial 64.5% of the variance in Student Engagement (SE), indicating strong explanatory power. The Q^2 predict values, all of which are well above zero, as shown in Table 9, confirm the model's out-of-sample predictive relevance (Hair et al., 2019). This indicates that the model possesses not only explanatory power but also the potential to predict future outcomes. The Q^2 value for Student Engagement ($Q^2 = 0.436$) is strong, signaling a large predictive relevance for the main construct of interest. The positive Q^2 values for the mediators affirm that the predictions for these variables are also substantially better than mere chance.

Furthermore, the effect size (f^2) of each predictor was calculated to evaluate its substantive impact. Following Cohen's (1987) guidelines, values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. The results, presented in Table 10, show that the significant f2 values have at least a small-to-medium effect on their respective endogenous constructs, while the f2 for AIFL → SE and PA → SE are not statistically significant ($p > 0.05$), indicating that these predictors explain little unique variance in student engagement beyond the shared effects of other mediators.

Table 8: In-sample Explanatory Power (R^2)

Construct	R-square	R-square adjusted
AIFL	0.223	0.220
GU	0.295	0.292
PA	0.329	0.326
SE	0.645	0.639

Table 9: Out-sample Predictive Relevance (Q^2)

Endogenous construct	Q^2 predict
AIFL	0.151
GU	0.190
PA	0.231
SE	0.436

Table 10: f^2 Effect Size Results

Predictor	Endogenous Construct	f^2 Value	p-value	Effect Size Interpretation
GC	PA	0.49	0.001	Large
GC	GU	0.418	0.003	Large
GC	AIFL	0.288	0.004	Medium to Large
GC	SE	0.117	0.019	Small to Medium
GU	SE	0.093	0.03	Small to Medium
PA	SE	0.039	0.166	Small
AIFL	SE	0.042	0.154	Small

Note: *Significant β but non-significant f^2; unique contribution is negligible due to shared variance among mediators (applies to AIFL → SE and PA → SE).*

DISCUSSION AND CONCLUSIONS

This study investigated the mechanisms linking Generative AI (GenAI) competence to student engagement in the Ghanaian higher education context. The findings provide strong support for the proposed integrated model, revealing a complex relationship characterized by both direct and indirect effects through key behavioural and psychological mediators, thereby offering a more detailed understanding than previous studies that focused primarily on adoption intentions (Essel et al., 2024; Arthur et al., 2025). Empirically, GenAI competence emerged as a significant direct predictor of student engagement ($\beta = 0.255$, $p < 0.001$), explaining a substantial proportion of variance ($R^2 = 0.645$) with a small-to-medium effect size ($f^2 = 0.117$). The model also demonstrated strong predictive relevance ($Q^2 = 0.436$), confirming its robustness. However, the most important insight is that this relationship is not merely direct, but is amplified through three complementary mediating pathways, namely, GenAI utilization, perceived autonomy, and AI formal learning, indicating that engagement is driven by an interconnected system of competence, behaviour, motivation, and institutional support rather than skill alone.

Theoretical Integration and Interpretation of Results

The significant direct effect of GenAI competence on engagement supports the central premise of Self-Determination Theory (SDT), which posits that competence is a fundamental psychological need that enhances intrinsic motivation (Deci & Ryan, 1985). In this context, students who feel capable of using GenAI tools are more confident and motivated to participate actively in learning tasks. This finding extends SDT into the GenAI domain and aligns with emerging evidence on digital competence and engagement (Ghimire, 2024; Liang et al., 2023).

More importantly, the mediation results clarify the mechanisms through which this motivation is enacted: The strongest mediation pathway through GenAI utilization ($\beta = 0.155$, $p < 0.001$) confirms that competence translates into engagement primarily through behavioral enactment. This finding integrates Uses and Gratifications Theory (UGT) (Katz et al., 1973) and TAM/UTAUT, demonstrating that students actively use GenAI to satisfy academic needs such as efficiency, comprehension, and content generation. Thus, engagement is not simply a function of competence, but of purposeful and goal-directed use, reinforcing the idea that utilization is the dominant behavioral driver of engagement, a pattern observed in other educational technology studies (Chiu & Hew, 2018; Nawaz et al., 2024).

The mediation through perceived autonomy ($\beta = 0.121$, $p = 0.005$) provides strong support for the autonomy component of SDT, showing that competence enhances students' sense of control over their learning processes. This psychological empowerment fosters intrinsic motivation (Ryan & Deci, 2020; Xie et al., 2024), which in turn sustains engagement. The result highlights that engagement is not only behavioral but also deeply motivational and self-regulatory.

The pathway through AI formal learning ($\beta = 0.092$, $p = 0.005$) reflects the role of institutional structures and aligns with UTAUT's facilitating conditions. Although comparatively smaller, this pathway demonstrates that structured training environments enhance students' ability to translate competence into effective engagement (Venkatesh et al., 2003; Hidayat-ur-Rehman, 2024). These findings agree with Sanz-Tejeda et al. (2026), who summarized recent evidence showing that GenAI competence directly enhances academic literacy and engagement outcomes. This convergence of evidence underscores the robustness of competence as a foundational driver of student engagement in AI-enhanced learning environment. Overall, the findings validate a multi-theoretical synthesis: TAM/UTAUT explain how competence translates into usage, SDT clarifies how competence becomes motivation, and UGT shows why utilization sustains engagement. This integrated perspective advances theory by moving beyond single-framework models.

Global Evidence and the Ghanaian Context

The findings both converge with and extend international research, situating the Ghanaian context within a broader global discourse on AI in education. Consistent with global studies, the significant roles of perceived autonomy and institutional support align with findings from Western and Asian contexts (Xie et al., 2024; Zhang & Aslan, 2021; Kasneci et al., 2023; Zawacki-Richter et al., 2019). These parallels suggest that core psychological mechanisms of engagement, particularly those explained by SDT, retain cross-cultural relevance.

However, this study also reveals a context-specific nuance: the dominance of GenAI utilization as the strongest mediator. While global literature acknowledges the importance of usage, the magnitude of its effect in this study suggests a stronger reliance on utilitarian engagement in the Ghanaian context. In resource-constrained environments, students may prioritize GenAI's immediate functional benefits, such as bypassing access barriers, improving efficiency, and supporting independent learning, as primary drivers of engagement. This pattern aligns with research from other developing regions, where technology adoption is often motivated by practical necessity and outcome-oriented use rather than exploratory or experimental engagement (Boateng et al., 2016; Tarhini et al., 2017; Almaiah et al., 2022). Thus, while the underlying theories are globally applicable, their relative influence varies by context, highlighting the importance of localized empirical validation. Furthermore, the comparatively smaller role of AI formal learning suggests that institutional integration of GenAI in Ghana is still evolving. Unlike in some Global North contexts, where AI is increasingly embedded in curricula, students in Ghana appear to rely more on self-directed learning and informal use, reinforcing the importance of strengthening institutional frameworks.

POLICY AND CURRICULUM IMPLICATIONS

The findings have significant implications for higher education policy and curriculum design, particularly in emerging educational contexts. Beyond competence, the mediating roles of utilization, autonomy, and formal learning underscore the interconnectedness of behavioral, psychological, and institutional mechanisms in shaping student engagement. Students who actively integrate GenAI into their learning processes report higher motivation and deeper engagement, consistent with global findings on personalized learning and self-efficacy (Liang et al., 2023; Yang, 2024). Earlier research further emphasizes that the effectiveness of GenAI depends on institutional support and pedagogical design, particularly in fostering transversal competencies such as critical thinking, autonomy, and collaboration (Deroncele-Acosta et al., 2025, 2026). In the present study, perceived autonomy emerged as a significant mediator, underscoring that students' sense of agency is critical for sustained engagement, especially when supported by structured training environments (Sozon et al., 2025).

Building on this insight, it becomes essential for institutions to translate these psychological and behavioural dynamics into deliberate educational strategies.

First, institutions must move beyond merely providing access to AI tools and instead focus on developing structured GenAI competencies. Embedding AI literacy into curricula, through dedicated modules, workshops, and assessments, will strengthen the foundational driver of engagement identified in this study.

Second, given that GenAI utilization is the strongest mediating pathway, educators should design AI-integrated pedagogies that require meaningful and purposeful application. Learning activities should extend beyond passive use and promote higher-order thinking (Chasokela & Hlongwane, 2024; Dhamija & Dhamija, 2024), including critical evaluation of AI-generated outputs, iterative prompt design, and problem-solving using GenAI tools.

Third, the significance of perceived autonomy suggests that learning environments should be student-centered and autonomy-supportive. Providing flexibility in task execution, tool selection, and learning pathways can enhance intrinsic motivation and sustain engagement.

Fourth, the role of AI formal learning underscores the need for institutional investment in training infrastructure. Universities should develop certified programs in key areas such as prompt engineering, data analysis, and ethical AI use (Akour et al., 2023; Acquah et al., 2024; Peterson, 2025). Equally critical is the need to build faculty capacity, equipping educators with the skills to integrate GenAI into teaching and assessment practices explicitly.

Importantly, these findings contribute to the ongoing global debate on whether GenAI constitutes a threat or a pedagogical tool in higher education. Contrary to concerns that AI use may promote academic dishonesty (Devaki, 2024; George et al., 2024; Zhai et al., 2024), the data indicate that competence is associated with more purposeful, engaged, and ethical use of GenAI (cf. Caling et al., 2025, who highlight the need for AI literacy to resolve moral conflicts). This suggests that academic misconduct may be mitigated not through restriction but through competence development, guided integration, and ethical training. Consequently, policy efforts should prioritize embedding responsible AI use within curricula rather than limiting access, aligning with emerging calls for proactive and structured AI integration in education (Chan & Zhou, 2023; Rudolph et al., 2024; Caling et al., 2025).

Theoretical Contributions

This study makes three key contributions to the literature. First, it develops an integrated mediation model that explains how GenAI competence influences student engagement in a Ghanaian higher education context. Second, it moves beyond adoption-focused research by identifying the behavioural, psychological, and institutional mechanisms underlying engagement. Third, it provides context-specific evidence from a developing African economy, demonstrating that while global theories are applicable, their dynamics vary across contexts.

Limitations

While this study provides valuable insights, several limitations are acknowledged. The cross-sectional design captures perceptions at a single point in time, limiting the ability to observe how the relationships between competence, mediators, and engagement evolve as students gain AI experience. Future studies should adopt a longitudinal approach to track these dynamics over an academic semester or year. Additionally, the study was conducted at a single, STEM-focused university. Although the gender imbalance reflects the institution's enrollment patterns, it, along with the single-site focus, limits the generalizability of the findings across genders and other educational contexts in Ghana. To enhance external validity, future research should replicate this study across a diverse range of Ghanaian universities, including humanities-focused, public, and private institutions, and conduct cross-cultural comparative studies in other developing economies.

Moreover, the reliance on self-reported data introduces the potential for common method bias. Although procedural remedies were applied, the measures of engagement and competence are subjective perceptions. Future research could incorporate objective metrics, such as learning analytics from AI platform usage or actual academic performance data, to triangulate findings and strengthen validity. Finally, while the model explains a substantial portion of the variance in engagement ($R^2 = 0.645$), other factors not included in our integrated model may influence these relationships. Further studies could introduce additional constructs from other theoretical frameworks, such as digital self-efficacy, personal innovativeness, or specific ethical concerns, to gain a more holistic understanding of the drivers of AI-enabled engagement

Conclusions

This study advances the literature on AI in education by integrating SDT, UTAUT, and UGT into a unified framework that explains how Generative AI competence translates into student engagement. The contribution lies in demonstrating that engagement is not a simple outcome of adoption, but the result of interconnected behavioural, psychological, and instructional pathways. By establishing competence as a direct and mediated driver of engagement, the study enriches theoretical understanding and provides empirical evidence from the Ghanaian higher education context. Practically, the findings underscore that nurturing engaged learners in the AI era requires a holistic strategy: building technical competence, fostering autonomy, and embedding formal AI learning opportunities within curricula. For Ghana, where infrastructural and institutional challenges persist, the results highlight the importance of policy interventions that prioritize equitable access to AI tools and structured training. Globally, the study reinforces the need for differentiated, autonomy-supportive curricula that empower students to use AI not only efficiently but also creatively and responsibly. These insights position GenAI as a catalyst for deeper, self-determined learning rather than a peripheral tool or perceived threat.

Despite its contributions, this study is not without limitations. The cross-sectional design restricts causal inference, the focus on a single institution limits generalizability, and reliance on self-reported data may introduce response bias. Future research should extend this work by employing longitudinal designs to track competence and engagement trajectories over time, exploring cross-cultural comparisons to identify contextual differences in AI adoption, and examining discipline-specific applications of GenAI in education. Additionally, investigating the ethical, cultural, and sustainability dimensions of AI integration will be critical for shaping policies that align with both local realities and global standards. In sum, by reframing GenAI competence as a multidimensional driver of student engagement, this study contributes to theory, informs practice, and opens new pathways for research that can transform higher education in Ghana and beyond.

Ethics Statement

This study was approved by the Ethics Committee of the Department of Educational Innovations in Science and Technology (EC-EIST-0172024, approved: July 1, 2024) at KNUST. The study adhered to the Helsinki Declaration (2013) and maintained the anonymity and confidentiality of the respondents.

Statement of Data Availability

Without reservation, the raw data used in this study will be made available upon request from the corresponding author. Please notify us if you require access, and it will be made available.

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Conflict of interest

The author declares that there are no competing interests, either financial or non-financial, that could have appeared to influence the work reported in this paper.

REFERENCES

Acquah, B. Y. S., Arthur, F., Salifu, I., Mensah, E., Opoku, E., Nortey, S. A., & Tetteh, S. A. (2025). Modelling economics students' use of ChatGPT and academic performance: insights from self-determination theory and epistemic curiosity. *Discovery Artificial Intelligence* 5, 134. doi:10.1007/s44163-025-00373-y

Acquah, B. Y. S., Arthur, F., Salifu, I., Quayson, E., & Nortey, S. A. (2024). Preservice teachers' behavioural intention to use artificial intelligence in lesson planning: A dual-staged PLS-SEM-ANN approach. *Computers and Education Artificial Intelligence*, *7*, 100307. doi:10.1016/j.caeai.2024.100307

Akour, I.A., Muhammad Alshurideh, H., Alzoubi, H.M., Alshurideh, M.T., & Ahmad Antouz, Y. (2023). Integrating Artificial Intelligence in Improving Educational System: The Mediating role of Smart Learning," *2023 International Conference on Business Analytics for Technology and Security (ICBATS)*, Dubai, United Arab Emirates, 2023, pp. 1-5, doi:10.1109/ICBATS57792.2023.10111284

Almaiah, M. A., Ayouni, S., Hajjej, F., Lutfi, A., Almomani, O., & Awad, A. B. (2022). Smart mobile learning success model for higher educational institutions in the context of the COVID-19 pandemic. *Electronics*, *11*(8), 1278. doi:10.3390/electronics11081278

Alqurni, J. (2026). Exploring the role of agentic AI in fostering self-efficacy, autonomy support, and self-learning motivation in higher education. *Frontiers in Artificial Intelligence*, *9*, 1738774. doi:10.3389/frai.2026.1738774

Al-Zahrani, A. M. (2024). The impact of generative AI tools on researchers and research: Implications for academia in higher education. *Innovations in Education and Teaching International*, *61*(5), 1029–1043. doi:10.1080/14703297.2023.2271445

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411–423. doi:10.1037/0033-2909.103.3.411

Arthur, F., Salifu, I., & Abam Nortey, S. (2025). Predictors of higher education students' behavioural intention and usage of ChatGPT: the moderating roles of age, gender and experience. *Interactive Learning Environments*, *33*(2), 993–1019. doi:10.1080/10494820.2024.2362805

Batista, J., Mesquita, A., & Carnaz, G. (2024). Generative AI and Higher Education: Trends, Challenges, and Future Directions from a Systematic Literature Review. *Information*, *15*(11), 676. doi:10.3390/info15110676

Benitez, J., Henseler, J., Castillo, A., & Schuberth, F. (2019). How to perform and report an impactful analysis using partial least squares: Guidelines for confirmatory and explanatory IS research. *Information & Management,* 57(2), 103168. doi:10.1016/j.im.2019.05.003

Bennett, E. E., & McWhorter, R. R. (2023). Digital technologies for teaching and learning. In *The Handbook of Adult and Continuing Education* (pp. 177-186). Routledge.

Boateng, R., Mbrokoh, A. S., Boateng, L., Senyo, P. K., & Ansong, E. (2016). Determinants of e-learning adoption among students of developing countries. *The International Journal of Information and Learning Technology*, 33(4), 248–262. doi:10.1108/ijilt-02-2016-0008

Borah, A.R., T N, N., & Gupta, S. (2024). Improved Learning Based on GenAI. 2024 *2nd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT),* 1527-1532. doi:10.1109/IDCIoT59759.2024.10467943

Briones-Peñalver, A. J., Bernal-Conesa, J. A., & de Nieves-Nieto, C. (2018). Analysis of corporate social responsibility in Spanish agribusiness and its influence on innovation and performance. *Corporate Social Responsibility and Environmental Management,* 25(2), 182–193. doi:10.1002/csr.1448

Caling, J. G., Antonio, J. K. T., Dimatatac, M. F. L., Sabellano, M. D., Vicencio, V. D. R., Prias, J. M., & Ramos, J. C. M. (2025). Pre-service teachers' use of ChatGPT and acquired moral dissonance. *Journal of Interdisciplinary Studies in Education*, *14*(4), 73-98. doi:10.32674/zmjq9089

Castillo-Martínez, I. M., Flores-Bueno, D., Gómez-Puente, S. M., & Vite-León, V. O. (2024). AI in higher education: a systematic literature review. *Frontiers in Education*, *9*. doi:10.3389/feduc.2024.1391485

Chan, C.K., & Zhou, W. (2023). An expectancy value theory (EVT) based instrument for measuring student perceptions of generative AI. *arXiv preprint arXiv:2305.01186*, 10, 1-22. doi:10.1186/s40561-023-00284-4

Chasokela, D., & Hlongwane, J. (2024). Assessing Higher-Order and Critical skills in the era of Artificial Intelligence. In *Advances in educational marketing, administration, and leadership book series* (pp. 285–314). doi:10.4018/979-8-3693-6351-5.ch010

Chiu, T. K. (2021). Digital support for student engagement in blended learning based on self-determination theory. *Computers in Human Behaviour*, 124, 106909. doi:10.1016/j.chb.2021.106909

Chiu, T. K., & Hew, T. K. (2018). Factors influencing peer learning and performance in MOOC asynchronous online discussion forum. *Australasian Journal of Educational Technology*, *34*(4). doi:10.14742/ajet.3240

Chiu, T. K., Meng, H., Chai, C. S., King, I., Wong, S., & Yam, Y. (2021). Creation and evaluation of a pretertiary artificial intelligence (AI) curriculum. *IEEE Transactions on Education*, 65(1), 30-39. doi:10.1109/TE.2021.3085878

Choi, S. (2024). Investigating students' intentions to use generative AI in college assignments: a moderated mediation analysis of perceived unfairness and detection possibility. *Korean Association for Learner-Centered Curriculum and Instruction*, *24*(6), 103–118. doi:10.22251/jlcci.2024.24.6.103

Chugh, R., Turnbull, D., Morshed, A., Sabrina, F., Azad, S., Mamunur, R. M., Kaisar, S., & Subramani, S. (2025). The Promise and Pitfalls: A Literature review of Generative Artificial intelligence as a learning assistant in ICT education. *Computer Applications in Engineering Education,* 33(2). doi:10.1002/cae.70002

Cohen, J. (1987). *Statistical Power Analysis for the Behavioural Sciences* (2nd ed.). Routledge. doi:10.4324/9780203771587

Collie, R. J., & Martin, A. J. (2024). Teachers' motivation and engagement to harness generative AI for teaching and learning: The role of contextual, occupational, and background factors. *Computers and Education Artificial Intelligence*, *6*, 100224. doi:10.1016/j.caeai.2024.100224

Das, S., & Datta, B. (2024). Application of UTAUT2 on Adopting Artificial Intelligence Powered Lead Management System (AI-LMS) in passenger car sales. *Technological Forecasting and Social Change*, 201, 123241. doi:10.1016/j.techfore.2024.123241

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly,* 13(3), 319. doi:10.2307/249008

de la Torre, A., & Baldeon-Calisto, M. (2024). Generative artificial intelligence in Latin American higher education: A systematic literature review. In *2024 12th International Symposium on Digital Forensics and Security (ISDFS)* (pp. 1-7). IEEE. doi:10.1109/ISDFS60797.2024.10527283

Deci, E. L., & Ryan, R. M. (1985). Conceptualizations of intrinsic motivation and self-determination. In *Intrinsic motivation and self-determination in human behavior* (pp. 11-40). Boston, MA: Springer US. doi:10.1007/978-1-4899-2271-7_2

Deroncele-Acosta, A., De Los Ángeles Sánchez-Trujillo, M., Palacios-Núñez, M. L., Del Ben, P. N., Atúncar-Prieto, C. A., & Soria-Valencia, E. (2026). ChatGPT at University: The Definitive Transition from Adoption to Quality of Student Interaction. *Education Sciences*, *16*(4), 515. doi:10.3390/educsci16040515

Deroncele-Acosta, A., Sayán-Rivera, R. M. E., Mendoza-López, A. D., & Norabuena-Figueroa, E. D. (2025). Generative Artificial Intelligence and Transversal Competencies in Higher Education: A Systematic review. *Applied System Innovation*, *8*(3), 83. doi:10.3390/asi8030083

Devaki, V. (2024). Academic integrity and human cognitive development of learners: Is artificial intelligence replacing the human brain? In *AI applications and strategies in teacher education* (pp. 195-222). IGI Global Scientific Publishing. doi:10.4018/979-8-3693-5443-8.ch007

Dhamija, A., & Dhamija, D. (2024). Understanding teachers' perspectives on ChatGPT-generated assignments in higher education. *Journal of Interdisciplinary Studies in Education*, *14*(1), 38-62. doi:10.32674/ptf9yd75

Eke, D. O. (2023). ChatGPT and the rise of GenAI: Threat to academic integrity? *Journal of Responsible Technology,* 13, 100060. doi:10.1016/j.jrt.2023.100060

Essel, H. B., Vlachopoulos, D., Essuman, A. B., & Amankwa, J. O. (2024). ChatGPT effects on cognitive skills of undergraduate students: Receiving instant responses from AI-based conversational large language models (LLMs). *Computers and Education: Artificial Intelligence,* 6, 100198. doi:10.1016/j.caeai.2023.100198

Essel, H.B., Vlachopoulos, D., Tachie-Menson, A., Johnson, E. E., & Baah, P. K. (2022). The impact of a virtual teaching assistant (chatbot) on students' learning in Ghanaian higher education. *International Journal of Educational Technology in Higher Education*, *19*(1), 57. doi:10.1186/s41239-022-00362-6

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics,* 5(1), 1-4. doi: 10.11648/j.ajtas.20160501.11

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research, 18*(1), 39–50. doi:10.1177/002224378101800104

Franke, G., & Sarstedt, M. (2019). Heuristics versus statistics in discriminant validity testing: a comparison of four procedures. *Internet Research*, Vol. 29 No. 3 pp. 430–447, doi:10.1108/IntR-12-2017-0515

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: potential of the concept, state of the evidence. *Review of Educational Research,* 74(1), 59–109. doi:10.3102/00346543074001059

Fredricks, J.A., McColskey, W. (2012). The Measurement of Student Engagement: A Comparative Analysis of Various Methods and Student Self-report Instruments. In: Christenson, S., Reschly, A., Wylie, C. (eds) *Handbook of Research on Student Engagement.* Springer, Boston, MA. doi:10.1007/978-1-4614-2018-7_37

George, A. S., Baskar, T., & Srikaanth, P. B. (2024). The erosion of cognitive skills in the technological age: How reliance on technology impacts critical thinking, Problem-Solving, and creativity. *Partners Universal Innovative Research Publication*, *2*(3), 147-163. doi:10.5281/zenodo.11671150

Ghimire, A. (2024). Generative AI in Education From the Perspective of Students, Educators, and Administrators" (2024). *All Graduate Theses and Dissertations, Fall 2023 to Present*. 124. https://digitalcommons.usu.edu/etd2023/124

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2019). Multivariate data analysis. Cengage Learning. *Hampshire, United Kingdom*, *633*(1), 321-344.

Hair, J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., Danks, N.P., Ray, S. (2021). Mediation Analysis. In: Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R. *Classroom Companion: Business*. Springer, Cham. doi:10.1007/978-3-030-80519-7_7

Heidari, E., Mehrvarz, M., Marzooghi, R., & Stoyanov, S. (2021). The role of digital informal learning in the relationship between students' digital competence and academic engagement during the COVID -19 pandemic. *Journal of Computer Assisted Learning*, *37*(4), 1154–1166. doi:10.1111/jcal.12553

Hensler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., Ketchen, D. J., Hair, J. F., Hult, G. T. M., & Calantone, R. J. (2014). Common beliefs and reality about PLS. *Organizational Research Methods,* 17(2), 182–209. doi:10.1177/1094428114526928

Hidayat-Ur-Rehman, I. (2024). Digital competence and students' engagement: a comprehensive analysis of smartphone utilization, perceived autonomy, and formal digital learning as mediators. *Interactive technology and smart education*, *21*(3), 461-488. doi:10.1108/itse-09-2023-0189

Holec, H. (1981). Autonomy is the ability to take charge of one's own learning.

Hsu, Y., & Ching, Y. (2023). Generative Artificial Intelligence in Education, Part One: the Dynamic Frontier. *TechTrends,* 67(4), 603–607. doi:10.1007/s11528-023-00863-9

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. doi:10.1080/10705519909540118

Kalota, F. (2024). A primer on generative artificial intelligence. *Education Sciences, 14*(2), 172. doi:10.3390/educsci14020172

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., ... & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274. doi:10.1016/j.lindif.2023.102274

Katz, E., Blumler, J. G., & Gurevitch, M. (1973). Uses and Gratifications research. *The Public Opinion Quarterly, 37*(4), 509–523. https://www.jstor.org/stable/2747854

Kelly, A., Sullivan, M., & Strampel, K. (2023). Generative artificial intelligence: University student awareness, experience, and confidence in use across disciplines. *Journal of University Teaching & Learning Practice, 20*(6). doi:10.53761/1.20.6.12

Law, L. (2024). Application of generative artificial intelligence (GenAI) in language teaching and learning: A scoping literature review. *Computers and Education Open*, *6*, 100174. doi:10.1016/j.caeo.2024.100174

Li, X., & Awang, M. M. B. (2026). Exploring the Role of Generative AI in Developing student Skills in Higher Education: A systematic literature review. *European Journal of Education*, *61*(1). doi:10.1111/ejed.70490

Liang, J., Wang, L., Luo, J., Yan, Y., & Fan, C. (2023). The relationship between student interaction with generative artificial intelligence and learning achievement: serial mediating roles of self-efficacy and cognitive engagement. *Frontiers in psychology*, *14*, 1285392. doi:10.3389/fpsyg.2023.1285392

Luo, Y., & Day, M. J. (2026). Determinants of lecturer readiness to adopt generative AI in higher education: survey evidence from UTAUT and self-determination theory. *Education and Information Technologies*. doi:10.1007/s10639-026-13931-3

Masouleh, N. S., & Jooneghani, R. B. (2012). Autonomous learning: A teacher-less learning! *Procedia - Social and Behavioural Sciences*, *55*, 835–842. doi:10.1016/j.sbspro.2012.09.570

Nawaz, N., Arunachalam, H., Pathi, B. K., & Gajenderan, V. (2024). The adoption of artificial intelligence in human resources management practices. *International Journal of Information Management Data Insights*, *4*(1), 100208. doi:10.1016/j.jjimei.2023.100208

Nordhoff, S., Madigan, R., Van Arem, B., Merat, N., & Happee, R. (2021). Interrelationships among predictors of automated vehicle acceptance: A structural equation modelling approach. *Theoretical issues in ergonomics science*, *22*(4), 383-408. doi:10.1080/1463922x.2020.1814446

Olga, A., Tzirides, Saini, A., Zapata, G., Searsmith, D., Cope, B., Kalantzis, M., Castro, V., Kourkoulou, T., Jones, J., Abrantes, D. S. R., Whiting, J., & Kastania, N. P. (2023). *Generative AI: Implications and Applications for Education*. arXiv.org. https://arxiv.org/abs/2305.07605

Peterson, S. (2025). Addressing student use of generative AI in schools and universities through academic integrity reporting. *Frontiers in Education*, *10*. doi:10.3389/feduc.2025.1610836

Priamono, G. H., Hakim, A. R., & Daryono, R. W. (2024). The influence of artificial intelligence (AI) and mobile learning on learning outcomes in higher education: Did the mediation of self-competence matter. *Jurnal Penelitian Dan Pengkajian Ilmu Pendidikan: E-Saintika*, *8*(2), 241-259. doi:10.36312/esaintika.v8i2.1902

Quarshie, A. N., Nkansah, G. B., & Oduro-Ofori, E. (2023). How Far Is Progress? Gender Dimensions of Student Enrollment in Higher Education in Ghana: The Case of Kwame Nkrumah University of Science and Technology. *SAGE Open, 13*(4). doi:10.1177/21582440231220456

R Core Team (2023). *R: A Language and environment for statistical computing.* (Version 4.3) [Computer software]. Retrieved from https://cran.r-project.org. (R packages retrieved from CRAN snapshot 2024-01-09).

Ringle, C.M., S. Wende, and J.-M. Becker (2022). *SmartPLS 4. Oststeinbek: SmartPLS*. Retrieved from https://www.smartpls.com/

Rosseel, Y., & Loh, W. W. (2024). A structural after measurement approach to structural equation modeling. *Psychological Methods, 29(*3), 561–588. doi:10.1037/met0000503

Rudolph, J., Ismail, M. F. B. M., & Popenici, S. (2024). Higher Education's Generative Artificial Intelligence Paradox: The Meaning of Chatbot Mania. *Journal of University Teaching and Learning Practice, 21*(6), 1-35. doi:10.53761/54fs5e77

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68. doi:10.1037/0003-066X.55.1.68

Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination theory perspective: Definitions, theory, practices, and future directions. *Contemporary Educational Psychology*, *61*, 101860. doi:10.1016/j.cedpsych.2020.101860

Sahar, R., & Munawaroh, M. (2025). Artificial intelligence in higher education with bibliometric and content analysis for future research agenda. *Discover Sustainability*, *6*(1). doi:10.1007/s43621-025-01086-z

Salifu, I., Arthur, F., Arkorful, V., Abam Nortey, S., & Solomon Osei-Yaw, R. (2024). Economics students' behavioural intention and usage of ChatGPT in higher education: a hybrid structural equation modelling-artificial neural network approach. *Cogent Social Sciences*, *10*(1). doi:10.1080/23311886.2023.2300177

Sanz-Tejeda, A., Domínguez-Oller, J. C., Baldaquí-Escandell, J. M., Gómez-Díaz, R., & García-Rodríguez, A. (2026). The impact of generative AI on academic reading and writing: a synthesis of recent evidence (2023–2025). *Frontiers in Education,* 10. doi:10.3389/feduc.2025.1711718

Soper D.S. (2023). *A-priori sample size calculator for structural equation models* [Computer Software]. Retrieved (July 15, 2024) from https://www.danielsoper.com/statcalc/calculator.aspx?id=8

Sozon, M., Parnther, C., Lun, W. W., & Chowdhury, M. A. (2025). Generative AI in higher education: navigating benefits and challenges in the technological era. *Journal of Applied Research in Higher Education*, 1–16. doi:10.1108/jarhe-02-2025-0103

Sullivan M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity. *Journal of Applied Learning & Teaching, 6*(1), 1-10. doi:10.37074/jalt.2023.6.1.17

Tarhini, A., Hone, K., Liu, X., & Tarhini, T. (2017). Examining the moderating effect of individual-level cultural values on users' acceptance of E-learning in developing countries: a structural equation modeling of an extended technology acceptance model. *Interactive Learning Environments, 25*(3), 306-328. doi:10.1080/10494820.2015.1122635

The jamovi project (2024). jamovi. (Version 2.5) [Computer Software]. Retrieved from https://www.jamovi.org.

Ursachi, G., Horodnic, I. A., & Zait, A. (2015). How Reliable are Measurement Scales? External Factors with Indirect Influence on Reliability Estimators. *Procedia Economics and Finance*, *20*, 679–686. doi:10.1016/s2212-5671(15)00123-9

Uslu, N. A., & Durak, H. Y. (2022). Predicting learner autonomy in collaborative learning: The role of group metacognition and motivational regulation strategies. *Learning and Motivation*, *78*, 101804. doi:10.1016/j.lmot.2022.101804

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view1. *MIS quarterly*, *27*(3), 425-478. doi:10.2307/30036540

Webb, R., Yuksel, D., & Dikilitas, K. (2026). Generative AI in English-medium instruction: Perceptions, usage, and impact on academic performance and language proficiency. *System*, *138*, 103973. doi:10.1016/j.system.2026.103973

Widaman, K. F., & Revelle, W. (2022). Thinking thrice about sum scores, and then some more about measurement and analysis. *Behaviour Research Methods*, *55*(2), 788–806. doi:10.3758/s13428-022-01849-w

Xie, Z., Wu, X., & Xie, Y. (2024). Can interaction with generative artificial intelligence enhance learning autonomy? A longitudinal study from comparative perspectives of virtual companionship and knowledge acquisition preferences. *Journal of Computer Assisted Learning*, *40*(5), 2369–2384. doi:10.1111/jcal.13032

Yang, H., & Kyun, S. (2022). The current research trend of artificial intelligence in language learning: A systematic empirical literature review from an activity theory perspective. *Australasian Journal of Educational Technology*, 180–210. doi:10.14742/ajet.7492

Yang, Y., Luo, J., Yang, M., Yang, R., & Chen, J. (2024). From surface to deep learning approaches with Generative AI in higher education: an analytical framework of student agency. *Studies in Higher Education*, *49*(5), 817–830. doi:10.1080/03075079.2024.2327003

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education–where are the educators? *International journal of educational technology in higher education*, *16*(1), 39. doi:10.1186/s41239-019-0171-0

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: a systematic review. *Smart Learning Environments*, *11*(1). doi:10.1186/s40561-024-00316-7

Zhang, K., & Aslan, A. B. (2021). AI technologies for education: Recent research & future directions. *Computers and Education Artificial Intelligence*, *2*, 100025. doi:10.1016/j.caeai.2021.100025

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