ORIGINAL RESEARCH ARTICLE

Unpacking the cognitive and ethical pathways of generative AI tools in higher education: a PLS-SEM study of learning performance mediation and moderation effects

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This study examines how Generative Artificial Intelligence Tools (GAIT) influence student learning performance (LP) through cognitive, affective and ethical pathways using Partial Least Squares Structural Equation Modeling (PLS-SEM). Data were collected from 292 Indonesian university students through a structured questionnaire. The results show that GAIT has a direct positive effect on LP ($\beta = 0.920$, $p < 0.001$). Mediation analysis identifies AI Knowledge (AIK) as the most dominant mediator ($\beta = 0.715$, $p < 0.001$), followed by AI Perception (AIP), Creativity (CRE), Fairness & Ethics (FE) and Cognitive Offloading (CO). Furthermore, AIK significantly moderates the GAIT–LP relationship ($\beta = 0.006$, $p = 0.048$). The model demonstrates high predictive power ($R^2 = 0.604$) and good model fit (Standardized Root Mean Square Residual (SRMR) = 0.068). These findings highlight the central role of AI literacy and ethical awareness in maximising the benefits of GAIT for learning. This study contributes theoretically by integrating cognitive, affective and normative dimensions into a unified model of GAIT adoption and offers practical implications for designing AI literacy and ethics-oriented curricula in higher education.

Keywords: AI-based learning; digital literacy; cognitive mediation; technology ethics; higher education

Introduction

Advances in artificial intelligence (AI) technology have brought fundamental disruption to the higher education landscape. One of the most transformative innovations is the emergence of Generative Artificial Intelligence Tools (GAIT), such as ChatGPT, GitHub Copilot and DALL E that enable real-time content production, problem solving and natural language-based interactions (Atenas et al., 2024). This technology has gone beyond the role of conventional learning support instruments and has begun to reshape students' cognitive practices in formulating ideas, understanding material and completing academic tasks (Geri, 2025). However, despite its increasingly widespread implementation, the in-depth understanding of the epistemic and pedagogical impacts of GAIT use on student learning performance (LP) remains relatively limited and fragmented (Islam, 2025).

Previous literature generally focuses on the functional efficiency of AI in the context of Education but has not comprehensively integrated the psychosocial and cognitive dimensions that accompany student interactions with the technology. Despite these advancements, little is known about how GAIT simultaneously affects cognitive, affective and ethical dimensions of student learning. Furthermore, studies on the role of mediating variables such as AI literacy (AI Knowledge (AIK)), perceptions of AI, creativity and ethical and fair values are still partial (Acosta-Enriquez, 2025). Meanwhile, the potential for moderating variables such as self-efficacy (SE) and conceptual understanding of AI that can strengthen or weaken the effects of GAIT use on learning outcomes have not been systematically tested (Bergdahl, 2025). This gap indicates the need for a conceptual model that is able to explain how GAIT operates not only as an aid but also as a complex cognitive partner that interacts dynamically with the internal characteristics of students (Blancaflor et al., 2023).

Although numerous studies have explored the use of AI in education, most have concentrated narrowly on adoption and efficiency, without synthesising how cognitive, affective and ethical dimensions collectively shape student learning. Systematic reviews (Passmore et al., 2025; Shahzad, 2025) indicate that research on generative AI in higher education remains fragmented often emphasising technical acceptance based on the Technology Acceptance Model (TAM) or cognitive offloading (CO) effects, while overlooking motivational and ethical mechanisms. This fragmentation hampers theoretical integration and creates uncertainty regarding how students internalise AI as both a cognitive and moral partner in learning. To address this gap, the present study develops an integrated, empirically tested model that unites key perspectives on technological understanding, cognitive regulation and self-belief to explain the impact of GAIT on learning outcomes.

Grounded in three complementary frameworks TAM (Davis, 1989), Cognitive Load Theory (Sweller et al., 2019) and SE Theory (Bandura, 1982), this study conceptualises GAIT as both a cognitive and affective agent influencing student LP. The TAM explains how perceived usefulness and ease of use shape technology adoption; Cognitive Load Theory highlights AI's potential to optimise mental effort; and SE Theory clarifies the motivational processes underlying learners' confidence in using technology. Through this theoretical synthesis, generative AI is positioned as both a cognitive enhancer and an ethical learning partner, providing a comprehensive lens for understanding its multidimensional influence in higher education.

The urgency of this research is reinforced by the empirical reality that students are increasingly intensively using GAIT in their learning process, often without adequate literacy regarding the limitations, ethical responsibilities or long-term impacts of its use. In this context, the use of technology without a deep conceptual understanding can have implications for reducing originality, decreasing critical thinking skills or even violating academic integrity (Acosta-Enriquez, 2025). Therefore, this study seeks to answer the key questions of to what extent and through what mechanisms GAIT contributes to students' LP, as well as what psychosocial factors play a mediating and moderating role in this relationship. Testing a model using Partial Least Squares Structural Equation Modeling (PLS-SEM), this study not only provides important theoretical contributions in developing an AI-based learning framework but also produces practical findings that can be used to improve curriculum design, digital literacy strategies and higher education policies that are better prepared for the era of AI. It is hoped that this study can broaden academic insights on how generative technologies

can be utilised ethically and effectively and bring positive changes to learning in the 21st century.

Background of the study

The rapid development of Generative Artificial Intelligence Tools (GAIT) has brought significant changes to the learning process in higher education. The use of GAIT allows students to access more interactive and adaptive learning resources, thereby directly improving LP. Research shows that the active use of GAIT is positively correlated with improved student academic outcomes (Anggoro & Khasanah, 2024). Besides that, Senent and Bueso (2022) assert that personalised AI-based learning environments are able to increase student engagement and academic achievement. In addition to direct impacts, the role of cognitive and affective factors as mediators is also increasingly being considered. Knowledge of AI is an important aspect that allows students to use generative technologies more effectively. Previous studies found that high AI literacy improves students' ability to critically understand, evaluate, and effectively utilize AI-generated content, which in turn contributes to improved learning performance. Attitudes and perceptions towards AI also influence motivation and acceptance of this technology in the learning context. Passmore et al. (2025) show that positive perceptions of AI encourage deeper engagement in the learning process, resulting in improved academic performance.

Creativity is a key mediator influenced by the use of GAIT. Punyani and Chhikara (2023) found that AI enhances creative tasks by stimulating innovative thinking and improving problem-solving, leading to better learning outcomes. Awareness of fairness and ethics in AI use also shape responsible usage. Passmore et al. (2025) emphasised that ethical understanding fosters more cautious and effective use, supporting academic achievement. CO delegating cognitive tasks to AI reduces mental load, allowing students to focus on complex learning. Richmond (2025) reported that students who engaged in CO with AI performed better on higher-level tasks. AI literacy further strengthens the positive relationship between AI use and learning outcomes. Additionally, SE enhances the impact of AI use on academic performance. Drawing on Bandura's (1982) theory, confidence in one's ability to handle tasks boosts motivation and outcomes. Bergdahl (2025) found that SE mediates the link between AI understanding and performance, suggesting that higher competence increases confidence, improving learning.

Overall, literature shows that GAIT affect learning not only directly but also through cognitive, affective and ethical pathways, with AI literacy and SE as key enablers. Building on these foundations, the proposed framework (Figure 1) integrates cognitive (AIK and CO), affective (AI Perception (AIP) and SE) and normative (Fairness & Ethics (FE)) constructs to examine how GAIT influences LP. This integrated approach reflects the multidimensional nature of AI-based learning and provides the basis for formulating hypotheses H_1–H_8.

Based on this, the following hypotheses are proposed:

H_1: The use of GAIT has a direct positive and significant effect on students' LP.
H_2: GAIT positively affects LP indirectly through the mediation of AIK.
H_3: GAIT positively affects LP indirectly through the mediation of AIP.
H_4: GAIT positively affects LP indirectly through the mediation of Creativity (CRE).

H$_5$: GAIT positively affects LP indirectly through the mediation of FE.

H$_6$: GAIT positively affects LP indirectly through the mediation of CO.

H$_7$: AIK moderates the relationship between GAIT and LP, so that the effect of GAIT on LP becomes stronger at higher levels of AI literacy.

H$_8$: SE serially mediates the relationship between GAIT and LP through AIK.

Method

Instrument

This study uses a scale construction approach because it involves latent variables that cannot be observed directly (Sarstedt et al., 2022), as can be seen in Figure 1. This research instrument was developed based on indicators adapted from related literature and measured using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) (Zhang et al., 2024). The GAIT construct is measured through five items (GAIT1–GAIT5) that assess the frequency and effectiveness of using AI such as ChatGPT in learning. AIK uses four items (AIK1–AIK4) to measure understanding of basic concepts and applications of AI. SE is measured with four items (SE1–SE4) about students' beliefs in using AI for academic tasks. Four items of AIP (AIP1–AIP4) evaluate perceived benefits and ethical concerns related to AI.

Three CRE items (CRE1–CRE3) assess the impact of AI on innovation and creative thinking, while three FE items (FE1–FE3) measure perceptions of fairness and transparency of AI use. CO (CO1–CO3) evaluates the role of AI in lightening cognitive load through three items. Five LP items (LP1–LP5) measure perceived learning outcomes, including improved achievement and understanding of the material. Prior to the main data collection, the instruments were piloted on 31 respondents to ensure clarity and construct validity (Zhang et al., 2024). LP was measured using a validated self-perception scale adapted from Wang et al. (2023). Respondents rated perceived improvement in understanding, task efficiency and academic achievement after using GAIT. Objective grade data were not collected
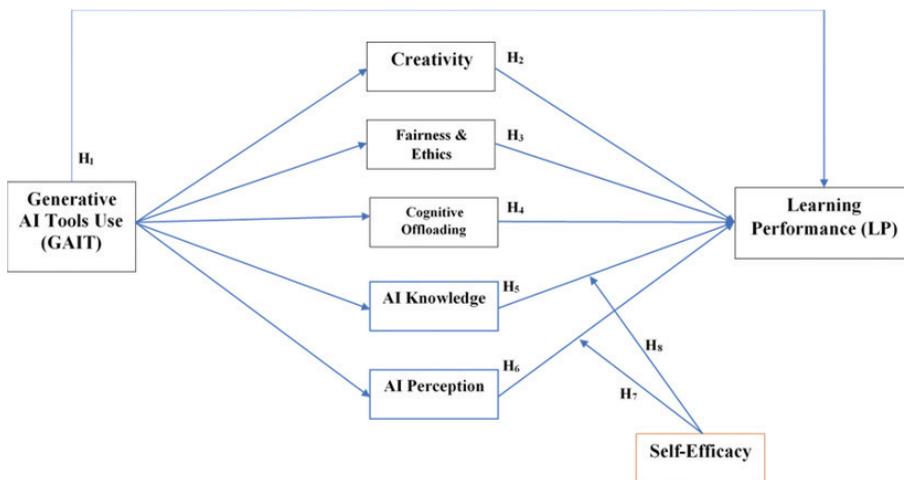

Figure 1. Conceptual framework.

due to institutional privacy regulations; however, perceived learning outcomes have been widely accepted in PLS-SEM studies as reliable proxies for academic performance (Hair et al., 2020; Shahzad et al., 2024b). Reliability analysis confirmed $\alpha = 0.869$, composite reliability [CR] = 0.905 and average variance extracted [AVE] = 0.658, indicating strong measurement consistency.

To further ensure the robustness of the measurement instrument, a pilot test and validation procedures were undertaken prior to the main data collection. A pilot test ($n = 31$) was conducted prior to the main survey to assess item clarity, reliability and construct consistency. All indicators demonstrated Cronbach's α values above 0.80, confirming internal reliability. Construct validity was further assessed using Confirmatory Factor Analysis (CFA) within SmartPLS 4, and all items met the recommended thresholds for factor loadings (>0.70), CR (>0.70) and AVE (>0.50). These results ensured that the measurement model was both valid and reliable for the main study.

Instrument validation and reliability

The measurement instruments were adapted from established scales validated in previous studies (Gansser, 2021; Wang et al., 2023). Content validity was ensured through expert review involving three scholars in educational psychology and learning technology. A pilot test ($n = 31$) was conducted to assess item clarity, translation accuracy and initial reliability. All constructs demonstrated strong internal consistency (Cronbach's $\alpha > 0.80$), indicating that the adapted items were suitable for the main data collection. Empirical validity and reliability were further tested through CFA using SmartPLS 4. Convergent validity was confirmed with all item loadings > 0.70 and AVE > 0.50. Discriminant validity was verified using Fornell–Larcker and Heterotrait–Monotrait Ratio (HTMT) criteria, both within recommended thresholds (<0.85). These results demonstrate that each latent construct possesses adequate validity and reliability for inclusion in the structural model. Table 3 presents the correlation matrix and discriminant validity results among the study constructs.

Sampling bias control and inclusion verification

The purposive sampling approach targeted university students who had at least one semester of experience using GAIT (e.g. ChatGPT, Copilot and DALL·E). To minimise bias, inclusion criteria were verified via self-report screening questions. Responses that did not meet criteria were automatically excluded. The sample of 292 valid responses represents four universities across different regions in Indonesia, ensuring variability in institutional context while maintaining homogeneity of AI exposure. As shown in Table 1, the sample characteristics indicate that the respondents represent diverse backgrounds in terms of gender, age, educational level, and field of study.

Data analysis and theoretical justification

Data were analysed using PLS-SEM with SmartPLS 4. This method was chosen because it is theoretically appropriate for testing complex models with multiple mediating and moderating variables and latent constructs (Hair et al., 2020). The inner model structure reflects theoretical linkages derived from the TAM, Cognitive Load

Table 1. Sample characteristics.

Demographics	Frequency	Percentage
Gender		
Woman	164	56.16
Man	128	43.84
Age		
18–24 Years	180	61.64
25–30 Years	85	29.11
31–36 Years	27	9.25
Over 36 Years	0	0
Educational background		
Bachelor's degree	210	71.92
Master degree	70	23.97
Doctorate	12	4.11
Field of study		
Natural science	110	37.67
Mathematics	75	25.68
Engineering	107	36.64

Theory and Self-Efficacy Theory, which jointly explain how cognitive, affective and normative dimensions influence LP. Model fit was assessed using R^2, SRMR and Q^2 values to confirm explanatory and predictive power.

Data collection and sampling techniques

Several universities in Indonesia have begun integrating Generative Artificial Intelligence Tools (GAIT) to predict learning content, academic challenges and provide personalised learning recommendations (Wang et al., 2023). This study used a purposive sampling technique to ensure that participants met two main criteria: (1) came from institutions that had implemented generative AI in management, teaching or learning; and (2) had direct experience using AI technology. Participants were purposively selected based on two inclusion criteria: (1) enrolment at higher-education institutions that had formally integrated GAIT into their teaching or learning processes and (2) a minimum of one-semester experience using AI technologies such as ChatGPT or Copilot. Ethical approval for the study was obtained from the affiliated institutional review board, and an informed consent was secured from all respondents prior to participation.

This study focused on students enrolled in Science, Technology, Engineering, and Mathematics (STEM)-related disciplines, including Natural Sciences, Engineering and Mathematics, where generative AI technologies such as ChatGPT, GitHub Copilot and DALL·E are actively integrated into coursework for content generation, coding and analytical reasoning. These disciplines were selected because they represent contexts with intensive AI adoption in academic activities, including problem-solving, simulation and creative experimentation. The focus on these domains aligns with Cognitive Tool Theory (Jordan, 2023), which posits that AI technologies enhance cognitive processing by enabling learners to offload complex informational tasks and concentrate on higher-order thinking. Data were collected online from 292 respondents at four universities via Questionnaire Star, with survey distribution via WhatsApp groups.

Demographic profile shows that the majority of respondents are female (56.16%) with a young age predominance (18–24 years: 61.64%; 25–30 years: 29.11%). Most have a bachelor's degree (71.92%), followed by a master's degree (23.97%) and a doctorate (4.11%). Fields of study are concentrated in Natural Sciences (37.67%), Engineering (36.64%) and Mathematics (25.68%), reflecting a strong focus on science and technology disciplines. There are no respondents over the age of 36, indicating a relatively young and highly educated population. The data collection techniques used ensure the validity of the results while facilitating access to relevant participants (Shahzad et al., 2024a).

Data analysis

This study uses the PLS-SEM approach to analyse the data, considering that the conceptual model is complex and contains predictive components (Sarstedt et al., 2022). SmartPLS 4 was used for the analysis due to its ability to handle models that include reflective and formative concepts, as well as providing robust statistical solutions for data that do not meet the normality assumption. This analysis allows for a better understanding of the relationship between the use of generative AI technologies and various variables that influence student LP in higher education.

Results

This section presents the findings of the PLS-SEM analysis in three main stages: (1) assessment of the measurement model, (2) evaluation of the structural model and (3) hypothesis testing. The results are systematically organised according to the proposed hypotheses (H_1–H_8) to improve clarity and logical flow. Table 2 presents the measurement model results, including reliability, convergent and discriminant validity indicators, whilst Table 4 summarises the structural relationships among constructs. Figure 2 illustrates the validated conceptual model, showing the direction and magnitude of the tested paths. The following subsections describe each stage of the analysis, highlighting significant path coefficients (β), *t*-values and *p*-values to provide an integrated understanding of how cognitive, affective and ethical factors influence LP in AI-enhanced education.

Common method bias

To minimise the potential for Common Method Bias (CMB) that can affect the validity of the results, this study implemented procedural and statistical strategies. Procedurally, the survey instrument was designed with careful item construction, pre-testing and explanation of the research objectives to respondents to ensure the accuracy of the responses. Statistically, Harman's one-factor test through Principal Component Analysis (PCA) in Statistical Package for the Social Sciences (SPSS) showed that the largest variance explained by one factor was below the critical threshold of 50%, indicating the absence of dominance of one factor. This result is supported by the application of the one-way test approach (Lamberti, 2023), which further strengthens that CMB is not a significant threat in this study.

Table 2. Measurement model results.

Constructs and items	FL	α	CR	AVE	Source
Generative artificial intelligence-based technology (GAIT)		0.943	0.958	0.821	(Shahzad et al., 2024)
GAIT1 I use generative AI tools (eg, ChatGPT and Copilot) to help me understand course material.	0.723				
GAIT2 I use generative AI to complete assignments or academic tasks.	0.951				
GAIT3 Generative AI helps me generate new ideas and inspiration in learning.	0.975				
GAIT4 I regularly use generative AI as part of my learning routine.	0.963				
GAIT5 I integrate generative AI to improve the quality of my academic work.	0.950				
Cognitive Unpacking (CO)		0.925	0.953	0.872	(Shum, 2024)
CO1 I use AI to remember information that is difficult to memorise.	0.868				
CO2 I often rely on AI to help organise complex information.	0.865				
CO3 AI helps me understand complicated topics more easily.	0.856				
Creativity (CRE)		0.935	0.959	0.886	(Wu, 2021)
CRE1 I can develop unique ideas after using generative AI.	0.860				
CRE2 Generative AI encourages me to think more creatively in my studies.	0.787				
CRE3 I can generate original solutions for academic tasks.	0.739				
Fairness & Ethics (FE)		0.716	0.875	0.777	(Bernabei et al., 2023)
FE1 I consider academic honesty when using AI.	0.905				
FE2 I understand the ethical boundaries of using AI in learning.	0.750				
FE3 I do not rely on AI to copy or plagiarise others' work.	0.709				
Learning Performance (LP)		0.869	0.905	0.658	(Wang et al., 2023)
LP1 I feel my academic performance has improved since using AI.	0.829				

Table 2. (*continued*)

Constructs and items	FL	α	CR	AVE	Source
LP2 I understand course material better when using AI as a support tool.	0.848				
LP3 I complete tasks more effectively after using AI.	0.838				
LP4 I complete assignments more quickly with the help of AI.	0.793				
LP5 My academic grades have improved through the use of AI in learning.	0.837				
AI Knowledge (AIK)		0.972	0.980	0.924	(Li, 2024)
AIK1 I understand how generative AI tools like ChatGPT work.	0.996				
AIK2 I know how generative AI generates responses or texts.	0.927				
AIK3 I am aware of the strengths and limitations of generative AI.	0.927				
AIK4 I can explain basic concepts of generative AI systems.	0.992				
Self-Efficacy (SE)		0.940	0.957	0.849	(Tan et al., 2021)
SE1 I am confident in completing academic tasks with AI support.	0.890				
SE2 I believe I can learn new topics, even difficult ones, with the help of AI.	0.945				
SE3 I have the ability to learn independently using AI.	0.932				
SE4 I am capable of using AI to support my learning process.	0.917				
AI Perception (AIP)		0.779	0.821	0.705	(Westphal et al., 2023)
AIP1 I find generative AI beneficial for supporting my learning.	0.844				
AIP2 Generative AI makes learning more efficient.	0.867				
AIP3 I believe AI use can improve academic outcomes.	0.747				
AIP4 I have a positive perception of using AI in education.	0.743				

FL: Factor loading; α: Cronbach's alpha; CR: Composite reliability; AVE: Average variance extracted; AI: artificial intelligence.

Table 3. Correlation matrix.

Inter-construct correlations	1	2	3	4	5	6	7	8
1. AIK	**0.961**							
2. AIP	0.157	**0.802**						
3. CO	0.009	0.328	**0.934**					
4. CRE	0.187	0.638	0.212	**0.941**				
5. FE	0.309	0.218	0.161	0.072	**0.792**			
6. GAIT	0.173	0.267	0.487	0.316	0.021	**0.906**		
7. LP	0.008	0.602	0.222	0.295	0.165	0.194	**0.811**	
8. SE	0.210	0.114	0.072	0.198	0.122	0.210	0.008	**0.921**

The values located on the diagonal are the square root of the AVE, while the values outside the diagonal reflect the level of correlation between constructs. This approach is in accordance with the Fornell-Larcker standard for testing discriminant validity. The calculation process of all data is carried out by applying the PLS Algorithm using SmartPLS software (Version 4.1.0.2) (Hu et al., 2025).

CO: Cognitive Unpacking; GAIT: Generative artificial intelligence-based technology; CRE: Creativity; FE: Fairness & Ethics; LP: Learning Performance; AIK: AI Knowledge; SE: Self-Efficacy; AIP: AI Perception; AVE: Average Variance Extracted.

Table 4. Structural model.

Hypothesis and relationship	β	SD	T	P	Outcomes
Immediate effects					
GAIT → LP (H_1)	0.920	0.920	0.012	0.000	Supported
GAIT → AIP	0.680	0.682	0.038	0.000	
GAIT → CO	0.864	0.864	0.021	0.000	
GAIT → CRE	0.896	0.895	0.017	0.000	
GAIT → FE	0.781	0.782	0.028	0.000	
GAIT → AIK	0.807	0.806	0.021	0.000	
GAIT → SE	0.911	0.911	0.012	0.000	
Mediation path					
GAIT → CRE → LP (H_2)	0.143	0.140	0.044	0.001	Supported
GAIT → FE → LP (H_3)	0.226	0.227	0.085	0.008	Supported
GAIT → CO → LP (H_4)	0.196	0.196	0.016	0.000	Supported
GAIT → AIK → LP (H_5)	0.246	0.256	0.050	0.000	Supported
GAIT → AIP → LP (H_6)	0.715	0.715	0.020	0.000	Supported
Serial mediation path					
GAIT → AIP → SE → LP (H_7)	0.006	0.004	1500	0.111	Not Supported
GAIT → AIK → SE → LP (H_8)	0.006	0.003	1898	0.048	Supported

CO: Cognitive Unpacking; GAIT: Generative artificial intelligence-based technology; CRE: Creativity; FE: Fairness & Ethics; LP: Learning Performance; AIK: AI Knowledge; SE: Self-Efficacy; AIP: AI Perception.

Evaluation of measurement models

This study ensures the validity and reliability of the instrument through three comprehensive approaches. Content validity was ensured through pre-survey testing and adaptation of published scales (Sarstedt et al., 2022). Statistical analysis showed that all indicators met the validity criteria with a loading factor >0.70 (Hair et al., 2020). Construct reliability is proven through Cronbach's Alpha and CR values >0.70 and AVE >0.50, which simultaneously confirms convergent validity. Discriminant validity is confirmed through two methods: (1) the square root of AVE, which is greater than the correlation between constructs, and (2) the HTMT value <0.90 (Shahzad
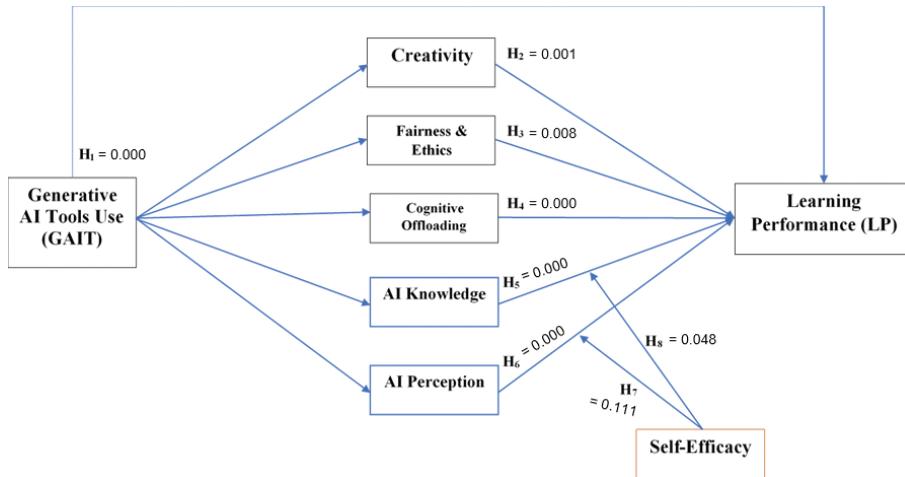
Figure 2. The model was analysed using bootstrapping with 5000 subsamples at a significance level of 0.05 in SmartPLS (v.4.1.0.2) (Wang et al., 2021). AI: artificial intelligence.

et al., 2024b), ensuring that each construct is unique and precisely measured. These findings as a whole guarantee the quality of the metrics used in the study.

Structural model evaluation

The results of the structural model analysis indicate that the use of GAIT has a positive and significant effect on students' LP ($\beta = 0.920$; $p < 0.001$). In addition to this direct effect, five partial mediation paths through AIK, AIP, CRE, FE and CO were also found to be significant, with $p < 0.001$ for AIK, AIP and CO; $p = 0.008$ for CRE; and $p = 0.001$ for FE. The serial mediation analysis further revealed that AIK significantly enhances LP through SE ($\beta = 0.006$; $p = 0.048$), while the pathway through AIP was not significant ($p = 0.111$). Overall, the model demonstrates high predictive power, with an R^2 value of 0.604 and an SRMR value of 0.068, indicating a good model fit.

Testing hypotheses H_1: direct effect of GAIT on learning performance

The first hypothesis (H1) proposed that the use of GAIT would have a direct positive and significant effect on students' LP. The results strongly supported this assumption, showing that GAIT had a substantial direct influence on LP ($\beta = 0.920$; $p < 0.001$). This indicates that students who actively utilise GAIT, such as ChatGPT, Copilot or DALL·E, tend to achieve better academic outcomes due to improved comprehension, faster task completion and enhanced engagement. Therefore, H_1 is supported.

Testing hypotheses H_2–H_6: mediating effects

Hypotheses H_2–H_6 examined whether the relationships between GAIT and LP were mediated by several psychosocial and cognitive variables, including AIK, AIP, CRE,

FE and CO. The mediation analysis revealed that all five constructs acted as significant mediators. Specifically, AIK emerged as the strongest mediator ($\beta = 0.715$; $p < 0.001$), followed by AIP ($\beta = 0.246$; $p < 0.001$), CRE ($\beta = 0.226$; $p = 0.008$), FE ($\beta = 0.143$; $p = 0.001$) and CO ($\beta = 0.196$; $p < 0.001$). These findings confirm that GAIT enhances LP not only through direct engagement but also through its effects on students' understanding, perception, creativity, ethical awareness and cognitive management. Hence, H_2–H_6 are supported.

Testing hypotheses H_7 & H_8: serial mediation

Hypothesis H_7 proposed that GAIT indirectly affects LP through a serial mediation pathway involving AIK and SE. The results of the serial mediation test confirmed this hypothesis ($\beta = 0.006$; $p = 0.048$). This suggests that students with higher AI literacy (AIK) tend to develop greater confidence (SE) in applying AI tools to academic tasks, which subsequently improves their LP. Therefore, H_7 is supported. Hypothesis H_8 predicted that GAIT would influence LP through AIP and SE. However, this pathway was found to be statistically insignificant ($p = 0.111$). This indicates that positive perceptions of AI alone are insufficient to enhance self-efficacy or translate into improved academic outcomes unless supported by solid AIK and skills. Thus, H_8 is not supported.

Moderation analysis

To further test moderation effects, this study examined whether AIK, AIP and SE moderated the relationship between GAIT and LP. The results showed that only AIK significantly strengthened the GAIT–LP relationship ($\beta = 0.006$; $p = 0.048$), indicating that students with higher levels of AI literacy gain more bene fits from GAIT use. Meanwhile, AIP and SE did not show significant moderating effects ($p > 0.05$). This reinforces the notion that knowledge-based readiness, rather than affective perception alone, determines how effectively students can leverage GAIT for learning. Overall, the results provide robust empirical support for the proposed conceptual model (Figure 1), confirming that GAIT influences student LP both directly and indirectly through cognitive, affective and ethical mechanisms.

Explanatory power of the model

The structural model shows substantial explanatory power. The R^2 value for the LP construct of 0.604 supports the claim that the variables in the model explain a large proportion of the variation in learning outcomes. The R^2 values for other constructs also show predictive power: CRE (0.131), FE (0.114), SE (0.040) and CO (0.187). Furthermore, the SRMR value of 0.068 is within the recommended range (<0.08), indicating that the model has adequate structural fit.

Predictive power of the model

The predictive power of the model was evaluated through cross-validated redundancy analysis (Q^2) using the blindfolding technique. Based on the approach Sarstedt et al.

(2022), the model is said to have predictive ability if the Q^2 value > 0. The results of the analysis show that all dependent constructs in the model have positive Q^2 values, which indicates that the model has good predictive ability for student learning achievement variables.

Discussion

The findings of this study indicate that the use of GAIT contributes significantly to improving student LP, both directly and indirectly. The findings not only reaffirm previous results but also extend the theoretical understanding of how GAIT influence learning. Specifically, the strong direct and indirect effects found in this study align with the TAM (Davis, 1989) by emphasising that AIK increases perceived usefulness and engagement. However, the results go beyond the original TAM framework by showing that the integration of cognitive and ethical constructs modifies the adoption mechanism of AI-based learning (Gansser, 2021). This demonstrates that the value of AI in education lies not only in technological acceptance but also in how students internalise it as a cognitive and ethical learning partner. Such insights expand TAM's applicability to the context of Generative AI, bridging cognitive and moral dimensions often absent in traditional acceptance studies.

The highly significant direct effect of GAIT on LP ($\beta = 0.920$; $p < 0.001$) confirms that the adoption of AI technology in the context of higher education has passed the experimental stage and has shown a real impact on learning outcomes. This is in line with recent literature that shows a paradigm shift in digital learning, where the presence of AI is not only assistive but also transformative (Matli, 2024). For instance, engineering students reported using ChatGPT to debug code and clarify algorithmic concepts, while mathematics students relied on GAIT tools to visualise formulas and proofs. Such practices demonstrate how generative AI functions as a cognitive partner that reduces mental load (Kennedy, 2024) and enhances self-efficacy (Bandura, 1982), resulting in accelerated comprehension and more efficient problem-solving. These practical examples support the statistical evidence and illustrate how GAIT not only improves task completion speed but also strengthens conceptual understanding in complex learning domains.

Furthermore, the contribution of the mediation pathway provides an in-depth understanding of the psychosocial mechanisms that mediate the relationship between AI use and academic achievement. AIK emerged as the most dominant mediator ($\beta = 0.715$; $p < 0.001$), confirming the importance of AI literacy in optimising the use of this technology. These results support the TAM theory, where the perception of usefulness and understanding of technology are the main determinants of the effectiveness of technology use (Gansser, 2021). In this context, students with a higher understanding of AI tend to be more able to integrate AI strategically into their learning activities, rather than simply as a passive tool (Lundberg & Mozelius, 2024). The dominant mediation of AIK corroborates the TAM proposition that technological understanding enhances perceived usefulness (Gansser, 2021). Similarly, the significant path through CO validates Cognitive Load Theory by demonstrating how GAIT reduces learners' mental burden when dealing with complex information (Kennedy, 2024). In addition, the positive contribution of SE confirms Bandura's (1982) principle that confidence in one's capability increases motivation and persistence, which consequently improves LP. Together, these results empirically reinforce the integrated theoretical model proposed in this study.

Another interesting finding is the positive contribution of AIP, CRE, FE and CO. The role of AIP as a significant mediator ($\beta = 0.246$; $p < 0.001$) indicates that positive perceptions of AI are correlated with higher academic engagement. However, it should be noted that this perception only acts as a mediator, not a moderator. This means that its influence is limited if it is not accompanied by adequate understanding and competence (Srinivasan, 2023). On the other hand, the contribution of CRE and CO shows that AI can act as a catalyst for ideas and also a cognitive tool that helps manage students' mental load (Rajput & Arora, 2024). This adds a new dimension to the study of cognitive load (Cognitive Load Theory), with AI serving as an external memory system that allows students to focus on high-level processing (Kennedy, 2024).

These results indicating on FE highlight the normative dimension of AI adoption. The significant mediation effect of FE ($\beta = 0.143$; $p = 0.001$) shows that the integration of ethical values in the use of AI is positively correlated with learning outcomes. This reinforces the view that digital ethics education is an integral element in shaping a generation of AI users who are not only technically proficient but also socially responsible (Shahzad, 2025). Significant serial mediation analysis through AIK and SE ($\beta = 0.006$; $p = 0.048$) adds an important conceptual layer in understanding the formation of academic self-confidence. High AIK contributes to increased SE, which then has a positive impact on LP (Kim, 2025). However, the mediation path through AIP and SE was not significant ($p = 0.111$), indicating that positive perceptions of AI do not automatically increase self-confidence, unless supported by substantial mastery of the technology. This finding underscores the importance of integrating skills-based AI training, rather than simply promoting positive perceptions. In the moderation analysis, only AIK showed a significant effect ($\beta = 0.006$; $p = 0.048$), confirming that the relationship between the use of GAIT and LP is highly dependent on students' AI literacy levels. This result not only strengthens the assumption that technology utilisation is knowledge-dependent but also challenges the popular narrative that access and exposure to AI are sufficient to generate learning benefits. On the contrary, the effect of GAIT on LP is optimal only when users have adequate conceptual and procedural understanding of AI. This finding is based on the principles of cognitive tool theory (Jordan, 2023), which states that technology will only expand cognitive capabilities if users are able to actively construct and manage the information obtained from it (Fabia, 2024).

The insignificance of AIP and SE as moderators also presents important conceptual implications. Positive perceptions of AI (AIP) or confidence in learning (SE) do not seem to be enough to bridge the use of AI with improved learning outcomes. This suggests that affective readiness alone is not enough; what is needed is epistemic readiness. In this context, AI literacy is not just technical skills (e.g. how to use ChatGPT), but rather a critical understanding of the functions, limitations and ethical implications of AI in the learning process (Kulangareth et al., 2024). Therefore, AI literacy should be positioned as an essential competency in higher education, not a complement (Lang, 2024). An important message that emerges from these findings is that higher education institutions need to shift from simply promoting the use of technology to establishing a learning ecosystem that is oriented towards deep AI literacy (Chen, 2025). Practical skills-based training needs to be integrated with a curriculum that encourages reflective and analytical understanding of technology. In this way, students will become not only passive users of AI but also learning agents who are able to use AI strategically and ethically (Yim, 2024).

Furthermore, the high explanatory power of the model ($R^2 = 0.604$ for LP) indicates that the conceptual framework developed in this study is able to capture the complexity of the relationship between technology, psychosocial and cognition in the context of AI-based learning. The existence of an SRMR value of 0.068, which is within the ideal limit, strengthens that this model is not only statistically adequate but also conceptually robust. The integration of cognitive (AIK, CO), affective (AIP, SE) and normative (FE) dimensions in the model reflects a holistic approach that is highly relevant in the increasingly digitalised higher education landscape. Overall, these findings present a new narrative that generative AI should not only be seen as instrumental technology but also as a cognitive-ethical partner in the learning process. When used by AI-literate learners, this technology not only accelerates academic achievement but also encourages the development of high-level thinking capacity, reflectivity and ethical responsibility. The practical implications are very broad, including curriculum design, lecturer training and national digital literacy policies. As illustrated in Figure 1 and supported by Table 4, the hypothesised model was empirically validated, demonstrating that cognitive (AIK, CO), affective (AIP, SE) and ethical (FE) dimensions jointly shape LP in AI-enhanced education.

Theoretically, this research advances the TAM and Cognitive Tool Theory by demonstrating how cognitive, affective and normative mediators operate concurrently within a unified PLS-SEM framework. The findings reveal that AIK not only enhances perceived usefulness (a core tenet of TAM) but also strengthens learners' self-efficacy, validating the motivational dimension of technology acceptance. Simultaneously, the integration of ethical and affective constructs extends Cognitive Tool Theory by positioning generative AI as a socio-cognitive partner one that supports CO, creative reasoning and ethical decision-making in complex learning contexts. Through this synthesis, this study deepens theoretical understanding of how learners cognitively and morally co-adapt to intelligent technologies in the digital learning ecosystem.

Practically, this study provides a multi-layered roadmap for embedding generative AI into higher education in ways that are pedagogically meaningful, ethically grounded and institutionally sustainable. Beyond promoting technical proficiency, universities must cultivate critical AI literacy the ability to question, interpret and ethically deploy AI outputs. This entails curriculum reform that integrates reflective and project-based engagement with AI tools, faculty development programs that equip educators to facilitate human–AI collaboration and governance frameworks that uphold academic integrity in AI-mediated learning environments. These insights position the study as a foundational reference for institutions seeking to align technological innovation with ethical stewardship and human-centred learning.

Conclusion

This study confirms that the use of GAIT significantly enhances student LP, both directly and indirectly through mediating channels involving AIK, AIP, CRE, FE, and CO. Among these mediators, AIK emerged as the most dominant, indicating that a deep understanding of AI serves as a critical foundation for optimising technology in educational contexts. Further moderation analysis revealed that only AIK significantly strengthened the relationship between GAIT and LP, emphasising the importance of AI literacy that is not merely technical but also conceptual and reflective. With high explanatory power and good model fit, these results provide a robust

empirical foundation for advancing AI-based learning frameworks in higher education. Beyond empirical findings, the results align closely with the theoretical frameworks underpinning this research. The observed relationships illustrate that perceived usefulness, cognitive support and motivational confidence interact to shape learning outcomes. This integration advances understanding of AI in education by positioning GAIT as both a cognitive enhancer and a socio-ethical learning partner. The findings also extend existing learning models by demonstrating how cognitive, affective and ethical dimensions jointly contribute to performance improvement in AI-supported environments.

Theoretically, this study contributes by providing a multidimensional explanation of AI adoption in learning contexts, integrating cognitive, affective and normative mediators within one framework. These findings strengthen the theoretical basis for viewing AI not just as a technological tool but as a transformative educational agent that supports human cognition and ethical awareness. Despite these contributions, this study has several methodological limitations, including its cross-sectional design, which limits causal inference, and its relatively narrow geographic and institutional scope. Future research should adopt longitudinal or mixed-method approaches and consider contextual factors such as faculty support, institutional readiness and access to digital infrastructure. Variables such as trust in AI, AI anxiety and algorithmic transparency may also offer valuable directions for further exploration.

Practically, these findings suggest that universities should move beyond technical promotion of AI and focus on embedding AI literacy and ethical reasoning into the curriculum. Faculty members should be trained to integrate GAIT-based pedagogy that emphasises CO benefits while safeguarding academic integrity. Institutional policies should therefore position AI literacy as a core academic competence rather than a peripheral skill. This aligns with international higher-education strategies advocating for critical AI literacy and responsible technology use as foundational competencies for the digital era. Furthermore, these insights provide strategic implications for curriculum development, AI literacy training and pedagogical design that can respond to technological disruption adaptively and ethically. Overall, this study not only provides empirical evidence for the multidimensional impact of GAIT on student LP but also offers a theoretical and practical roadmap for the ethical and effective integration of AI in higher education. The findings underscore that the success of AI-enhanced learning depends not solely on technology itself but also on how institutions and educators foster reflective, ethical and human-centred engagement with intelligent tools.

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