Beyond the hype: Decoding how generative AI shapes academic achievement in higher education

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The study investigated how university students' adoption and usage of ChatGPT influences their academic achievement. The study further explored how these relationships differ by gender and field of study. Using an online cross-sectional survey, data were collected from 461 students at a Ghanaian public university. Measures consisted of ChatGPT literacy, self-efficacy, behavioural intention to use ChatGPT and academic achievement. Structural equation modelling and multi-group analysis were employed to test hypothesised relationships and examine potential gender and discipline differences. Findings show that higher ChatGPT literacy and self-efficacy significantly boost students' behavioural intention to use ChatGPT, which positively impacts academic achievement. Notably, the effect of behavioural intention on achievement was stronger among science, technology, engineering and mathematics (STEM) students, highlighting the role of field of study in shaping ChatGPT's educational benefits. The study presents a predictive model linking ChatGPT adoption factors to academic success and emphasises the need for targeted support, especially for non-STEM students, to foster equitable artificial intelligence (AI) integration. It offers practical guidance for educators and policymakers to develop discipline-sensitive strategies that enhance ChatGPT literacy and self-efficacy, ensuring more inclusive and effective use of generative artificial intelligence (GenAI) tools in higher education.

Implications for practice or policy:

- University administrators should mandate AI literacy training during orientation to ensure equitable student engagement.
- Non-STEM programme leaders can improve outcomes by embedding discipline-specific AI tasks into core curricula.
- Equity and inclusion officers must monitor demographic disparities in adoption to provide targeted support.
- Institutional policymakers should establish integrity frameworks that balance AI-assisted learning with rigorous assessment.

Keywords: academic achievement, self-efficacy, higher education, generative AI, ChatGPT, AI literacy, cross-sectional survey

Introduction

Universities are undergoing a transformative phase as generative artificial intelligence (GenAI) and large language models like OpenAI's ChatGPT become integral to teaching and learning (Singh et al., 2024; Wu & Yu, 2024). Surpassing 100 million weekly users by March 2024, ChatGPT's adoption is largely student-driven, with surveys indicating approximately 89% use it for academic purposes (Bhattacharya et al., 2024; Hasselqvist Haglund, 2023). This provides unprecedented opportunities for personalised learning and task automation (Mai et al., 2024).

The process of integrating ChatGPT into learning activities is becoming increasingly profound, necessitating significant adjustment in pedagogical approaches, assessment methods and institutional policies (Sandu et al., 2024; Timotheou et al., 2023). Globally, as universities continue to explore the adoption of ChatGPT and other GenAI tools, understanding how students interact with and benefit from these models becomes critical ((Essel, Vlachopoulos, Essuman, et al., 2024). Studies have suggested that student success with new technologies depends not only on accessibility but also on determinants such as behavioural intention (BI), literacy and self-efficacy (SE) towards using these tools (Essel, Vlachopoulos, Nunoo-Mensah, et al., 2024; Wang & Wang, 2010). ChatGPT's potential to enhance academic performance is significant, yet the extent to which its use affects students' learning outcomes remains underexplored, specifically in Ghana.

While recent studies explored the influence of conversational artificial intelligence on learning (Bozkurt, 2026a, 2026b; Chang et al., 2022; Essel et al., 2022), findings remain inconsistent. Significant gaps exist regarding the relationship between ChatGPT literacy, SE and BI to use these tools, particularly how these factors collectively influence academic achievement (AA) in the Ghanaian university context (Essel, Vlachopoulos, Nunoo-Mensah, et al., 2024; Tlili et al., 2023). Related literature has highlighted the relationship between SE and AI literacy (Montag et al., 2023) in relation to the intention to use AI chatbots, but few have examined the broader implications of ChatGPT across diverse fields of study.

Given the rapid adoption of ChatGPT among university students in Ghana and globally ((Essel, Vlachopoulos, Essuman, et al., 2024), there was a need to develop a predictive model that examined the complex interplay between ChatGPT literacy, BI to use ChatGPT and ChatGPT SE, and their effects on AA. Moreover, this study examined invariance across gender and fields of study (science, technology, engineering and mathematics [STEM] vs non-STEM) among a diverse student population. Drawing on established frameworks such as the extensions of the technology acceptance model (Davis, 1993; Venkatesh et al., 2003), as well as recent literature on conversational AI chatbots in education (Carolus et al., 2023; Wang & Chuang, 2024), the study proposed a robust model of ChatGPT adoption and its relationship with AA.

Literature review and hypothesis development

ChatGPT literacy, ChatGPT SE and BI to use ChatGPT

The increasing prevalence of AI in the context of higher education requires users to develop higher AI literacy: an understanding of the systems, uses, limitations and ethical implications (Ma et al., 2024; Wang et al., 2025). Thus, in the context of this study, ChatGPT literacy emphasises the significance of identifying biases, knowing the right uses and making informed choices about incorporating ChatGPT into learning activities. This involves comprehending its ethical implications, limitations and functionalities without needing deep technical knowledge (Liang et al., 2023; Ma et al., 2024). Studies indicate that students with advanced AI literacy are likely to adopt AI systems to enhance their learning activities (Ma & Lei, 2024; Stolpe & Hallström, 2024).

BI, a critical determinant of technology acceptance, refers to an individual's readiness to adopt and use a particular technology in the future (Davis, 1993). The technology acceptance model (Davis, 1993) posits that an individual's intentions to use a particular technology are driven by the technology's perceived ease

of use (PEOU) and perceived usefulness. Prior studies (Al-Abdullatif & Alsubaie, 2024; Singh et al., 2024) emphasise that students' perceived confidence and willingness to engage with AI tools are enhanced by their AI literacy in their routine learning. However, these studies did not specifically focus on ChatGPT literacy as a context-specific predictor of BI. Regarding ChatGPT, we extend the literature by hypothesising that students with higher ChatGPT literacy are likely to perceive the tool as a valuable academic aid, thereby strengthening their BI to use it.

SE is associated with behaviour and reflects an individual's belief to undertake a task competently (Davis, 1993). Rooted in Bandura's (2014) social cognitive theory, SE plays a critical role in how users adopt and use new technologies. Its adoption in recent studies on student learning and motivation has increased. ChatGPT SE refers to a student's confidence in their ability to use ChatGPT successfully. Research shows a positive relationship between technological literacy and SE, with students who better understand a tool, reporting greater confidence in adoption for academic purposes (Gomez et al., 2022; Han & Yi, 2019; Wu et al., 2023). Among university students – particularly Generation Z (born between 1995 and 2010; Mahapatra et al., 2022) – ChatGPT SE tends to be high, given their familiarity with emerging technologies (Singh et al., 2024). Based on previous literature, this study proposed the following hypotheses:

> H1. There is a relationship between ChatGPT literacy and SE in using ChatGPT.
> H2. There is a relationship between ChatGPT literacy and BI to use ChatGPT for academic activities.

BI to use ChatGPT and technology SE

Technology SE can influence BI both directly and indirectly through PEOU, perceived usefulness and user attitudes (Bai et al., 2024; Pan, 2020). In educational settings, SE is essential in shaping students' attitudes towards adopting tools like ChatGPT. Users with higher confidence are more likely to perceive these tools as beneficial and incorporate them into their academic routines. Studies have shown an indirect relationship between SE and BI in organisational contexts (Bai et al., 2024), and SE has been identified as a key predictor of PEOU in technology adoption (Khoa, 2023; Li et al., 2024). Within the technology acceptance model, SE enhances PEOU, which strengthens BI (Venkatesh et al., 2003). However, Park et al. (2012) found that although SE influenced PEOU, PEOU did not significantly affect students' intention to learn with technology. In contrast, Han and Yi (2019) reported a significant and positive relationship between SE and BI, varying across user groups.

SE also affects BI through affective factors such as reduced anxiety and increased enjoyment (Chai et al., 2021; Chang et al., 2024). Students who are confident in using ChatGPT tend to experience less anxiety and increased motivation (Li et al., 2022). Prior experience with GenAI further enhances students' SE by providing familiarity and confidence in handling AI interactions (Jochim & Lenz-Kesekamp, 2025; Lee & Song, 2024). This experiential familiarity reduces anxiety and reinforces PEOU, both of which are known precursors of BI (Venkatesh et al., 2023). BI is shaped by expectations and attitudes (Maruping et al., 2017), and students with high SE show greater willingness to adopt digital tools (Pan, 2020; Xu et al., 2024). Furthermore, when students perceive ChatGPT as relevant to their learning needs, this relevance reinforces their belief in their capability to use the tool effectively – a dimension of SE – thereby increasing their intention to adopt it (Acosta-Enriquez et al., 2024; Park et al., 2012; Suriano et al., 2025). Therefore, the link between technology SE and BI was proposed through the following hypothesis:

> H3. There is a relationship between SE in using ChatGPT and BI to use ChatGPT for learning activities.

Usage intention, ChatGPT SE and AA

Studies have explored the impact of emerging technologies on AA, defined as a student's performance in completing academic tasks (Goodhue & Thompson, 1995). Performance is measured in terms of productivity and task value (McGill et al., 2011), and alignment between technology and academic tasks can enhance grades and task completion (Liu et al., 2023; Wang et al., 2013). While measuring ChatGPT's

impact is complex, this study used students' self-reported perceptions to assess its influence on AA. Students with higher SE are more confident in using technology, which improves learning outcomes (Wang et al., 2013). ChatGPT SE can enhance learning efficiency and performance (Chang et al., 2022; Chen et al., 2023; Javaid et al., 2023), as developing this confidence may be key to improving achievement. The literature indicates that students' belief in a technology's educational value is associated with better academic outcomes (Hanham et al., 2021). As such, when students perceive ChatGPT as relevant and useful, their intention to use it strengthens, enhancing engagement and performance (Shin et al., 2011). Thus, fostering strong ChatGPT SE and intention to use ChatGPT may positively influence AA. Accordingly, the present study proposed the following hypotheses:

H4. There is a relationship between ChatGPT literacy in leveraging ChatGPT and AA.
H5. There is a relationship between intention to use ChatGPT and AA.
H6. There is a relationship between SE in leveraging ChatGPT and AA.

Given prior studies indicating gender-based differences in adoption and AI engagement (Bouzar et al., 2024; Møgelvang et al., 2024), as well as disciplinary differences in digital tool utilisation (Hernandez et al., 2025), it is plausible that the relationships proposed in the study's model might vary across student subgroups.

H7. The relationship between ChatGPT literacy, SE, intention to use ChatGPT and AA differ significantly between male and female students.
H8. The relationship between ChatGPT literacy, SE, intention to use ChatGPT and AA differ significantly between STEM and non-STEM students.

Figure 1 illustrates the conceptual model, emphasising the direct and indirect relationships between the exogenous (ChatGPT), mediating (ChatGPT SE and BI) and endogenous (AA) variables, as informed by the reviewed literature and theoretical framework.

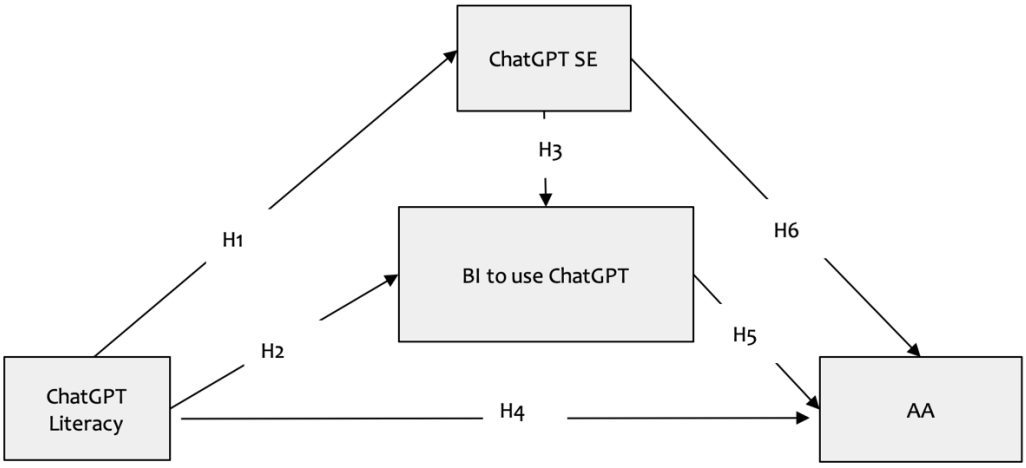

Figure 1. Conceptual path model

Methods

Design, participants and setting

This paper adopted a quantitative research paradigm and a cross-sectional correlational research design (Creswell, 2002). A purposive sample was employed to recruit undergraduate students from STEM and non-STEM departments across six colleges at Kwame Nkrumah University of Science and Technology, Ghana. Students were invited through selected undergraduate courses in which digital tools and AI-supported learning were already being discussed or informally adopted. Participants were university students (n = 461) who had used ChatGPT for at least 3 months prior to data collection. Of the 800 online

questionnaires administered, 461 respondents met this usage criterion. Among the participants, the majority (57.3%, *n* = 264), were male. Furthermore, 62.0% (*n* = 286) of the participants were from non-STEM disciplines (including education, fine arts and industrial arts and social sciences) in the university. Table 1 presents additional descriptive statistics for the sample.

Table 1
Descriptive statistics of respondents' characteristics (N = 461)

Variable	Category	*M (SD)*	*f* (%)
Gender	Male		264(57.3)
	Female		197(42.7)
Age		22.4(4.38)	
Field of study	STEM		175(38.0)
	Non-STEM		286(62.0)

Procedure and ethics

An online survey questionnaire was administered in January 2024. A total of 498 students returned the survey out of 800 purposively selected participants from STEM and non-STEM disciplines, yielding a response rate of 62.25%. After excluding null responses, 461 respondents were included in the present study. The study's respondents provided informed consent as they completed and submitted the online survey. The study had been approved by the ethics committee of the Department of Educational Innovations in Science and Technology at Kwame Nkrumah University of Science and Technology, Ghana (EIST-EC/REF No.:/January 01, 2024).

Measures

This study measured ChatGPT literacy with a construct adapted from the Meta AI Literacy Scale (Carolus et al., 2023), a measure capturing higher-order (metacognitive) dimensions of AI literacy. The AI literacy construct had 22 items and was employed to estimate ChatGPT literacy among students, with item wording adjusted to suit the study context. Each item was rated on a 5-point Likert-type scale, where 1 = *strongly disagree* and 5 = *strongly agree*. The original Meta AI Literacy Scale demonstrated good internal reliability, with Cronbach's α values above 0.80. To measure ChatGPT SE, a general SE scale for use with AI was employed. The unidimensional scale comprised six items adapted from Morales-García et al. (2024). For scale consistency, response options ranged from 1 = *not at all true* to 5 = *exactly true*. The original scale reported high reliability (Cronbach's α = 0.91) across non-clinical samples and diverse cultural contexts. BI to learn with ChatGPT was measured using three items adapted from Teng et al. (2022). Respondents rated their agreement on a 5-point Likert-type scale (1 = *strongly disagree* to 5 = *strongly agree*). AA was measured using students' self-reported cumulative weighted averages, expressed on a scale from 0 to 100 points. Kwame Nkrumah University of Science and Technology provides students with access to their academic scores and rankings through an academic information manager system.

Statistical data analysis

Prior to conducting the path analysis examining the relationship between students' ChatGPT usage and AA, a confirmatory factor analysis was performed to estimate construct validity. The results indicated good reliability, with satisfactory Cronbach's α coefficients. The path analysis exclusively utilised AA as an endogenous variable. The confirmatory factor analysis estimated composite constructs as the items' mean scores in each construct. Table 2 presents the descriptive statistics for these composite constructs. Normality tests indicated symmetric distributions, with skewness and kurtosis values within ±2. Data were analysed utilising Jamovi (version 2.6.13). A path analysis was conducted to examine the relationships among students' ChatGPT SE, literacy, BI to use ChatGPT and AA, with BI and SE specified as mediators. Model fit was assessed across gender and field of study using chi-square (χ^2), comparative fit index (CFI ≥ 0.95), root-mean-square error of approximation (RMSEA ≤ 0.08) and standardised root-mean-square residual (SRMR ≤ 0.08), with both direct and indirect effects assessed for significance (Hu & Bentler, 1999).

Table 2
Descriptive statistics of variables

Variables	*M*	std error	*SD*	Min	Max	Skewness Skew	std error	Kurtosis Kurt	std error	*α*
ChatGPT literacy	69.7	1.032	22.16	30	108	-0.019	0.114	-1.13	0.227	0.89
ChatGPT SE	17.3	0.287	6.17	7	28	0.200	0.114	-1.37	0.227	0.91
BI to use ChatGPT	10.4	0.100	2.15	7	14	0.133	0.114	-1.15	0.227	0.90
AA	67.9	0.374	8.02	18	81	-0.374	0.114	1.71	0.227	-

Note. std error = standard error; Min = minimum; Max = maximum; α = Cronbach's alpha.

Results

Path analysis for all groups

The path model analysis demonstrated a significant relationship between ChatGPT SE and BI to leverage ChatGPT, as well as AA. Table 3 presents the estimated path model coefficients. The results indicated that not all path coefficients were significant; thus, not all hypothesised paths were supported. ChatGPT SE was significantly influenced by ChatGPT literacy (β = 0.690; p < .001), explaining 47.6% of the variance (R^2 = 0.476). ChatGPT literacy (β = 0.718; p < .001) and ChatGPT SE (β = 0.002; p = .922) influenced BI to use ChatGPT, explaining approximately 51.2% of the variance in students' BI to use ChatGPT (R^2 = 0.512). Moreover, ChatGPT literacy (β = 0.002; p < .001), ChatGPT SE (β = 0.085; p = .023) and BI to use ChatGPT (β = 0.058; p = .134) influenced AA, explaining 65.9% of the variance (R^2 = 0.659). Thus, H1, H2, H3 and H6 were supported, while H4 and H5 were not supported. Figure 2 illustrates the path model. Model fit indices were χ2/df = 2.911, CFI = 0.96, Tucker-Lewis index (TLI) = 0.94, RMSEA = 0.05 and SRMR = 0.07, indicating good model fit.

Table 3
Path model parameter estimates

	Dependent	Predictor	Estimate	std error	95% confidence intervals (CI) Lower	Upper	*β*	*p*	Decision
H1	ChatGPT SE	ChatGPT literacy	0.192	0.009	0.174	0.211	0.690	<.001	supported
H2	BI to use ChatGPT	ChatGPT literacy	0.070	0.004	0.061	0.078	0.718	<.001	supported
H3	AA	ChatGPT literacy	0.256	0.017	0.223	0.290	0.708	<.001	supported
H4	AA	BI to use ChatGPT	0.217	0.145	-0.067	0.501	0.058	0.134	not supported
H5	BI to use ChatGPT	ChatGPT SE	-0.002	0.016	-0.032	0.029	-0.004	0.922	not supported
H6	AA	ChatGPT SE	0.111	0.049	0.0149	0.207	0.085	0.023	supported

Note. Decision indicates whether the hypothesis was supported.

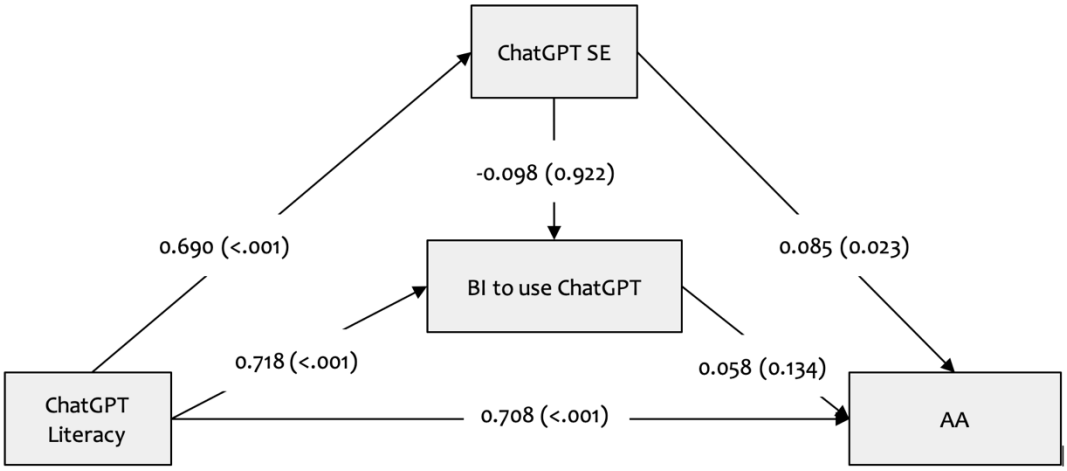

Figure 2. Empirical path model for all groups

Multiple group analysis

Table 4 presents descriptive statistics for the key study constructs grouped by gender (male and female). Male students scored lower than the female students on all constructs: ChatGPT literacy (M_{male} = 65.28 vs M_{female} = 75.67), ChatGPT SE (M_{male} = 16.41 vs M_{female} = 18.59), BI to use ChatGPT (M_{male} = 9.98 vs M_{female} = 10.96) and AA (M_{male} = 66.41 vs M_{female} = 69.92). Further, one-way analysis of variance (ANOVA) results indicated that the differences between male and female students were significant for all constructs (p < .001), with F values ranging from 14.6 to 26.1.

Table 4
Descriptive statistics for male and female groups

	ChatGPT literacy	ChatGPT SE	BI to use ChatGPT	AA
Male				
Mean (M)	65.28	16.41	9.98	66.41
SD	21.09	5.83	2.03	7.28
Skewness	0.36	0.52	0.53	0.53
Kurtosis	-0.75	-0.93	-0.69	-0.88
Female				
Mean (M)	75.67	18.59	10.96	69.92
SD	22.22	6.39	2.20	8.53
Skewness	-0.55	-0.21	-0.39	-1.38
Kurtosis	-0.90	-1.52	-1.03	1.35
F (1, 459)	26.1	14.6	24.5	22.5
p-value	< .001	< .001	< .001	< .001
η^2	.48	.36	.47	.45

Note. η^2 = eta squared (effect size)

Table 5 illustrates the descriptive statistics for key study constructs categorised by STEM and non-STEM. STEM students scored higher than the non-STEM students on all constructs: ChatGPT literacy (M_{STEM} = 73.7 vs $M_{non\text{-}STEM}$ = 67.3), ChatGPT SE (M_{STEM} = 18.1 vs $M_{non\text{-}STEM}$ = 16.9), BI to use ChatGPT (M_{STEM} = 10.7 vs $M_{non\text{-}STEM}$ = 10.2) and AA (M_{STEM} = 68.4 vs $M_{non\text{-}STEM}$ = 67.6). One-way ANOVA results indicated significant differences between STEM and non-STEM students for ChatGPT literacy (F = 9.13, p = 0.003), ChatGPT SE (F = 4.34, p = 0.04) and BI to use ChatGPT (F = 4.88, p = 0.03). However, the difference in AA was not statistically significant (F = 1.17, p = 0.28).

Table 5
Descriptive statistics for STEM and non-STEM groups

	ChatGPT literacy	ChatGPT SE	BI to use ChatGPT	AA
STEM				
Mean (M)	73.70	18.1	10.7	68.4
SD	22.48	6.32	2.24	8.68
Skewness	-0.18	0.07	0.02	-1.04
Kurtosis	-1.20	-1.49	-1.27	1.48
Non-STEM				
Mean (M)	67.3	16.9	10.2	67.6
SD	21.65	6.04	2.08	7.59
Skewness	0.06	0.28	0.22	0.19
Kurtosis	-1.04	-1.28	-1.02	-1.25
F (1, 459)	9.13	4.34	4.88	1.17
p-value	0.003	0.04	0.03	0.28
η^2	.29	.20	.21	.10

Note. η^2 = eta squared (effect size)

To carry out the multiple group analysis, the study hypothesised that the structural relationship among ChatGPT literacy, SE, BI and AA would differ significantly between male and female students. Table 6, presents a hypothetical path model used to estimate these relationships for male and female students. The fully unconstrained path model demonstrated good fit to the data ($\chi 2$ = 112.4, CFI = 0.975, SRMR = 0.032 and RMSEA = 0.059). For female students, the path model coefficients indicated that direct relationship were statistically discernible (significant). ChatGPT literacy was positively linked with ChatGPT SE (β = 0.752, p < .001) and BI to use ChatGPT (β = 0.698, p < .001). ChatGPT literacy also showed a positive relationship with AA (β = 0.686, p = .012). However, ChatGPT SE did not significantly predict BI to use ChatGPT (β = -0.009, p = .940). The indirect relationship of ChatGPT literacy on AA via ChatGPT SE was statistically significant (β = 0.698, p < .001).

For male students, ChatGPT literacy was positively associated with ChatGPT SE (β = 0.654, p < .001) and BI to use ChatGPT (β = 0.713, p < .001), and it was also positively associated with AA (β = 0.711, p = .012). However, ChatGPT SE did not significantly predict BI to use ChatGPT for male students (β = -0.011, p = .940). Furthermore, the model's path showed that the indirect relationship of ChatGPT literacy with AA via BI to use ChatGPT was significant (β = 0.460, p < .0.021).

To carry out the multiple group analysis, the study hypothesised that the structural relationship among ChatGPT literacy, SE, BI and AA would differ significantly between STEM and non-STEM students. Table 7 presents a hypothetical path model used to estimate these relationships across STEM and non-STEM groups. The fully unconstrained model illustrated that the data matched the model: ($\chi 2$ = 157.9, CFI = 0.95, SRMR = 0.052 and RMSEA = 0.07). For STEM students, ChatGPT literacy was positively associated with ChatGPT SE (β = 0.678, p < .001) and BI to use ChatGPT (β = 0.771, p < .001), and it was also positively associated with AA (β = 0.647, p = < .001). However, ChatGPT SE did not significantly predict AA (β = 0.046, p = .453). Furthermore, the model showed that the indirect relationship of ChatGPT literacy on AA via BI to use ChatGPT was statistically significant (β = 2.419, p = 0.016).

Table 6
Results of path analysis across gender groups

Type	Effect	Estimate	std error	95% CI Lower	95% CI Upper	*β*	*z*	*p*
Male (*N* = 264)								
Indirect	chat_lit ⇒ chat_intent ⇒ acad_ach	0.016	0.013	0.090	0.047	0.460	10.25	0.021
	chat_lit ⇒ chat_self ⇒ acad_ach	0.014	0.009	-0.004	0.032	0.040	1.56	0.120
Component	chat_lit ⇒ chat_intent	0.068	0.004	0.060	0.076	0.705	16.15	<.001
	chat_intent ⇒ acad_ach	0.234	0.187	-0.132	0.600	0.065	1.25	0.210
	chat_lit ⇒ chat_self	0.158	0.014	0.131	0.185	0.571	11.31	<.001
	chat_self ⇒ acad_ach	0.088	0.056	-0.022	0.198	0.071	1.57	0.116
Direct	chat_lit ⇒ acad_ach	0.246	0.020	0.206	0.285	0.711	12.12	<.001
Total	chat_lit ⇒ acad_ach	0.275	0.013	0.250	0.301	0.797	21.43	<.001
Female (*N* = 197)								
Indirect	chat_lit ⇒ chat_intent ⇒ acad_ach	0.012	0.016	-0.019	0.042	0.0298	0.730	0.465
	chat_lit ⇒ chat_self ⇒ acad_ach	0.029	0.022	-0.014	0.072	0.0745	1.303	0.193
Component	chat_lit ⇒ chat_intent	0.069	0.005	0.059	0.078	0.6933	13.505	<.001
	chat_intent ⇒ acad_ach	0.167	0.229	-0.281	0.616	0.0430	0.732	0.464
	chat_lit ⇒ chat_self	0.231	0.012	0.207	0.255	0.8026	18.884	<.001
	chat_self ⇒ acad_ach	0.124	0.095	-0.062	0.310	0.0928	1.306	0.192
Direct	chat_lit ⇒ acad_ach	0.268	0.031	0.207	0.329	0.6972	8.642	<.001
Total	chat_lit ⇒ acad_ach	0.308	0.016	0.276	0.340	0.8015	18.765	<.001

Note. Standard errors were estimated using the delta method. Lower and Upper = 95% confidence interval bounds. chat_lit = ChatGPT literacy; chat_intent = BI to use ChatGPT; chat_self = ChatGPT SE; acad_ach = AA.

For non-STEM students, the path analysis results indicated that direct relationships were statistically significant; ChatGPT literacy was positively associated with ChatGPT SE (β = 0.692, p < .001) and BI to use ChatGPT (β = 0.712, p < .001), and it was also positively associated with AA (β = 0.764, p = <.001). ChatGPT SE significantly predicted AA (β = 0.104, p = .023). In addition, the model illustrated that the indirect relationship of ChatGPT literacy on AA via ChatGPT SE was statistically significant.

Table 7
Results of path analysis across STEM and non-STEM groups

Type	Effect	Estimate	std error	95% CI Lower	95% CI Upper	*β*	*z*	*p*
STEM (*N* = 175)								
Indirect	chat_lit ⇒ chat_intent ⇒ acad_ach	0.044	0.018	0.008	0.079	0.1131	2.419	0.016
	chat_lit ⇒ chat_self ⇒ acad_ach	0.012	0.016	-0.020	0.044	0.031	0.749	0.454
Component	chat_lit ⇒ chat_intent	0.071	0.005	0.061	0.081	0.711	13.379	<.001
	chat_intent ⇒ acad_ach	0.616	0.250	0.125	1.106	0.159	2.459	0.014
	chat_lit ⇒ chat_self	0.191	0.016	0.160	0.221	0.678	12.191	<.001
	chat_self ⇒ acad_ach	0.064	0.085	-0.103	0.230	0.046	0.750	0.453
Direct	chat_lit ⇒ acad_ach	0.250	0.029	0.193	0.307	0.647	8.622	<.001
Total	chat_lit ⇒ acad_ach	0.306	0.018	0.271	0.341	0.791	17.065	<.001
Non-STEM (*N* = 286)								
Indirect	chat_lit ⇒ chat_intent ⇒ acad_ach	-0.004	0.012	-0.027	0.019	-0.011	-0.322	0.747
	chat_lit ⇒ chat_self ⇒ acad_ach	0.025	0.011	0.0037	0.047	0.072	2.244	0.025
Component	chat_lit ⇒ chat_intent	0.069	0.004	0.061	0.076	0.712	17.156	<.001
	chat_intent ⇒ acad_ach	-0.055	0.172	-0.393	0.282	-0.015	-0.322	0.747
	chat_lit ⇒ chat_self	0.193	0.012	0.170	0.217	0.692	16.231	<.001
	chat_self ⇒ acad_ach	0.131	0.058	0.018	0.244	0.104	2.266	0.023
Direct	chat_lit ⇒ acad_ach	0.268	0.020	0.228	0.308	0.764	13.169	<.001
Total	chat_lit ⇒ acad_ach	0.290	0.012	0.267	0.313	0.826	24.693	<.001

Note. Standard errors were estimated using the delta method. Lower and Upper = 95% confidence interval bounds; β = standardised coefficient; z = test statistic; p = p value. chat_lit = ChatGPT literacy; chat_intent = BI to use ChatGPT; chat_self = ChatGPT SE; acad_ach = AA.

Discussion

The present study examined the relationship among ChatGPT literacy, ChatGPT SE, BI to use ChatGPT and AA in university students in Ghana. The path analysis indicated that ChatGPT literacy and SE significantly predicted BI and AA. Furthermore, BI exhibited weaker direct effect on achievement. Also, multiple group analysis indicated gender and discipline-based variances, with female and STEM students reporting higher ChatGPT literacy, SE and achievement levels. While ChatGPT has gained increasing adoption in

educational contexts, limited studies have explored how the usage of this technology influences students' learning processes and AA. This study offers valuable insights and implications for education policymakers, administrators and instructors on the potential impact of integrating ChatGPT into teaching and learning activities on student AA.

This study presents a model illustrating how ChatGPT can be effectively integrated into university students' learning activities. The proposed model suggests that prior to embedding ChatGPT in curriculum-bound or learning activities, it is beneficial to enhance students' familiarity with ChatGPT beyond purely academic contexts, particularly in institutionally regulated, assessment-driven tasks such as graded assignments, examinations and formally evaluated coursework. In contrast, exploratory activities such as brainstorming or informal knowledge synthesis, while supportive of learning, are typically low-stakes and self-directed. Wang et al. (2025) emphasise AI literacy as a predictor of BI; however, the distinction between structured academic use and exploratory engagement represents a conceptual extension introduced in this study. Increasing ChatGPT literacy in this way can improve students' BI and SE towards using ChatGPT, ultimately influencing AA. This model may help explain inconsistencies in previous research regarding the effects of technology on AA. The mere availability of ChatGPT might not guarantee academic benefits, as the impact may vary based on the approach used to introduce the technology (ElSayary, 2024). The model highlights the importance of encouraging students to develop a broad understanding of ChatGPT's capabilities before integrating it into structured learning activities.

This study adds to understanding the role of students' ChatGPT literacy in enhancing SE for ChatGPT use. Like the shift from traditional to smartphone-based communication skills (Han & Yi, 2019; Kang & Jung, 2014), the shift towards AI-based assistance may develop students' confidence in leveraging ChatGPT for academic tasks. As students become more familiar with ChatGPT, they are likely to experience greater SE in managing the tool for academic purposes, which include formulating prompts, evaluating AI-generated information and effectively applying responses to course tasks. In this study, ChatGPT SE encompasses learning activities such as reviewing learning objects, knowledge acquisition, creating presentations and conducting research. The study thus reveals an underlying relationship between students' ChatGPT literacy and their ChatGPT SE in executing these academic tasks. The study also observed a link between university students' ChatGPT literacy and BI to use ChatGPT for learning activities. Students who acquired ChatGPT literacy, either indirectly or directly, inclined to show a BI to use ChatGPT for their learning activities (Duong et al., 2025; Ma et al., 2024). This indirect effect may stem from students' high SE in using ChatGPT. Previous studies (Li et al., 2024; Wang & Chuang, 2024) have emphasised that SE is a critical factor in enhancing the relationship between students' familiarity with technology and their BI to adopt it. Consistent with these findings (Essel et al., 2026; Sabeh, 2024; Xie et al., 2024), students' ChatGPT SE likely amplifies their intention to use it as a tool to acquire knowledge or as a virtual learning companion.

The study also supports previous research, which indicated a positive relationship between students' technology SE and their BI to use it. Studies have shown that one's confidence in using technology influences their intention to adopt it (Ho et al., 2020; Park et al., 2012; Wang & Wang, 2010). In previous studies, PEOU and perceived usefulness were categorised as mediators in the relationship between BI and technology SE (Han & Yi, 2019; Park et al., 2012). This study extends these findings by confirming that SE influences BI towards ChatGPT specifically in an educational context, suggesting that students who perceive ChatGPT as user-friendly and useful knowledge acquisition tool or virtual companion are more likely to incorporate it into their learning. A distinct finding of this study is the relationship between ChatGPT SE, BI to use ChatGPT and AA. Path analysis results indicate that students with higher ChatGPT SE and BI perceive positive impacts of ChatGPT use on their learning and expect improvements in their AA.

Consistent with existing literature (Bouzar et al., 2024; Donaldson, 2025; Galindo-Domínguez et al., 2024; Møgelvang et al., 2024), the multigroup analysis illustrates that male and female students exhibit discernible differences across all constructs related to ChatGPT usage: literacy, SE, BI and AA. Unlike most studies (Donaldson, 2025; Galindo-Domínguez et al., 2024; Møgelvang et al., 2024), female students

scored higher on average than male students for each construct, with discernible effect sizes, indicating moderate to large gender differences in ChatGPT-related constructs. This suggests that female students may have greater familiarity, confidence and intention in using ChatGPT for learning activities, which aligns with their relatively higher AA. These outcomes could be interpreted in two conditions. First, the higher ChatGPT literacy and ChatGPT SE among female students may increase their BI to use ChatGPT for learning activities, which enhances their AA. Second, the elevated ChatGPT SE and BI to use ChatGPT among female students could translate into more frequent and effective engagement with ChatGPT as a learning tool, potentially contributing to the constructive influence on their AA. This aligns with prior research suggesting that BI and technology SE are critical for AA in digital learning environments (Han & Yi, 2019; Hanham et al., 2021; Park et al., 2012).

Regarding STEM and non-STEM students, the multigroup analysis correspondingly indicates that they demonstrate discernible differences on the paths between constructs. This means that the relationship among these constructs differs depending on students' field of study. Specifically, STEM students exhibited higher mean scores for ChatGPT literacy, SE, BI to use ChatGPT and AA compared to non-STEM students, confirming Hernandez et al. (2025). This variance between STEM and non-STEM students could similarly be understood in two conditions. First, STEM students demonstrated a stronger inclination and confidence in leveraging ChatGPT for learning activities, which may increase their BI to use ChatGPT on AA. Second, STEM students who frequently use ChatGPT for learning purposes may perceive a greater positive impact of the model on their AA, aligning with findings from prior studies that underscores the role of technology SE and BI in enhancing AAs (Han & Yi, 2019; Hanham et al., 2021; Park et al., 2012).

Limitations and further studies

This study acknowledges several limitations. First, the study's cross-sectional design restricts causal relationships among ChatGPT literacy, ChatGPT SE, BI to use ChatGPT and AA. Also, the study employed data which is self-reported by students and may introduce social desirability bias in students' responses. These findings can be validated in future studies by using objective measures generated via actual usage logs or performance data. This study engaged with the academic applications of ChatGPT and did not consider its potential misuse, which could adversely affect AA. Future studies should investigate both the positive and adverse impacts of ChatGPT use and consider mediating factors like motivation or institutional support. Ultimately, the study was conducted within a specific cultural and educational context – universities in Ghana – which may constrain the generalisability of the results to student populations in other regions. Longitudinal and cross-cultural studies are recommended to deepen understanding of ChatGPT's educational impact.

Conclusion and implications

In contrast to prior literature on technology and its influence on student AA, the present study focused on ChatGPT, which is an emerging GenAI model used in education. It indicated that students with higher ChatGPT literacy and SE demonstrated higher BI to use ChatGPT, which correlates with improved AA. Gender and field of study emerged as critical factors, with female and STEM students demonstrating higher ChatGPT literacy, SE and AA related to ChatGPT use. These findings suggest that ChatGPT could introduce new inequalities in educational opportunities if some student groups are less prepared or less inclined to utilise it effectively. Thus, students with limited AI literacy may face challenges in integrating ChatGPT into their learning processes, potentially widening the gap between them and their more technologically adept peers. These findings underscore the need for targeted institutional support to bridge digital divides. A balanced approach to GenAI integration in higher education could ensure that models such as ChatGPT function as a constructive learning aids for all students, regardless of background.

The study introduced a model to measure ChatGPT literacy, ChatGPT SE and BI to use ChatGPT, tailored to assess its application in academic contexts. By building on these perspectives, this study provides a foundation for future studies on ChatGPT and related GenAI models, enabling further exploration of students' psychological and behavioural factors in GenAI adoption. Overall, it provides valuable insights

for educators and policymakers seeking to integrate GenAI tools like ChatGPT equitably and effectively into higher education.

Author contributions

Harry Barton Essel: Conceptualisation, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualisation, Writing – original draft, Writing – review & editing; **Esi Eduafua Johnson:** Conceptualisation, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualisation, Writing – original draft, Writing – review & editing; **Francis Kofi Nimo Nunoo:** Conceptualisation, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualisation, Writing – original draft, Writing – review & editing; **Beatrice Sarpong-Danquah:** Conceptualisation, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualisation, Writing – original draft, Writing – review & editing; **Aras Bozkurt:** Methodology, Writing – original draft, Writing – review & editing.

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