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Thinking Through AI: Perceptions and Adoption of Generative AI Research Tools Among Ghanaian Tertiary Students In the Dawn of a New Dispensation

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Abstract

The adoption of generative artificial intelligence (AI) tools like ChatGPT, Claude, Grammarly, Quillbot, and Perplexity has been reshaping academic research and learning in higher education. Although generative AI is increasingly used by students, there are few empirical studies on determinants of generative AI adoption in African higher education. This study uses the Technology Acceptance Model (TAM) to gain insight into the perception and adoption of generative AI tools among tertiary students in Ghana. A quantitative cross-sectional survey design was adopted to collect data from 200 tertiary students across various institutions in Ghana. Data were analysed using descriptive statistics, reliability analysis, Principal Component Analysis (PCA), chi-square tests, ANOVA, and ordinal logistic regression. The results showed positive attitudes towards generative AI. The regression results revealed that perceived ease of learning, ease of becoming skilled, confidence in evaluating AI-generated content, and perceived efficiency gains are significant variables that positively predict students' intention to continue using generative AI tools, whereas academic integrity concern is significant and negatively predicts students' intention to continue using generative AI tools. The findings suggest that generative AI in tertiary institutions among Ghanaian students is determined by its functional usefulness and ethical prudence. The study recommends a structured AI literacy education process and precise guidelines for the responsible use of AI in higher education institutions. The study contributes to emerging discussions on AI governance, AI literacy, and responsible adoption of generative AI in African higher education.

Introduction

The widespread emergence of AI-powered technologies has infiltrated and rewritten the 21st century's cluttered economy and politics as well as the education landscape (Youvan, 2024). Jora et al. (2024) describe this leap in technological advancement in this 'AI civilisation' as the *fourth industrial revolution* (IR 4.0), mainly because these "radical changes" reflect the term "revolution". This huge technological shift has also generated significant cultural changes in this civilisation, particularly in how humans respond to specific tasks.

One of the earliest and perhaps the most well-known concepts was effectively provided by Turing (1950) in his seminal work "Computing Machinery and Intelligence", where he proposed the imitation game (later known as the Turing Test) as an operational benchmark: if a machine's behaviour is indistinguishable from that of a human in conversation, it may be considered intelligent trying to evade an abstract consideration of intelligence (Turing, 1950).

Barely six years after Turing's seminal work, the eight-week Dartmouth Summer Research Project coined the term "Artificial Intelligence" in the summer of 1956; the proposal quoted "*how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves*" (McCarthy, 1956). This definition emphasises AI as a long-standing scientific research target as opposed to an attempt at examining surface behaviours.

Unlike previous AI systems, which tended to be task and solution-specific, Zhao et al. (2025) argue that generative AI technologies are able to act as an interactive knowledge system that can help with reasoning, writing, research, and learning tasks. The current wave of generative AI, however, is unique because it is accessible to the masses, including students (Ma et al., 2025; García-Peñalvo et al., 2023). These tools, including ChatGPT, Claude, QuillBot, Grammarly, and Perplexity, enable students to summarise lengthy texts, paraphrase academic content, brainstorm research ideas, create outlines, get explanations, and revise written assignments in mere seconds. This has led to a new research and learning landscape in which students access knowledge not just through libraries, lecturers, and search engines, but also through conversational AI systems.

This change has brought optimism but also anxiety in the field of higher education. Generative AI tools can assist in learning by offering immediate feedback, breaking down very complex matters, improving the quality of writing, saving time for repetitive academic work, and making learning support more accessible (Oye, 2024; Yan et al., 2024; Mital et al., 2024). These may be significant in situations where students are likely to have limited academic assistance time, high class sizes or other factors that may result in more inconsistent access to academic assistance. Conversely, there are significant concerns related to Generative AI and misinformation, false citations, bias, plagiarism, dependency, limited critical thinking, and violations of academic integrity rules (Sodangi & Isma'il, 2025). As noted by scholars such as Hutson (2024), Cotton et al. (2024), and Mille (2025), generative AI poses new threats to academic integrity, as it can make it more difficult for institutions to maintain a proper differentiation between supported learning and unauthorised authorship. Likewise, Dwivedi et al. (2023) indicate that generative conversational AI can enable productivity gains and innovation but can also cause issues with bias, misinformation, privacy and misuse.

The debates are very relevant in tertiary education in Ghana. Despite the ubiquitous exposure of Ghanaian students to these AI-backed tools for academic flexibility (Essel et al., 2025; Kwakye et al., 2025), the depth of their adoption, the driving factors of continued use and ethical dilemmas are not well researched. Research on educational technology in Ghana is primarily focused on studies of e-learning systems, learning management systems, mobile learning, and digital learning technologies (Boateng 2023; Amadiok et al., 2025; Asamoah & Oheneba-Sakyi, 2025), with limited attention given to generative AI alone. This has led to a knowledge gap regarding the perception and utilisation of such generative research tools among Ghanaian tertiary students in the evolving AI-centred academic landscape.

The focus of this study is to fill this gap; thus, it seeks to examine the adoption of generative AI among tertiary students in Ghana by applying the Technology Acceptance Model (TAM). This study emphasises perceived usefulness and perceived ease of use by the students, confidence in assessing AI-generated content, academic integrity issues, and motivation to continue using AI generative tools.

The study aims to address four objectives: First, gain an understanding of the adoption of generative research tools among Ghanaian tertiary students; second, understand the perceived usefulness and perceived ease of use and how these determine adoption; third, understand perceived risks and challenges associated with the use of generative AI tools; and fourth, understand how generative AI tools are potentially influencing a new research paradigm in tertiary education in Ghana.

Theoretical Focus: Technology Acceptance Model (TAM)

This study is grounded in the Technology Acceptance Model (TAM), one of the most widely used frameworks in the literature for explaining technology adoption behaviours. TAM was first developed by Davis (1989) based upon Ajzen and Fishbein's (1975) Theory of Reasoned Action. It assumes that usage intentions towards technology can be shaped through two main psychological constructs, labelled 'perceived usefulness' (PU) and 'perceived ease of use' (PEOU) (Kumar & Krishnan, 2020; Marian et al., 2025). According to Davis (1989), perceived usefulness is the degree to which an individual believes that utilising a technology will increase his or her performance or productivity, and perceived ease of use is the degree to which an individual believes operating or learning a technology will be easy.

For the purposes of higher education, 'perceived usefulness' refers to students' attitudes and thoughts about using generative AI tools, like ChatGPT, Claude, Grammarly, QuillBot, Perplexity, etc., to enhance their research quality, assist in academic writing, improve assignment completion efficiency, and expand access to information resources (Sallam et al., 2024). According to Tan et al. (2024), perceived ease of use depends on the perceived user-friendliness, intuitiveness, and ease of use these tools have for students, without even needing to rely on advanced technical knowledge. Technology that appears to be easier to use is perceived as being more useful, which increases the probability of adoption and continued use (Setterstrom et al., 2013; Adams, 1992).

In this study, TAM becomes more important as the use of generative AI by tertiary students is largely voluntary and consumer-driven. While institutional LMS systems might be required within the universities, generative AI tools are usually seen as useful and usable and thus adopted by students according to their evaluations. The more students believe that using AI will help them succeed academically, save time, make difficult tasks easier, and aid in idea generation, the more likely they are to use it.

The potential of TAM in educational technology research has been well established. The theory of technology acceptance has been proven successful for investigating technology adoption in Higher Education for systems such as e-learning systems, mobile learning technologies, digital libraries, and collaborative learning platforms (Cheung & Vogel, 2013; Šumak et al., 2011). In the same manner, research in developing country settings like Ghana found that the ease of use and usefulness perceived by students greatly determine willingness to use digital learning technologies (Boateng et al., 2016). Generative AI tools are the next step in the evolution of educational technologies, going beyond mere access to information to creating content, facilitating brainstorming, summarising texts, and enabling educational interactions with others.

Although TAM has proven to be satisfactory, it has also been found to neglect various contextual and moral aspects of technology use beyond perceived usefulness and ease of use (Marangunić & Granić, 2015). Students recognise the benefits of AI technology, such as convenience, but at the same time, have concerns about misinformation, plagiarism, biased output, and breaches of academic integrity. This study, therefore, builds on TAM by adding confidence to evaluate generated AI content and academic integrity concerns. The concept of confidence encompasses students' capacity to evaluate and question the reliability, quality, and validity of AI-generated texts, whereas academic integrity encapsulates concerns about plagiarism and institutional norm violations. These variables are integrated and discussed in relation to the mechanism of how functions can be adopted in accordance with the limitations of TAM, as well as the mechanism of caution for ethical issues in academic environments mediated by AI.

Methods and Materials

Research Design

This study used a quantitative, cross-sectional survey design. The design was appropriate in that it aimed to understand the students' perceptions, usage patterns, and behavioural intentions at a specific time. A cross-sectional survey was conducted because the use of generative AI is relatively new and fast-changing, which enabled the researchers to capture the existing trend and pattern of students' AI usage in tertiary education in Ghana.

An extended Technology Acceptance Model guided the study. The perceived usefulness and perceived ease of use constructs were viewed as core constructs in the TAM, and the remaining constructs were viewed as extended constructs: confidence in evaluating AI-generated content and academic integrity concern. The dependent variable was students' intention to continue using the generative AI tools.

Population and Sampling

The population targeted was tertiary students in universities, technical universities, colleges of education, and nursing and midwifery training institutions in Ghana. The categories were used to cover the diversity within the tertiary education system in Ghana. Data were collected using a self-administered questionnaire distributed through student networks and academic communication platforms.

A total of 200 valid responses were analysed. Due to the lack of a centralised sampling frame of tertiary students in Ghana who use generative AI tools, the convenience and snowball sampling methods were used. While not suitable for statistical generalisation, the method is suitable for exploratory research on new technologies, especially those that are being slowly adopted and not yet formalised.

Measures and Instrumentation

Data were collected using a structured questionnaire. The questionnaire consisted of sections regarding demographic characteristics, institution type, field of study, awareness of generative AI tools, use of AI tools in academic activities, usage frequency, aims of usage, user perceptions of usefulness, ease of use, behavioural intention, confidence, concerns, and general feedback.

Perceptual items were measured on a 5-point Likert scale ranging from 'Strongly Disagree' (1) to 'Strongly Agree' (5). The perceived usefulness included items related to whether generative AI can enhance the quality of academic work, facilitate academic tasks more quickly and easily, and improve performance on assignments and research. Perceived ease of use was evaluated using items related to the ease of learning and user-friendliness of generative AI tools, as well as the ease with which one can master using them. The three measures of behavioural intention were intention to continue using an AI tool, expected frequent use, and willingness to recommend an AI tool. The students' concerns were explored by asking about their concerns in relation to biased or inaccurate information and in relation to academic integrity violations.

The category of study was consolidated into three fields: STEM, STEM (Health), and Non-STEM. The separation of health-related fields from general STEM was driven by the unique academic and ethical considerations around accuracy, evidence and professional responsibility within the field of health sciences.

Reliability and Construct Validity

The internal consistency of the measurement constructs was assessed using Cronbach's alpha coefficient. Cronbach's alpha values greater than 0.70 were regarded as being acceptable indicators of internal consistency. For construct validation or to confirm the underlying structure of Likert scale items, Principal Component Analysis (PCA) was conducted, and observed scale factors were checked for their reliability on the expected factors. PCA was deemed suitable for the study due to the aim of revealing the underlying dimensions of students' perceptions and acceptance of generative AI tools.

Data Analysis

Data were analysed using Python. Demographic characteristics, patterns of use of the AIs, and Likert scale responses were summarised using descriptive statistics. Cronbach's alpha was used for reliability analysis. The structure of the Likert Scale constructs was explored through PCA. The relationship between familiarity with generative AI tools and gender was analysed using a Chi-Square test. A one-way ANOVA was used to determine if the intention to continue using AI varied among field-of-study groups. Lastly, ordinal logistic regression was conducted to determine potential predictors of continued use of generative AI tools. Since the dependent variable used the ordered 5-point Likert scale, the use of ordinal logistic regression was found to be suitable.

Model Specification

Because the dependent variable, intention to continue using generative AI tools, was measured on a five-point ordered Likert scale, ordinal logistic regression was employed to examine the factors influencing students' behavioural intention. Ordinal Logistic regression is useful for a dependent variable that is ordinal and with known or natural ordering among the response categories (Long & Freese, 2014).

The ordinal logistic regression model estimated in this study is expressed as:

$$\text{logit}\,[P\,(Y \le j)] = \alpha_j - (\beta_1 PU + \beta_2 PEOU + \beta_3 CONF + \beta_4 CONCERN + \beta_5 X)$$

where:

Y represents students' intention to continue using generative AI tools

'j' represents the ordered response categories

PU represents indicators of perceived usefulness

PEOU represents indicators of perceived ease of use.

CONF represents confidence in evaluating AI-generated content

CONCERN represents an academic integrity concern

X represents control variables such as gender, age group, institution type, and field of study.

α_j represents the threshold parameters

and β represents the estimated coefficients

Positive coefficients indicate that the respondents were more likely to report a higher likelihood of using generative AI tools in the future, and negative coefficients indicate that a lower likelihood was more likely to be reported.

Results

Descriptive Statistics

A total of 200 valid responses were analysed from the tertiary students of Ghana. Respondents were from various institution types and academic disciplines, divided into STEM, STEM (Health), and Non-STEM. The findings revealed familiarity with generative AI tools, with more than 90% reporting some exposure to at least one generative AI tool. A substantial proportion of respondents also reported using AI tools every week or even daily, indicating that generative AI tools are becoming more widely adopted in students' academic practices.

The descriptive statistics for the key perception variables are given in Table 1. In terms of usability, students expressed high levels of agreement that generative AI tools make study tasks easier and faster (M = 3.94, SD = 1.30) and that they enjoy using these tools to facilitate learning and research (M = 3.94, SD = 1.28). Students further agreed that generative AI helps them improve performance in assignments and research (M = 3.87, SD = 1.24) and improves the quality of academic work (M = 3.84, SD = 1.29). Additional indicators regarding ease of use were positive, with students indicating that AI is easy to use (M = 3.83, SD = 1.28), easy to learn (M = 3.80, SD = 1.26), and relatively easy to become skilled at using (M = 3.64, SD = 1.29).

The variables for behavioural intention were also above the neutral point. Students indicated a future desire to use AI resources again (M = 3.71, SD = 1.33), recommend AI tools for a classmate (M = 3.72, SD = 1.32), and see themselves using AI tools frequently in the future (M = 3.64, SD = 1.29). However, students also expressed notable concerns. The average scores for "concern about biased or inaccurate information" and "concern about violation of academic standards" were 3.51 (SD = 1.34) and 3.47 (SD = 1.28), respectively. The results reveal overall positive perceptions of students with some level of ethical and informational caution.

Table 1
Descriptive Statistics of Likert-Scale Items (N = 200)

Variable	Mean	SD	Interpretation
Easier_Faster	3.94	1.30	Positive perception
Enjoy_Use	3.94	1.28	Positive perception
Performance	3.87	1.24	Positive perception
Use_Quality	3.84	1.29	Positive perception
User_Friendly	3.83	1.28	Positive perception
Learn_Easy	3.80	1.26	Positive perception
Inst_Training	3.74	1.34	Support for training
Recommend	3.72	1.32	Positive intention
Intent_Continue	3.71	1.33	Positive intention
Skill_Easy	3.64	1.29	Moderate and positive ease
Intent_Freq	3.64	1.29	Moderate and positive intention
Good_Idea	3.61	1.33	Moderate and positive attitude
Conf_Eval	3.61	1.29	Moderate confidence
Concern_Bias	3.51	1.34	Moderate concern
Concern_Acad	3.47	1.28	Moderate concern
Note. The Likert scale ranged from 1 (Strongly Disagree) to 5 (Strongly Agree).			

Reliability and Construct Validity

Table 2 presents reliability results for the main constructs. The Cronbach's alphas indicated that perceived usefulness, PEOU and behavioural intention had excellent reliability, with values over 0.90. Confidence and concerns showed acceptable reliability (α = 0.715). The values indicate that the constructs were reliable internally and appropriate for further analysis.

Table 2
Reliability of Key Constructs

Construct	Items Included	Cronbach's α	Interpretation
Perceived Usefulness	Use_Quality, Easier_Faster, Performance	.934	Excellent
Ease of Use	Learn_Easy, User_Friendly, Skill_Easy	.901	Excellent
Behavioral Intention	Intent_Continue, Intent_Freq, Recommend	.934	Excellent
Confidence and Concerns	Conf_Eval, Concern_Bias, Concern_Acad	.715	Acceptable

Construct validity was explored using Principal Component Analysis (PCA). The PCA supported the reliability results. The first component accounted for 67.2% of the variance and was positive on perceived usefulness, ease of use, enjoyment, and behavioural intention. This indicates a positive dominant dimension in terms of adoption. A second component accounted for 7.6% of the variance and had a high loading on both concern about biased or inaccurate information (loading = .648) and concern about academic integrity (loading = .635). Based on this, one could argue that there are two intertwined, yet separate processes that students experience in their interaction with generative AI: perceived academic usefulness and ethical caution.

Group Differences

A chi-square test was performed to see if there were gender differences in familiarity with generative AI. The result was not statistically significant, $\chi^2(1) = 0.10$, $p = .7518$. This indicates that gender was not a factor in whether respondents were familiar with generative AI tools.

A one-way ANOVA was also performed to see if there was a difference in intention to use generative AI tools between groups within the field of study. Results indicated that there was no significant difference between the STEM students, the STEM (Health) students and the Non-STEM students, $F(2, 197) = 0.637$, $p = .5298$. This indicates that generative AI adoption intention is broadly similar across disciplines.

Table 3
Group Difference Tests

Test	Variables	Statistic	p-value	Interpretation
Chi-square	Gender × AI Familiarity	$\chi^2(1) = 0.10$	.7518	Not significant
One-way ANOVA	Intent_Continue × Field_Group	$F(2,197) = 0.637$	.5298	Not significant

Ordinal Logistic Regression

Ordinal logistic regression was used to determine factors associated with the intention to continue using generative AI tools. The model consisted of perceived usefulness, perceived ease of use, confidence in the assessment of AI-generated texts, concerns related to academic integrity, and demographic controls. The model was based on 200 observations and had a log-likelihood of − 164.61, an AIC of 391.2 and a BIC of 493.5.

As shown in Table 4, perceived ease of learning was a significant positive predictor of continued use intention ($\beta = 0.869$, $SE = 0.266$, $p = .001$). The odds ratio of 2.38 indicates that a one-unit increase in perceived ease of learning more than doubles the odds of being in a higher intention category. Ease of becoming skilled was also significant ($\beta = 0.726$, $SE = 0.229$, $p = .001$; $OR = 2.07$), indicating that students who find it easier to become skilled with generative AI are more likely to intend to continue using it.

Another statistically significant positive predictor was confidence in assessing the content created by AI ($\beta = 0.694$, $SE = 0.210$, $p = .001$; $OR = 2.00$). This indicates that when students are highly confident in evaluating the output generated by AI, they are about two times more likely to report greater continued-use intention. Perceived efficiency gains were also significant ($\beta = 0.648$, $SE = 0.285$, $p = .023$; $OR = 1.91$), as was perceived improvement in academic work quality ($\beta = 0.495$, $SE = 0.225$, $p = .028$; $OR = 1.64$).

In contrast, concern about academic integrity had a significant negative effect on intention to continue using generative AI tools ($\beta = -0.492$, $SE = 0.197$, $p = .013$; $OR = 0.61$). This suggests that a one-unit increase in academic integrity concern decreases the likelihood of continued use intention by about 39%. Gender was also significant, as male students had higher ORs for the variable of continued use intention ($\beta = 0.744$, $SE = 0.358$, $p = .038$; $OR = 2.10$). Other demographic variables, such as age, level of study, institution type, field of study and frequency of use, had no statistical significance as predictors in this study.

Table 4
Ordinal Logistic Regression Predicting Intention to Continue Using Generative AI

Predictor	β	SE	OR	p-value	Interpretation
Learn_Easy	0.869	0.266	2.38	.001	Positive and significant
Skill_Easy	0.726	0.229	2.07	.001	Positive and significant
Conf_Eval	0.694	0.210	2.00	.001	Positive and significant
Easier_Faster	0.648	0.285	1.91	.023	Positive and significant
Use_Quality	0.495	0.225	1.64	.028	Positive and significant
Concern_Acad	−0.492	0.197	0.61	.013	Negative and significant
Gender_Male	0.744	0.358	2.10	.038	Positive and significant

Model statistics: Log-Likelihood = − 164.61; AIC = 391.2; BIC = 493.5; Observations = 200.

Note

OR = odds ratio. Only statistically significant predictors are presented for clarity.

Discussion of Findings

Quantitative Analysis

This study investigated the perception and adoption of generative AI research tools among tertiary students in Ghana based on an extended Technology Acceptance Model (TAM). The results reveal generally positive attitudes towards generative AI among students, particularly regarding the efficiency, enjoyment, performance, and ease of use of these tools. These findings are consistent with studies conducted in different educational contexts. These include studies conducted by Wang et al. (2026), where undergraduate nursing students also reported great positive concern about the use of AI in academic practice, as well as studies from Yilmaz et al. (2024), Liang and Mao (2025), and Güngören et al. (2026). However, students have moderate concerns about misinformation and the integrity of academic work. The coexistence of these indicates that the adoption of AI by tertiary students in Ghana is not being done blindly; instead, it reflects a form of personalisation of AI applications in relation to academic benefits and ethical considerations.

The results revealed strong attitudes towards the ease of use and time-saving of academic tasks using generative AI, which supports the findings of Almassaad et al. (2024) in South Arabia, who similarly reported an agreeable figure of "ease of access and use (90.7% agree) and time-saving (92.0% agree)" (p. 11). The results are consistent with the usefulness logic of TAM, as described by Davis (1989), Deshaw and Strong (1999), as well as Isaac et al. (2018). Integrating user satisfaction and performance impact with the technology acceptance model (TAM) to examine the internet usage within organisations in Yemen, Isaac et al. (2018) argue that people are more likely to accept technologies that they believe to be useful in enhancing their performance. In this study, the highest-rated item was the perception that AI makes study tasks easier and faster. This indicates that efficiency is central to students' AI adoption. Use of generative AI tools is not merely about generating content but also about the reduction in time and cognitive load needed to complete academic tasks like summarising, brainstorming, paraphrasing or drafting. This is visible in the studies of Rind (2026) and Mehta (2025) and especially in Qamar et al. (2025), where the authors argue about the interdependence of the usage of AI tools and cognitive load. In the discussion, they note that their "*finding demonstrates that AI-centred interventions produced a significant and beneficial effect on the cognitive strain reduction among students*" (Qamar et al., 2025, p. 1123).

This mechanism is more strongly supported in the regression results. Perceived ease of learning proved to be the most significant for the continued use intention. The odds ratio suggests that students who report that generative AI products are easier for them to learn are more than twice as likely to report a higher intention to use them in the future. This is significant because it indicates that usability plays a major role in the adoption of generative AI by students. It is therefore imperative to note that this expands the scope of *intention* in Strzelecki (2024) and Park (2026) to include *usability*. However, if students believe that a tool is challenging to implement, they are not likely to adopt it (Mexhuani, 2025). This is consistent with the notion of TAM that perceived ease of use is not a convenience factor but a primary condition for acceptance (Venkatesh & Davis, 2000).

Also, the ease of becoming skilled made a significant prediction of continued use intention. This extends the dimension of ease of use beyond just being easy for people to access (Klein et al., 2019). Consistent with the literature of Delcker et al. (2024), students do not just wonder about how easy it is to use AI tools; they also wonder whether they can become competent users. This is particularly important for generative AI as it requires prompting, assessing output, editing, and understanding when to trust or reject generated content. As a consequence, adoption of skills becomes an integral component of the adoption process, which, in turn, builds the confidence of the user over the periods of time. Students who believe they can become skilled at using AI are more likely to continue using it.

Additionally, perceived usefulness was statistically significant. The perceived efficiency gain and perceived improvement in the work quality both contributed to the intention of continued use. The results herein provide corroborating evidence that generative AI applications are adopted with the aim

of providing a concrete educational advantage. For students to maintain their use of AI, they need to believe that it speeds up their work, which results in higher-quality learning activities. This confirms previous research, where usefulness was confirmed to be one of the most important factors in determining acceptance of educational technology (King & He, 2006; Šumak et al., 2011).

One of the most significant findings of this research is the impact of confidence in assessing AI-generated content. Confidence significantly increased intention to continue use, with an odds ratio of 2.00. This posits that students who are confident in evaluating the output of AI are nearly two times more likely to report a high intention to continue using it. The result indicates a broader understanding that using generative AI is not only about usefulness and ease of use. According to Keller (2010), students who felt confident utilising technology for learning tended to be more eager to learn, a finding also subsequently confirmed by studies from Jong (2020). In other words, a person is more likely to use technology in the future if they feel more comfortable using it (Chien et al., 2020; Chang et al., 2020; Huang et al., 2019), which is derived from the skills gained over the period of time (Keller, 2010). It is also influenced by epistemic self-efficacy: the student's confidence in their ability to determine whether the content produced by AI is accurate, relevant and accepted in an academic setting.

This is an essential continuation of the TAM. While traditional technologies in education offer structured delivery or platforms, generative AI creates new content that can be misleading, biased, or even fabricated. Hence, the user will have to critically assess the output produced by the tool instead of just using it. In this context, confidence is the link between the possibility and the responsible use of resources. Students with low confidence would not use AI or use it passively, while students with high confidence would use it more actively and critically (Silitubun, 2023). This means that AI literacy needs to go beyond technical training to encompass critical evaluation, fact-checking, and ethical consideration.

The academic integrity counterpart of the above is also very significant. The regression results show that concern about violating academic standards significantly reduces the intention to continue using generative AI tools. This again demonstrates that ethical uncertainty constitutes a barrier to adoption. Students might appreciate the help of AI but not want to use it if they worry about the risk of plagiarism, punishment, or breaching academic rules. The findings confirm the dichotomy in the literature between the educational benefits of AI and the repercussions that it might have for academic integrity (Yusif et al., 2024; Cotton et al., 2024; Dwivedi et al., 2023).

In this mechanism, the ethical inhibiting factor is at play. If students are unclear about the acceptability of AI use, they might also minimise their adoption intention despite their understanding of AI benefits. This is particularly common in settings where there are either ambiguous or poorly communicated AI policies. Even in an AI user-friendly environment, Gonsalves (2025) argues that most students do not disclose their AI use and therefore perpetuate the habit of non-compliance in AI use declarations, which affects academic integrity. According to the study, "*79% of students reported using AI tools like ChatGPT, Grammarly, and QuillBot in their coursework. Yet, only 65% of these students reported consistently completing the AI declaration on their coursework coversheets*" (Gonsalves, 2025, p. 598). Therefore, academic integrity issues must not be seen as an opposition to AI. Instead, it indicates students' knowledge of ethical limits and the ensuing questions regarding responsible use within institutions. This is a productive concern that can be addressed by institutions by setting up clear guidelines.

The non-significant ANOVA result indicates that the intention to continue using generative AI does not differ significantly across STEM, STEM (Health), and Non-STEM fields. This indicates that the use of generative AI is not limited to technical fields. Rather, it seems to be an overall learning capacity across disciplines. This is crucial, as it reinforces the notion that generative AI is a research paradigm shift rather than a research discipline-specific tool. In a similar study conducted by Liang and Mao (2025), the authors acknowledged that students in non-humanities like Science and Engineering, Medicine and Health disciplines demonstrated more positive attitudes toward generative AI than students in Humanities and Social Sciences. Nonetheless, the findings in this study may reflect the growing normalisation and accessibility of AI tools in higher education, where students across disciplines increasingly engage with generative AI to support their academic work irrespective of their programme of study. Other studies from Parades-Aguirres et al. (2025) provide detailed evidence that STEM students (non-Humanities) primarily use AI for task-specific work, whereas non-STEM students (Humanities) reported broader gains in digital confidence and efficiency. Students can leverage AI to support them in writing, summarising, brainstorming, revision, and information seeking, regardless of their major in STEM, health sciences, humanities, or education.

Similarly, the chi-square test revealed no significant differences between gender and awareness of AI tools, indicating that access to generative AI tools is relatively equal across genders. Gender, however, was statistically significant in the regression model, where male students demonstrated higher levels of continued-use intention. This suggests that familiarity alone may not fully explain patterns of AI adoption. This finding differs from Liang and Mao (2025), who reported that "*female students exhibited significantly more positive attitudes toward GAI in terms of Learning/Utility and Usefulness*" (p. 7). However, the two findings may reflect different dimensions of technology engagement. While male and female students may be equally familiar with AI tools, their confidence, perceptions of risk, and willingness to continue integrating AI into academic activities may differ. This finding should therefore be interpreted cautiously, but it highlights the importance of inclusive AI literacy interventions that strengthen confidence and responsible AI use across gender groups.

Qualitative-word frequencies

The data obtained from the qualitative word-frequency analysis corroborates the quantitative analysis. Frequently occurring words such as "learning", "research", "help", "easier", and "ideas" reflect students' perception of AI as a learning support tool. Meanwhile, terms like "wrong", "inaccurate", "information", "academic", and "critical" indicate concerns with the accuracy and responsible use. This aligns with the findings in the quantitative

analysis, where students appreciate AI but also understand its boundaries. The need for curriculum integration and training also means that students are not just looking to access AI but to learn how to use it responsibly and effectively.

As a result, the study puts forward an adoption mechanism in which four elements are linked. The first is that perceived ease of use reduces the barriers to AI adoption. Secondly, perceived usefulness implies motivation for continued use by showing academic value. Third, the students' confidence in assessing AI-generated outputs allows them to make responsible contributions as they gain the capacity to evaluate the quality of the generated content. Fourth, the extent of academic integrity concerns serves as a moderating factor that can make acceptance of academic integrity concerns less likely when rules are not clear. All four factors have to be taken care of to achieve sustainable adoption of AI. However, universities and other tertiary institutions must do more than just encourage students' enthusiasm for AI; they must also cultivate trust and establish ethical boundaries.

Practical and Policy Implications

The findings have relevant implications for tertiary institutions in Ghana. First and foremost, universities and other tertiary institutions must offer structured AI literacy training. The ease of learning and acquisition of skills is a strong predictor of continued use; therefore, training should aim at passing on knowledge on how to use generative AI to understand usage, how to write good prompts, how to improve the output, and how to use AI for valid academic support.

Also, institutions need to build confidence in students in assessing the quality of AI-generated content. This means that students need to be taught how to confirm what the AI has produced, how to compare what the AI produces with academic sources, how to detect information that is hallucinated by the AI, and how not to rely too heavily on the AI. The focus on AI literacy must thus be incorporated into research methods and academic writing courses, information literacy and digital skills courses.

Furthermore, tertiary institutions should clearly define academic integrity policies for artificial intelligence use. The negative impact of the academic integrity concern indicates that uncertainty around academic integrity is a driver of reduced adoption. Institutions should instead specify what can and cannot be done with AI tools. In other words, for instance, using AI for brainstorming, grammar, summarisation, and developing ideas can be allowed, but not authoring final-length submissions without citing sources. The regulations should be established in a clear manner because the absence of such guidance would create some confusion and lead to irresponsible use.

Moreover, AI integration should be "inclusive". Since gender was significant in the regression model, institutions should ensure that AI training does not unintentionally favour students who are already confident with technology. These interventions include inclusive workshops, peer support and hands-on demonstrations, which can mitigate the differences in confidence and intent to adopt.

Lastly, Ghanaian higher education policy needs to embrace generative AI as a component of the future of higher education. Amidst the uncertainty of whether students will use AI, the question now becomes whether institutions are equipped to lead the way in doing so responsibly. Therefore, a balance of innovation and ethics with equity is an essential prerequisite for establishing AI governance.

Limitations and Future Research

This study has some limitations. First, the use of convenience and snowball sampling limits generalisability to all Ghanaian tertiary students. Second, due to the self-report nature of the collected data, response bias may be present. Third, because of a cross-sectional design, perceptions are measured at one point in time, and this means that causality cannot be determined. Further research should involve larger sample sizes that are more representative across Ghanaian tertiary institutions. Longitudinal research could look to see if intention will result in sustained use over time. Additionally, qualitative interviews might also offer a more profound understanding of student conceptions of ideal use of AI, the reactions of lecturers to student AI-generated work and the impact of institutional policies on student behaviour. Future studies may also compare student and lecturer perspectives to develop more comprehensive AI governance frameworks.

Conclusion

This study investigated the perception and adoption of generative research tools among tertiary students in Ghana in the context of the extended Technology Acceptance Model (TAM). The results indicate that students generally have a positive attitude towards generative AI tools and are more inclined to view them positively regarding their utility, engagement, learning outcomes, and ease of use. Perceived ease of learning, ease of becoming skilled, confidence in the evaluation of AI-generated content, perceived efficiency gains, and perceived improvement in academic quality substantially contributed to the intention to continue using generative AI tools. Academic integrity had a comparatively strong negative impact on the continued use intention. Based on this, the study suggests that the adoption of generative AI among tertiary students in Ghana is driven by both its functional utility and ethical apprehensions. Unlike traditional passive consumers of information, students are active producers who assess the usefulness of AI outputs as they consider issues like accuracy, originality, and academic quality. This outline indicates a paradigm shift in research through the application of generative AI in the context of higher education in Ghana, and responsible use requires institutional preparedness, AI literacy, and ethical governance.

Declarations

Author Contribution

CAA wrote the introduction, literature review and contributed to the discussion of the findingsDA wrote the methodology section, the results as well as findings. All authors reviewed the manuscript.

Data Availability

Data availabilityThe datasets used and analysed during the current study are available from the corresponding author on request.

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Figures

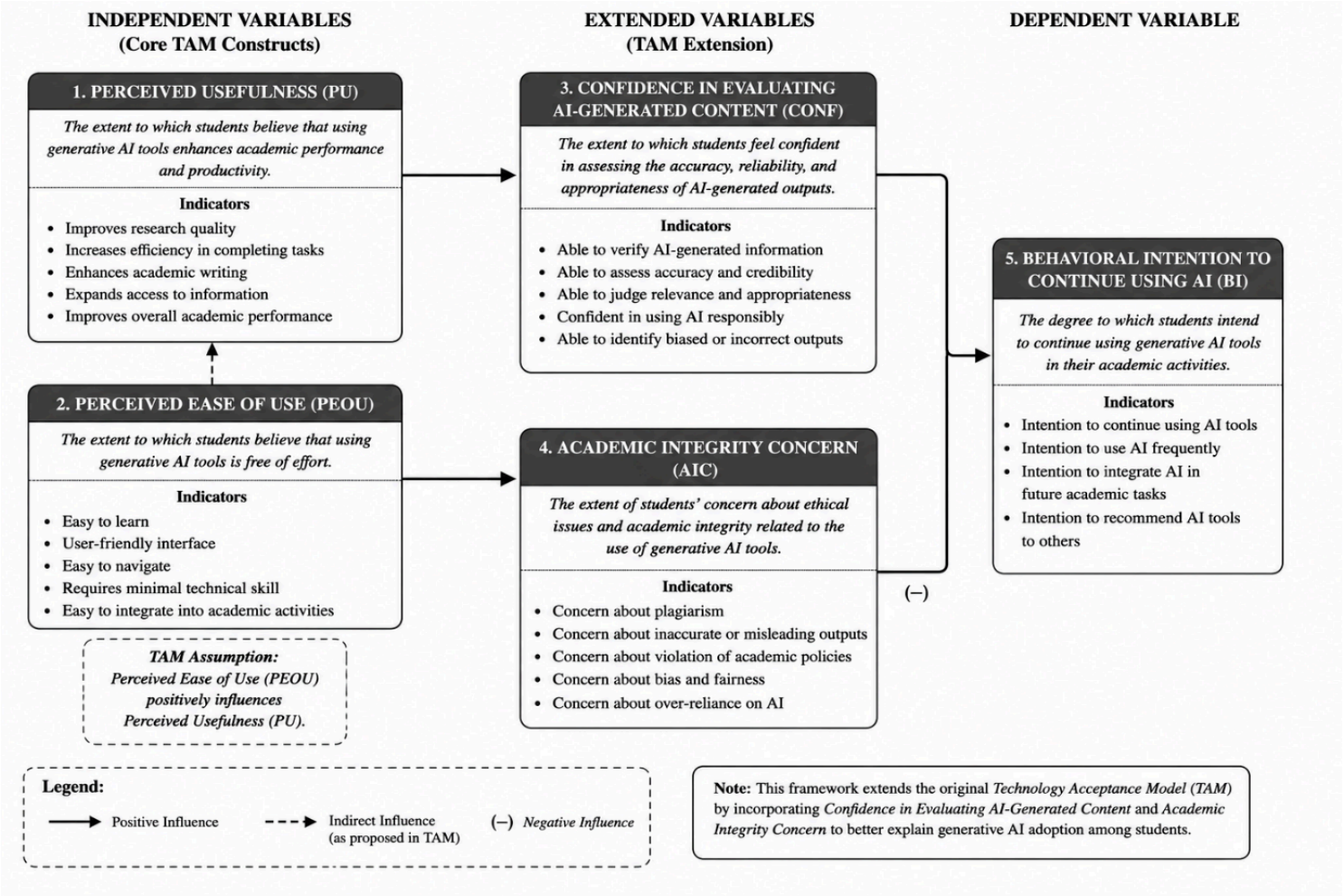

Figure 1

Conceptual framework of generative AI adoption among Ghanaian tertiary students based on the extended Technology Acceptance Model (TAM)

Figure 1 presents the conceptual framework guiding the study.

Source: Authors' conceptualisation (2026).