



Impact of AI tools on learning behaviours among undergraduate students in federal universities in South East Nigeria

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Abstract

The rapid diffusion of generative artificial intelligence (AI) tools has transformed students' access to personalised academic assistance and raised important questions about their effects on university learning. This study examined the relationship between AI adoption factors and learning behaviours among undergraduate students in federal universities in South-East Nigeria. Specifically, it investigated frequency of AI use, perceived usefulness of AI and AI self-efficacy in relation to critical thinking, self-regulated learning, collaborative learning, academic integrity, learning performance and overall positive learning behaviour. The study was anchored on the Technology Acceptance Model and Self-Regulated Learning Theory and adopted a quantitative cross-sectional survey design. The analytical sample comprised 220 undergraduate students drawn from the University of Nigeria, Nsukka (UNN), Federal University of Technology, Owerri (FUTO), Michael Okpara University of Agriculture, Umudike (MOUUAU), Nnamdi Azikiwe University (NAU), and Alex Ekwueme Federal University, Ndufu-Alike (FUNAI). Data were obtained through a structured questionnaire measured principally on five-point Likert-type scales and analysed using descriptive statistics, correlation and regression-oriented procedures. The response pattern indicated high AI adoption and generally positive learning behaviours. AI adoption was positively associated with critical thinking, self-regulated learning, learning performance and overall positive learning behaviour, while collaborative learning was comparatively weaker. Academic integrity behaviour was generally positive, although its self-reported nature requires cautious interpretation. The study concludes that AI can contribute to undergraduate learning when its use is accompanied by critical inquiry, self-regulation, ethical awareness and adequate AI competence. Universities should institutionalise AI literacy, establish responsible-use policies, redesign assessment for authentic learning and promote AI-supported collaborative activities.

Keywords: Artificial intelligence, generative AI, learning behaviour, self-regulated learning, critical thinking, AI self-efficacy, academic integrity, undergraduate students, higher education, Nigeria

Introduction

Artificial intelligence (AI) has moved rapidly from a specialist computational technology to a general-purpose learning resource used by students for explanation, summarisation, idea generation, translation, coding, formative feedback and academic writing support. The emergence of generative AI systems such as ChatGPT, Gemini and Claude has intensified this transition because students can now interact with conversational systems that produce context-sensitive responses in natural language. In higher education, the central question is therefore no longer whether students will encounter AI, but how the technology is shaping the processes through which they plan, regulate, evaluate and demonstrate learning. Global evidence suggests that students value generative AI for immediacy, personalisation and accessibility, while educators remain concerned about over-reliance, hallucinated information, weak source verification, loss of independent reasoning and academic-integrity risks (Digital Education Council, 2024; UNESCO, 2023) [11, 20].

The educational significance of AI depends on the distinction between technology adoption and learning quality. Frequent use of AI does not automatically imply meaningful learning. A student may use an AI tool intensively for surface-level answer production, or may use it strategically for concept clarification, self-testing, feedback, comparison of alternative explanations and reflective revision. Consequently, research must move

beyond simple measures of awareness or intention to use AI and examine the behavioural mechanisms that connect adoption with learning. Recent reviews indicate that generative AI can support academic skills, personalised feedback and self-regulated learning when students remain cognitively engaged and when instructional design requires verification and reflection (Banihashem *et al.*, 2025; Chen & Cheung, 2025; Daniel, 2025; Lan & Zhou, 2025; Xia *et al.*, 2026) [7–9, 13, 21].

This behavioural emphasis is especially important in Nigerian higher education. Universities are operating within an environment of expanding digital participation, uneven internet access, variable student digital literacy and increasing exposure to AI-enabled tools. Nigerian studies have documented growing student awareness and use of ChatGPT and related technologies, as well as positive perceptions of their relevance to learning and research (Abubakar *et al.*, 2024; Aiyebelehin *et al.*, 2025; Orok *et al.*, 2024; Shittu *et al.*, 2024) [2, 3, 15, 18]. At the same time, adoption occurs within institutional contexts where explicit AI policies, staff development, assessment redesign and ethical guidance are still evolving. This creates a need for empirical evidence that connects students' AI-use characteristics with concrete dimensions of learning behaviour rather than treating adoption as an end in itself.

The present study focuses on federal universities in South-East Nigeria and examines three adoption-related factors: frequency of AI use, perceived usefulness of AI and AI self-

efficacy. These variables reflect complementary dimensions of engagement. Frequency captures the extent of use; perceived usefulness captures the student's judgement that AI improves academic task performance; and self-efficacy captures confidence in one's ability to use AI effectively. The study relates these factors to critical thinking, self-regulated learning, collaborative learning, academic-integrity behaviour, perceived learning performance and overall positive learning behaviour. By doing so, the study addresses both the enabling and risk dimensions of generative AI in undergraduate education.

The conceptual logic is that AI produces educational value through the manner in which learners use it. A useful and accessible tool may encourage adoption, but beneficial outcomes are more likely when students formulate purposeful queries, interrogate responses, compare generated material with credible sources, regulate study activities and integrate AI support into authentic academic work. Conversely, weak AI competence or uncritical dependence may undermine learning even when usage frequency is high. This logic makes the interaction between technology acceptance and learner agency central to understanding AI in contemporary higher education.

South-East Nigeria provides a relevant context for this inquiry because the zone contains several large federal universities with diverse disciplinary populations and growing exposure to digital learning technologies. Examining students across UNN, FUTO, MOUAU, NAU and Alex Ekwueme Federal University, Ndufu-Alike (FUNAI) broadens the evidence beyond a single institution and allows the study to capture a more heterogeneous federal-university context. The study is particularly timely because institutions are increasingly expected to establish responsible AI-use frameworks while preserving innovation, inclusion and academic standards. Evidence about how AI adoption relates to actual learning behaviours can therefore inform curriculum design, student support, assessment policy and staff development.

Statement of the Problem

The rapid uptake of generative AI by university students has created a practical and empirical problem. On one hand, AI tools can provide rapid explanations, personalised feedback, study support and assistance with complex academic tasks. On the other hand, the same tools can facilitate shortcut learning, passive dependence, unverifiable information and inappropriate outsourcing of assessed work. Institutional responses are often based on either optimism about technological innovation or concern about misconduct, yet both positions can be incomplete when they are not linked to evidence about students' actual learning behaviours.

Existing Nigerian research has contributed important evidence on awareness, perceptions, acceptance and behavioural intention to use AI (Aiyebilehin *et al.*, 2025; Orok *et al.*, 2024; Owan *et al.*, 2025; Shittu *et al.*, 2024; Yakubu *et al.*, 2025) [3, 15, 16, 18, 22]. However, fewer studies simultaneously examine whether frequency of AI use, perceived usefulness and AI self-efficacy correspond with critical thinking, self-regulation, collaboration, academic integrity and perceived learning performance. This gap is consequential because high adoption could coexist with either productive or counterproductive learning practices. Without a multidimensional behavioural assessment,

universities may be unable to distinguish responsible educational use from mere technological enthusiasm.

A further problem is methodological. Much of the emerging literature is cross-sectional and self-reported, making causal interpretation difficult. Measures of perceived performance may not correspond perfectly with independently verified grades, and self-reported integrity behaviour may be vulnerable to social-desirability bias. The present study therefore interprets associations cautiously while providing context-specific evidence on the pattern of AI adoption and learning behaviour among undergraduates in federal universities in South-East Nigeria.

Purpose and Significance of the Study

The main purpose of the study was to examine the relationship between AI-tool adoption factors and learning behaviours among undergraduate students in selected federal universities in South-East Nigeria. Specifically, the study sought to: (i) determine the prevailing levels of frequency of AI use, perceived usefulness and AI self-efficacy; (ii) assess students' critical-thinking, self-regulated, collaborative and academic-integrity behaviours; (iii) examine the pattern of perceived learning performance and overall positive learning behaviour; and (iv) determine whether stronger AI adoption is associated with more positive learning-behaviour outcomes.

The study was guided by the following research questions: What is the level of AI-tool adoption among the sampled undergraduates? What is the prevailing pattern of critical thinking, self-regulated learning, collaborative learning, academic-integrity behaviour and perceived learning performance? How do the learning-behaviour dimensions vary in relative strength? To what extent is stronger AI adoption associated with positive learning behaviours and perceived learning outcomes?

The study is significant to university management, lecturers, students and policy makers. For universities, the findings provide an empirical basis for AI-literacy programmes, responsible-use policies and assessment redesign. For lecturers, the study clarifies the need to structure AI-supported tasks around verification, reflection and higher-order thinking. For students, it highlights AI competence and self-regulation as conditions for deriving educational value from generative tools. For researchers, it contributes evidence from a multi-institution federal-university context in South-East Nigeria and integrates technology-adoption and learning-behaviour perspectives within one framework.

Review of related literature

1. Conceptual Review

Artificial intelligence in education refers broadly to computational systems capable of performing tasks that ordinarily require aspects of human intelligence, including language processing, prediction, classification, recommendation and adaptive interaction. Generative AI is a subset that produces new content—such as text, code, images or structured explanations—in response to user prompts. In higher education, conversational generative AI is distinctive because it can operate as an always-available interface for dialogue, explanation and feedback. UNESCO (2023) [20] nevertheless emphasises that educational use should be human-centred, ethically governed and accompanied by attention to privacy, transparency and the reliability of generated outputs.

AI adoption in this study is represented by frequency of use, perceived usefulness and AI self-efficacy. Frequency of use indicates how regularly students employ AI tools in academic activities. Perceived usefulness reflects the extent to which students believe that AI improves their learning efficiency or effectiveness and corresponds closely with the Technology Acceptance Model (Davis, 1989) ^[10]. AI self-efficacy refers to confidence in one's capacity to operate AI tools, formulate effective prompts, interpret outputs and apply them to learning tasks. The self-efficacy construct draws on Bandura's (1997) broader proposition that perceived capability influences effort, persistence and performance-related behaviour.

Critical-thinking behaviour concerns the learner's tendency to analyse claims, compare alternatives, question assumptions, evaluate evidence and verify conclusions. AI can support such behaviour when it is used as an object of critique or as a source of alternative explanations; however, it may weaken critical engagement when generated responses are accepted without evaluation. Daniel (2025) ^[9] and Chen and Cheung (2025) ^[8] indicate that the learning impact of generative AI depends substantially on task design and the cognitive activity retained by the learner.

Self-regulated learning (SRL) describes the learner's active management of goals, strategies, time, monitoring and reflection. Zimmerman (2002) ^[23] conceptualises self-regulation as a cyclical process involving forethought, performance and self-reflection. AI tools can support SRL by helping students plan study sessions, generate practice questions, obtain immediate feedback and clarify difficult concepts. Recent reviews find substantial potential at the intersection of AI and SRL, while also warning that poorly scaffolded AI assistance can displace rather than strengthen learner regulation (Banihashem *et al.*, 2025; Lan & Zhou, 2025; Xia *et al.*, 2026) ^[7, 13, 21].

Collaborative learning refers to learning through interaction, shared problem solving, peer explanation and co-construction of knowledge. Although generative AI is frequently experienced as an individual conversational tutor, it can also be integrated into group tasks—for example, by generating cases for debate, producing alternative viewpoints, supporting peer review or helping groups interrogate competing solutions. Whether this potential is realised depends on pedagogy and on whether AI is embedded in social learning structures rather than used only for private task completion.

Academic-integrity behaviour concerns responsible participation in academic work, including appropriate authorship, attribution, avoidance of plagiarism and compliance with institutional rules. Generative AI complicates traditional integrity norms because the boundary between legitimate assistance and unacceptable substitution can be unclear. Nigerian evidence has begun to document ethical concerns associated with student AI use (Bakre & Tukur-Bello, 2026) ^[5]. Accordingly, a positive learning framework should not treat AI adoption independently of disclosure, verification and responsibility for submitted work.

Learning performance in this study refers to students' perceived effectiveness and improvement in learning, not independently verified examination scores or GPA. This distinction is important. Perceived performance can capture students' experience of efficiency, understanding and confidence, but it cannot establish objective academic gains

without external performance measures. Overall positive learning behaviour is treated as a broader composite orientation reflecting constructive engagement with learning in the presence of AI support.

2. Theoretical Review

The study is anchored principally on the Technology Acceptance Model (TAM) and Self-Regulated Learning Theory, with self-efficacy providing a complementary social-cognitive lens. TAM, developed by Davis (1989) ^[10], proposes that perceived usefulness and perceived ease of use are central determinants of technology acceptance and use. In the context of generative AI, perceived usefulness is particularly relevant because students are more likely to adopt a tool when they believe it improves task completion, understanding, speed or quality. Although the present study does not reproduce the full TAM structure, perceived usefulness and use frequency provide a technology-adoption pathway for understanding students' engagement with AI.

TAM alone, however, is insufficient for explaining learning quality. A technology can be accepted and frequently used without producing deep learning. Self-Regulated Learning Theory addresses this limitation by focusing on how learners plan, monitor and evaluate their own learning (Zimmerman, 2002) ^[23]. From this perspective, AI becomes one resource within the student's regulatory system. Beneficial use is expected when the learner sets goals, selects appropriate strategies, checks AI-generated information and reflects on the quality of the resulting understanding.

Bandura's (1997) concept of self-efficacy strengthens the integrated framework. Students who believe they can use AI competently may be more persistent in experimenting with prompts, refining queries and evaluating responses. Yet self-efficacy should be interpreted as capability confidence rather than as a guarantee of correct or ethical use. The integrated theoretical proposition is therefore that adoption factors create opportunities for engagement, while self-regulatory and critical processes shape whether that engagement translates into positive learning behaviour and perceived performance.

The resulting conceptual framework may be expressed as AI Adoption Factors (frequency of use, perceived usefulness and AI self-efficacy) → Learning Behaviours (critical thinking, self-regulation, collaboration and academic integrity) → Learning Outcomes (perceived learning performance and overall positive learning behaviour). In this cross-sectional study, the arrows represent a theoretically ordered association rather than experimentally verified causal pathways.

3. Empirical Review

International evidence increasingly suggests that generative AI can produce educational benefits when it is used as a scaffold rather than a replacement for learner cognition. Daniel (2025) ^[9], in a systematic review of generative AI and academic skills development, reported potential benefits for feedback, idea development and learning support, while emphasising the need for pedagogical structure. Chen and Cheung (2025) ^[8], through a systematic review and meta-analysis, similarly found evidence of positive learning effects across university contexts, although effect sizes and outcomes vary with design, task and implementation conditions. An *et al.* (2026) further synthesised evidence on

student use and learning outcomes and underscored the heterogeneity of educational applications and research designs.

Research specifically linking AI and self-regulated learning has expanded rapidly. Banihashem *et al.* (2025) ^[7] mapped the intersection of AI and SRL and identified important roles for adaptive support, feedback and learner monitoring. Lan and Zhou (2025) ^[13] concluded that AI can facilitate planning, personalised assistance and reflection but that learner agency remains essential. Xia *et al.* (2026) ^[21] likewise highlighted the design challenge of ensuring that generative AI supports, rather than substitutes for, the phases of self-regulated learning. These findings support the inclusion of self-regulation as a key behavioural outcome in the present study.

Nigerian studies confirm that AI adoption is no longer peripheral among university students. Abubakar *et al.* (2024) ^[2] reported student perspectives on AI integration in Nigerian tertiary pedagogy, demonstrating both perceived usefulness and concerns surrounding use. Shittu *et al.* (2024) ^[18] found meaningful levels of knowledge, attitude and perception of ChatGPT among learners at the University of Ibadan. Orok *et al.* (2024) ^[15], studying pharmacy students, documented awareness and perceptions of chat-based AI tools, illustrating the spread of generative AI into discipline-specific learning environments.

Aiyebelehin *et al.* (2025) ^[3] showed that awareness and digital-literacy skills predict ChatGPT use among undergraduates in a Nigerian university, reinforcing the importance of competence-related factors. Owan *et al.* (2025) ^[16] modelled higher-education students' ChatGPT-use behaviour through a modified UTAUT framework, demonstrating the value of established technology-adoption models for explaining student use. Yakubu *et al.* (2025) ^[22] likewise examined behavioural intention to use content-generative AI for learning and research through a UTAUT perspective. Collectively, these studies provide a strong adoption literature, but adoption intention does not by itself reveal whether students are becoming more critical, self-regulated, collaborative or academically responsible.

Nigerian scholarship also draws attention to context. Essien *et al.* (2024) ^[12] examined socio-cultural influences on generative AI engagement and showed that AI use is embedded within institutional and social environments rather than determined solely by technical availability. Olatunde-Aiyedun (2024) ^[14] argued for systematic integration of AI into university science curricula, while Peters and Olojede (2025) ^[17] discussed the influence of generative AI in Nigerian higher education more broadly. Tijani and Adeduyigbe (2026) ^[19] examined student perceptions of AI for adaptive learning, suggesting that personalisation is becoming a significant dimension of the Nigerian AI-education discourse.

Academic integrity remains one of the most contested empirical areas. Bakre and Tukur-Bello (2026) ^[5] examined ethical considerations in AI-driven education in selected Nigerian universities, reflecting the need for clear institutional boundaries and student guidance. This issue is consistent with UNESCO's (2023) emphasis on responsible use and human oversight. The emerging evidence therefore supports a balanced position: generative AI can enhance access, feedback and regulation, but its value depends on

how students use it and how institutions structure acceptable practice.

Overall, the empirical literature points to three consistent themes. First, student adoption of generative AI is high and expanding. Second, positive learning effects are plausible but contingent on pedagogy, digital competence and learner agency. Third, ethical and assessment concerns remain unresolved. The present study extends this literature by examining several adoption and learning-behaviour dimensions together within a multi-university South-East Nigerian sample.

4. Gap in the Literature

Four gaps motivate the study. First, a substantial proportion of Nigerian research has concentrated on awareness, perceptions, behavioural intention or general acceptance rather than on a multidimensional set of learning behaviours. Second, evidence from South-East Nigeria is comparatively fragmented and often institution-specific, limiting understanding across federal universities in the zone. Third, the relationship between AI adoption and constructive behaviours such as critical thinking, self-regulation and collaboration has not been sufficiently integrated with academic-integrity considerations. Fourth, many emerging studies risk treating perceived educational benefit as equivalent to objective academic achievement. The present study addresses these gaps by combining adoption factors, behavioural dimensions and perceived learning outcomes while explicitly limiting performance claims to self-reported learning effectiveness.

Methodology

1. Research Design

The study adopted a quantitative cross-sectional survey design. This design was appropriate because the purpose was to describe prevailing patterns of AI adoption and learning behaviour and to examine statistical associations among measured variables at a defined point in time. The design supports estimation of relationships but does not establish temporal precedence or experimental causality.

2. Area, Population and Sample

The study covered selected federal universities in South-East Nigeria: the University of Nigeria, Nsukka (UNN), Federal University of Technology, Owerri (FUTO), Michael Okpara University of Agriculture, Umudike (MOUAU), Nnamdi Azikiwe University (NAU), and Alex Ekwueme Federal University, Ndufu-Alike (FUNAI). The target population comprised undergraduate students, with the analytical dataset containing 220 respondents. The study focused on students at advanced undergraduate levels and included respondents from broad disciplinary groupings such as STEM, social sciences, arts and medical/health-related programmes, thereby providing variation in academic context.

The sample size of 220 is treated as the achieved analytical sample represented in the supplied dataset. Because the manuscript source does not provide a verified sampling frame or population count for all eligible students across the five institutions, no unsupported claim is made that the sample is statistically representative of the entire undergraduate population of the institutions or the South-East geopolitical zone.

3. Sampling Technique

A multi-institution sampling approach was used to obtain respondents across the five universities and relevant student categories. Institution, gender and broad academic discipline were retained as control or classification variables in the dataset. The available manuscript materials do not document the exact first-stage allocation, department-level sampling fractions or response-rate calculation; consequently, these details should be inserted from the original field protocol before journal submission if they are available. The analysis reported here is therefore based on the achieved sample rather than on an assumed probability-sampling structure.

4. Instrument and Operationalisation

Data were collected with a structured questionnaire. The instrument comprised background variables and composite measures reflecting AI adoption and learning behaviours. AI adoption was operationalised through frequency of AI use (AI_FREQ), perceived usefulness of AI (AI_PERC_USE) and AI self-efficacy (AI_SELF_EFF). Learning behaviours were represented by critical thinking (BEH_CRIT), self-regulated learning (BEH_SELFREG), collaborative learning (BEH_COLLAB) and academic-integrity behaviour (BEH_ACADEMIC). Perceived learning performance was represented by BEH_PERF, while OVERALL_LEARN captured overall positive learning behaviour.

The principal constructs were measured on five-point Likert-type scales, with higher values indicating stronger endorsement or a higher level of the measured behaviour. The study treats the reported variables as composite scores. Interpretation therefore focuses on relative level and direction rather than on item-specific diagnostics that cannot be recovered from composite data alone.

5. Validity and Reliability

Content validity was addressed by aligning the measures with established concepts in technology adoption, self-efficacy and self-regulated learning and with the substantive domains identified in contemporary AI-in-education literature. The manuscript dataset supplied for analysis contains composite scores rather than the underlying item-level responses. For that reason, internal-consistency coefficients, factor loadings, average variance extracted and discriminant-validity statistics cannot be independently recomputed from the present file. Any final publication claim concerning Cronbach's alpha, composite reliability, confirmatory factor analysis or discriminant validity should therefore be based on the original item-level dataset and reported output, not inferred from the composites.

This limitation is important because several constructs in the supplied data show very strong covariance patterns. Before publication, a full measurement-model assessment should verify that conceptually distinct constructs—particularly perceived usefulness, AI self-efficacy and the positive learning-behaviour measures—demonstrate adequate empirical distinctiveness.

6. Data Analysis

Data analysis was organised in two stages. First, descriptive statistics were used to summarise the central pattern of the AI-adoption and learning-behaviour constructs. For interpretation of five-point scales, higher mean values were treated as indicating stronger adoption or more positive

learning behaviour, with the present manuscript reporting rounded composite-score patterns. Second, association and regression-oriented procedures were conceptually specified to examine the relationship between AI-adoption factors and learning-behaviour outcomes, with university, gender and disciplinary grouping available as control variables where appropriate.

Because the clean row-level dataset and reproducible statistical output are not embedded in the submitted Word file, the completed manuscript does not fabricate exact coefficients, p values, confidence intervals or model-fit statistics. Inferential claims are therefore expressed at the level supported by the supplied manuscript: positive association patterns, relative construct strength and cautious interpretation. Exact regression tables should be generated from the final clean dataset before journal submission.

7. Ethical Considerations and Limitations

Participation was treated as voluntary, and responses were intended for research purposes. The study concerns educational behaviour rather than clinical intervention, but standard principles of informed consent, confidentiality and non-identification remain applicable. The main limitations are the cross-sectional design, reliance on self-report, possible social-desirability bias in academic-integrity responses, use of perceived rather than independently verified learning performance, and the inability of composite-only data to support a full measurement-model reassessment. These limitations require restraint in causal and psychometric interpretation.

Results and discussion

1. Overview of Results

The results are organised around the study's adoption variables and learning-behaviour outcomes. The available composite-score dataset indicates a generally high level of engagement with AI tools. Frequency of AI use and perceived usefulness show the strongest adoption pattern, while AI self-efficacy is also high. Among learning behaviours, perceived learning performance is strongest; collaborative learning is the lowest of the measured behavioural dimensions, although it remains above the scale midpoint.

The findings should be read as evidence of pattern and association rather than experimental effect. The cross-sectional data cannot establish that AI use caused the reported behaviours, and the manuscript does not contain verified raw-data output sufficient to report exact inferential coefficients. This distinction is retained throughout the discussion.

2. Descriptive Summary

Table 1 summarises the rounded descriptive pattern. Frequency of AI use (approximately 4.1) and perceived usefulness (approximately 4.1) indicate that AI has become a regular and valued learning resource among respondents. AI self-efficacy (approximately 3.9) is also high, implying that most students perceive themselves as reasonably capable of engaging with AI tools for academic purposes. The learning-behaviour indicators are broadly positive. Critical thinking records an approximate mean of 3.7 and self-regulated learning approximately 3.8, suggesting that respondents generally report using AI alongside behaviours associated with questioning, planning, monitoring and

independent study. Collaborative learning is lower at approximately 3.5. This relative difference is substantively important because it suggests that current AI use may be more individualised than socially embedded in peer-learning processes.

Academic-integrity behaviour is approximately 3.8 and should be interpreted cautiously because it is self-reported. Perceived learning performance is comparatively high at approximately 4.0, while overall positive learning behaviour is approximately 3.9. These scores support the conclusion that students perceive AI-supported learning favourably, but they do not establish objective achievement gains.

Table 1: Descriptive Pattern of AI Adoption and Learning-Behaviour Constructs

Construct	Code	General Mean Pattern	Interpretation
Frequency of AI use	AI_FREQ	≈4.1	High
Perceived usefulness of AI	AI_PERC_USE	≈4.1	High
AI self-efficacy	AI_SELF_EFF	≈3.9	High
Critical thinking	BEH_CRIT	≈3.7	High
Self-regulated learning	BEH_SELFREG	≈3.8	High
Collaborative learning	BEH_COLLAB	≈3.5	Moderately high
Academic integrity	BEH_ACADEMIC	≈3.8	High
Learning performance	BEH_PERF	≈4.0	High
Overall positive learning behaviour	OVERALL_LEARN	≈3.9	High

Note. Values are reported as rounded descriptive patterns from the supplied composite-score dataset; exact inferential statistics should be computed from the clean raw dataset before publication.

The descriptive pattern indicates that students generally use AI frequently and regard it as useful for learning. AI self-efficacy is also relatively high, suggesting confidence in interacting with AI tools. Collaborative learning is comparatively lower, implying that AI may currently function more strongly as an individual learning assistant than as a peer-collaboration mechanism.

AI adoption was positively associated with critical-thinking and self-regulated learning behaviour. This pattern is consistent with Daniel (2025)^[9], Chen and Cheung (2025)^[8], Lan and Zhou (2025)^[13] and Banihashem *et al.* (2025)^[7], whose findings indicate that appropriately structured AI use can support higher-order cognition, personalised feedback and learner autonomy.

Academic-integrity behaviour was generally positive, indicating that AI use is not inherently incompatible with ethical academic conduct. Nevertheless, this variable is self-reported and may be affected by social-desirability bias. The findings therefore support explicit responsible-use policies rather than an assumption that positive self-reports eliminate integrity risks.

Learning-performance behaviour and overall positive learning behaviour were also positively associated with AI adoption. However, BEH_PERF reflects perceived learning performance rather than independently verified grades. The substantive conclusion is therefore that stronger AI adoption is associated with stronger perceived learning effectiveness, not that AI has been experimentally proven to increase

GPA.

The conceptual pattern supports AI Adoption Factors → Learning Behaviours → Learning Outcomes. However, formal mediation claims require bootstrapped indirect-effect estimates. In addition, the supplied dataset displays exceptionally regular score patterns and strong covariance among constructs. This raises potential multicollinearity and discriminant-validity concerns. Near-perfect relationships among conceptually distinct constructs should not be interpreted as conclusive proof of the theoretical model. Future research should use heterogeneous item-level data and formal measurement-model assessment.

3. AI Adoption and Critical-Thinking Behaviour

The positive association pattern between AI adoption and critical-thinking behaviour suggests that students who report stronger engagement with AI also tend to report more constructive analytical learning practices. This is consistent with the view that generative AI can support higher-order learning when students compare alternatives, question outputs and verify claims rather than accept generated text uncritically. The finding aligns with Daniel (2025)^[9] and Chen and Cheung (2025)^[8], who identify potential gains in academic skills and learning outcomes under appropriately designed use conditions. The implication is not that AI automatically produces critical thinking, but that educationally productive use can coexist with and potentially scaffold critical inquiry.

4. AI Adoption and Self-Regulated Learning

Self-regulated learning shows a positive pattern in relation to AI adoption and a relatively high descriptive score. This supports the emerging literature that positions generative AI as a possible aid to planning, feedback, practice and reflection (Banihashem *et al.*, 2025; Lan & Zhou, 2025; Xia *et al.*, 2026)^[7, 13, 21]. Students may use AI to break complex tasks into stages, generate revision questions, obtain rapid explanations and monitor understanding. However, effective self-regulation requires the learner to remain in control of goals and evaluation. When AI becomes a substitute for effort or judgement, the same technology could weaken rather than strengthen self-regulation.

5. Collaborative Learning

Collaborative learning is the weakest of the measured behavioural dimensions, though still moderately high. This suggests that AI may currently operate primarily as a one-to-one digital assistant rather than as a structured component of peer learning. The result identifies a practical pedagogical opportunity. Lecturers can design group activities in which students jointly critique AI-generated answers, compare prompts, verify evidence or debate alternative outputs. Such designs would reposition AI from an individual answer-generating tool to a shared object of inquiry.

6. Academic Integrity

The relatively positive academic-integrity score indicates that respondents generally portray their AI use as compatible with responsible academic conduct. This finding should not be interpreted as evidence that integrity risks are absent. Self-reports in ethically sensitive domains can be affected by social desirability, and generative AI continues to create ambiguity around authorship, disclosure and acceptable assistance. The appropriate institutional response

is therefore explicit guidance rather than either prohibition or uncritical acceptance. This interpretation accords with UNESCO (2023) ^[20] and the Nigerian ethical concerns discussed by Bakre and Tukur-Bello (2026) ^[5].

7. Perceived Learning Performance and Overall Learning Behaviour

Perceived learning performance and overall positive learning behaviour record among the strongest outcome patterns. Students who report higher AI adoption also report stronger perceived learning effectiveness. This is broadly compatible with international synthesis evidence indicating that generative AI can support learning outcomes under appropriate conditions (Chen & Cheung, 2025) ^[8]. Nevertheless, BEH_PERF is a subjective measure. The study therefore supports a conclusion about perceived learning effectiveness and constructive learning behaviour, not a causal claim that AI improves GPA or examination performance.

8. Integrated Discussion

Taken together, the results support the theoretical value of integrating TAM and SRL perspectives. Perceived usefulness helps explain why students engage with AI, while AI self-efficacy reflects confidence in using the technology. The learning-behaviour findings then show that adoption has educational meaning only in relation to how students think, regulate, collaborate and act ethically. The pattern is also consistent with Nigerian evidence that digital literacy and adoption conditions shape student use (Aiyebilehin *et al.*, 2025; Owan *et al.*, 2025; Yakubu *et al.*, 2025) ^[3, 16, 22]. The comparatively weaker collaborative dimension and the caution surrounding integrity are especially important because they identify areas where institutional design can improve the quality of AI-supported learning.

9. Robustness and Interpretation Cautions

The supplied composite dataset exhibits unusually regular score patterns and strong covariance among several constructs. This raises two analytical concerns. First, multicollinearity can make individual regression coefficients unstable even when the overall association is strong. Second, conceptually distinct constructs may appear empirically indistinguishable if item-level measures do not demonstrate discriminant validity. Accordingly, the study's strongest defensible conclusions concern the overall positive pattern of AI adoption and learning behaviour, the relative weakness of collaboration, and the need for responsible-use structures. Exact causal, mediation or unique-predictor claims should await analysis of the clean item-level dataset with variance-inflation diagnostics, measurement-model testing and bootstrapped indirect effects where mediation is proposed.

Conclusion and recommendations

1. Conclusion

The study examined the relationship between artificial intelligence tools and the learning behaviours of undergraduate students in selected federal universities in South-East Nigeria. The findings indicate that AI tools have become an important component of undergraduate learning within the sampled institutions. Students generally demonstrated high levels of AI utilisation, perceived

usefulness and confidence in using AI technologies for academic purposes.

Stronger AI adoption was associated with more positive critical-thinking and self-regulated learning behaviours. Collaborative learning was also positively related to AI adoption but was comparatively weaker, suggesting that students may currently use AI predominantly as an individual learning assistant. Academic-integrity behaviour was generally positive, although its self-reported nature requires cautious interpretation. Learning-performance behaviour and overall positive learning behaviour were likewise positively associated with AI adoption. Taken together, the evidence supports the conceptual framework AI Adoption Factors → Learning Behaviours → Learning Outcomes and the complementary application of TAM and SRL. Nevertheless, the cross-sectional design does not establish experimental causality, and the unusually strong interrelationships among several variables require caution when interpreting individual regression effects. Overall, AI can contribute meaningfully to undergraduate learning when its use is accompanied by critical thinking, self-regulation, ethical awareness and adequate AI competence.

2. Recommendations

- Federal universities should institutionalise AI literacy programmes covering prompt formulation, verification of generated information, hallucination and bias detection, responsible citation, privacy and ethical use.
- Lecturers should integrate AI into critical-thinking activities that require students to evaluate, challenge and verify AI-generated responses against scholarly evidence.
- AI should be incorporated into self-regulated learning support, including study planning, formative practice, revision, concept clarification and reflective feedback.
- More AI-supported collaborative learning activities should be introduced because collaborative learning was comparatively weaker than individual learning dimensions.
- Universities should develop explicit institutional policies distinguishing legitimate AI assistance from academic misconduct and clarifying disclosure and attribution requirements.
- Assessment practices should be redesigned to preserve authentic learning through oral presentations, reflective commentaries, project defence, iterative assignments and context-specific problem-solving.
- Lecturers should receive continuing professional development in AI-supported pedagogy, responsible AI use and assessment redesign.
- Students should be taught to verify AI-generated information against credible academic and primary sources rather than treating AI output as authoritative.
- Universities should improve equitable access to reliable internet connectivity, suitable devices and digital learning infrastructure.
- Future studies should use longitudinal, experimental or quasi-experimental designs, collect item-level measurement data, assess discriminant validity, and incorporate objective academic-performance measures such as GPA or examination scores.

3. Contribution of the Study

The study contributes to the literature by integrating technology-adoption and learning-behaviour perspectives within a single empirical framework and by providing context-specific evidence from federal universities in South-East Nigeria. It demonstrates the importance of examining behavioural processes rather than treating AI adoption itself as the final educational outcome. The central implication is that universities should neither treat generative AI as inherently beneficial nor approach it solely as a threat to academic integrity; its educational value depends on how students are prepared, guided and assessed.

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