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Contributions of ChatGPT Adoption and Academic Integrity to Learning Engagement among Undergraduates

Achi Ndifon Bekomson
University of Calabar
Catherine Kaning Agbongiasede
University of Calabar
Ettah Ettah Omini
University of Calabar
Dorn Cklaimz Enamhe
University of Calabar
Matilda Ernest Eteng
University of Calabar
Emeka Samuel Nnaji
University of Calabar
Mary Iyaji Ngaji
University of Calabar
Ajim Ferdinard Mpuah
University of Calabar
Edmond Asu Odok
University of Calabar
Roseline Asuquo Okon
University of Calabar
Samson Akinwumi Aderibigbe
University of Calabar
Ovat Egbe Okpa
University of Calabar
Victoria Simon Akpama
University of Calabar
Joy Anthony Ukam
University of Calabar
Samuel Eburu Odey
University of Calabar
Samson Chidubem Ugwu

University of Calabar

John Edwin Effiom

johnedwin425@yahoo.com

University of Calabar

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Abstract

This research work examined how the adoption of ChatGPT relates to learning engagement among undergraduates in public universities in Cross River State, Nigeria, namely, the University of Calabar, the University of Cross River, and the University of Education and Entrepreneurship, and whether self-regulated learning and academic integrity serially mediate this relationship. The study further compared the structural relationships across gender using multigroup analysis (MGA); a companion analysis of the same dataset examining age-group differences is reported in a separate paper. The study is grounded in theories of technology acceptance and self-regulated learning. Literature was reviewed based on the variables under study. The study adopted a cross-sectional survey design. The population of the study comprised 1,507 final-year undergraduate students. The sampling technique utilized for this research was proportionate stratified sampling. A serial mediation model was specified and tested on survey data from 452 undergraduates. Partial least squares structural equation modelling (PLS-SEM) was estimated in Smart PLS. The instrument for data collection was a questionnaire titled "ChatGPT Adoption, Academic Integrity, and Learning Engagement" (CAAILEQ). The measurement model satisfied reliability, convergent, and discriminant validity standards. Analyses were conducted using SmartPLS 4. Results show that ChatGPT adoption positively predicted self-regulated learning, academic integrity, and learning engagement; self-regulated learning predicted academic integrity; and academic integrity was the strongest predictor of learning engagement. The hypothesized four-step serial chain (ChatGPT adoption, self-regulated learning, academic integrity, and learning engagement) was statistically significant, and the model explained 38.7% of the variance in learning engagement. The multigroup analysis indicated that one structural path (adoption → integrity) differed significantly by gender, while all other paths were invariant across the gender groups compared. The findings inform the responsible integration of generative AI in Nigerian university education and in Cross River State specifically.

Keywords: ChatGPT adoption; academic integrity; learning engagement; self-regulated learning; PLS-SEM; gender; multigroup analysis.

Introduction

Technological advancement is an integral aspect of human history. Every generation has produced more inventions than its predecessor; hence, the 21st century is similarly remarkable. Global educational environments have noted the rapid integration of AI tools like ChatGPT; however, a significant lack of comprehension remains. The century has seen significant advancements in emerging technologies like artificial intelligence (AI). This era exemplifies the Fourth Industrial Revolution (Arawi et al., 2024). Bozkurt (2023) said that artificial intelligence is transforming mankind at an unparalleled pace. Based on this premise, particularly in the realm of education, artificial intelligence is transforming pedagogy and scholarship. Artificial Intelligence (AI) is among the most transformative digital technologies in fields such as medicine, research, healthcare, aviation, and education. Artificial intelligence (AI), also known as machine intelligence, involves creating computer software to do activities that often need human cognitive abilities (Arawi et al., 2024). Chaudhry and Kazim (2022) characterize AI as a computational

system capable of executing certain tasks via designated talents (like voice or vision) and exhibiting intelligent behavior previously considered exclusive to human capability. Arawi et al. (2024) emphasize the pivotal function of AI in contemporary society, suggesting that it is fostering a collaboration between technology and humanity.

A notable AI innovation presently gaining attention in this field is ChatGPT, a sophisticated language model created by OpenAI (Feyijimi et al., 2025). Teachers and students already utilize writing tools such as Grammarly, Quillbot, Google Lens, ProWriter, Article Rewriter, etc. (Bakare et al., 2023). The launch of the interactive model, ChatGPT, in November 2022, has introduced a transformative framework that is already redefining the educational AI environment. The domain of education is undergoing swift changes due to artificial intelligence, namely via ChatGPT, influencing students' access to resources, assignment completion, and learning engagement (Kasneci et al., 2023). ChatGPT is an AI-driven chatbot that utilizes extensive language models such as GPT-3 and GPT-4 to generate responses based on user prompts (Gambo et al., 2026). ChatGPT is an artificial intelligence that uses deep learning techniques to analyze and produce natural language writing. Consequently, it is capable of engaging in intricate dialogs, offering insights on diverse subjects, and delivering precise responses to inquiries necessitating advanced analysis, synthesis, and data application (Roumeliotis and Tselikas, 2023).

ChatGPT is special in that it can produce responses that are similar to human conversation (Oladokun et al., 2024). The widespread adoption of these technologies raises concerns regarding the consequences for academic integrity and student engagement (Cotton et al., 2024; Chan and Hu, 2023; Zawacki-Richter et al., 2019). Some researchers emphasize the potential of ChatGPT to foster understanding and motivation (Yilmaz and Karaoglan, 2023; Tlili et al., 2023), while others warn about the dangers it poses to education (Eke, 2023; Perkins, 2023). In this regard, it is important to understand how adoption translates to involvement and the role of integrity in this process, especially in under-researched African contexts (Iddris et al., 2026; Adeniyi, 2021).

The emergence of artificial intelligence, exemplified by ChatGPT, has transformed the educational landscape by offering exceptional avenues for individualized learning and enhanced academic outcomes (Nduneche and Tolulope, 2024). The rapid integration of AI tools like ChatGPT in diverse educational environments globally has been noted; however, there remains a significant lack of comprehension regarding the perceptions and applications of these technologies among undergraduates, particularly in Nigerian public universities (Dake and Gbagbo, 2026).

Empirical research conducted by Al-kfairy (2024) and Gasaymeh et al. (2025) has examined the awareness and implementation of generative AI within the educational domain across several nations. Nonetheless, a considerable void exists in the literature regarding research on the knowledge and use of ChatGPT among Nigerian students. Limited research has been undertaken, including works by Frank and Idowu (2024) and Oladokun et al. (2024), mostly concentrating on the colleges of education. To the researchers' knowledge, there has been no investigation of the use of ChatGPT, academic integrity, and learning engagement among undergraduates at the public universities of Cross River State, Nigeria. This research investigated the adoption of ChatGPT, academic integrity, and learning engagement among undergraduates in public universities in Cross River State, Nigeria, utilizing a multigroup PLS-SEM approach across genders.

This study suggests that the use of ChatGPT influences learner engagement by mediating through self-regulated learning and academic integrity. Self-regulated learning—active planning, monitoring, and control of one’s own learning by students—is a well-established predictor of academic success (Pintrich, 2004; Zimmerman, 2000). Academic integrity, or the adherence to

honest and responsible scholarship, governs students' use of AI technologies and fosters meaningful engagement (McCabe et al., 2001; Cotton, 2024). The authors suggest that first, the adoption of self-regulation promotes integrity, which in turn encourages participation.

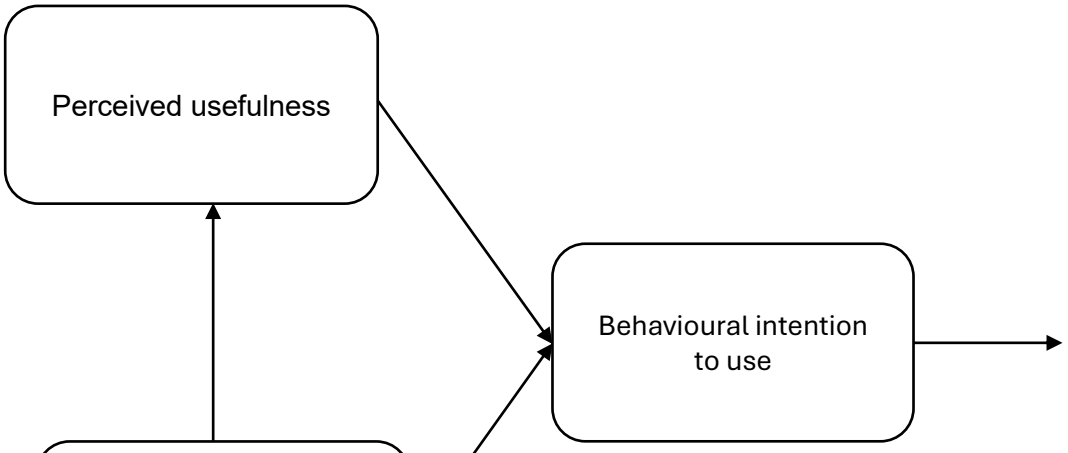
Because undergraduate populations are heterogeneous, the study further asks whether these relationships differ across gender, using multigroup structural equation modeling (Hair, 2022; Sarstedt et al., 2011). This comparison is a key contribution, providing evidence on whether the mechanism generalizes across gender groups. A companion analysis of the same dataset, examining age-group differences in the same structural model, is reported separately. The study integrates technology-acceptance and self-regulation perspectives and offers guidance for the responsible integration of generative AI.

Theoretical framework

The study makes use of technology-acceptance models, which connect technology adoption and use to learning and behavioural outcomes (Davis, 1989; Venkatesh, 2003; Strzelecki, 2024). The engagement literature indicates that engagement is a multifaceted construct consisting of behavioural, emotional, and cognitive components (Fredricks et al., 2004; Schaufeli et al., 2002; Bond et al., 2020). This paradigm posits that adoption affects engagement via intermediary self-regulatory and ethical mechanisms.

The Technology Acceptance Model (TAM) – Fred Davis introduced the Technology Acceptance Model (TAM) in 1989. The model indicates that a person's choice to adopt a new technology is shaped by two key elements: perceived usefulness and perceived ease of use. Perceived Usefulness is the degree to which a person feels that using a certain approach will enhance their work efficiency. In contrast, perceived ease of use refers to the degree to which a person thinks that using the system would demand little effort (Fridkin et al., 2025). These two traits are essential for understanding the adoption and use of technology in diverse settings. The perceived utility is an essential element of the Technology Acceptance Model (TAM) and has a direct impact on consumers' perceptions of technology adoption. The individual is more predisposed to adopt a new technology if they see it as augmenting their efficiency, productivity, or overall effectiveness (Marian et al., 2025). This concept is particularly relevant in the realm of education, where resources like ChatGPT may enhance the learning process by offering immediate access to knowledge and personalised support. Learners are more predisposed to embrace and use ChatGPT if they believe it would enhance their scholarly performance.

The uptake of technology Perceived ease of use influences the uptake of technology. by perceived ease of use. The system should be user-friendly, easily accessible, and quickly embraced by users. When users encounter seamless navigation and fluidity, it reduces barriers to adoption, resulting in more incorporation by students and educators into their educational practices. This theory is very relevant, since it offers a robust structure for comprehending the factors affecting students' adoption and use of ChatGPT. The Technology Acceptance Model (TAM) is based on perceived usefulness and ease of use. It aids in discerning the primary factors that drive students to use this novel tool for educational purposes.



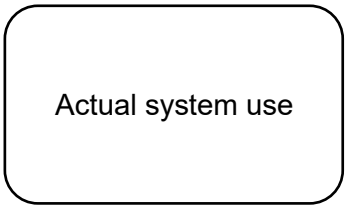


Figure 1: Technology Acceptance Model
Source: Authors field work (2026)

The Technology Acceptance Model (TAM) was originally designed to clarify the initial decision to adopt a technology, rather than the ongoing actions of the learner after adoption. In this context, the current model expands upon TAM instead of merely appropriating it. While the perceived utility and ease of use likely explain why a student engages with ChatGPT, they do not address whether this engagement is organized, evaluated, and modified systematically, as outlined by self-regulated learning theory. Additionally, they do not consider whether this engagement adheres to the principles of academic integrity. The current framework views self-regulated learning and academic integrity not as simple additions to the Technology Acceptance Model (TAM) but as crucial post-adoption mechanisms that transform TAM's adoption construct into the behavioural and ethical practices that ultimately influence learning engagement. Adoption (TAM) provides the tools and motivation for use; self-regulation offers the discipline that guides its application; and integrity establishes the normative boundaries that ensure honest usage. This integration supports the classification of self-regulated learning and academic integrity as sequential mediators, rather than as parallel or independent correlates, within the adoption–engagement link investigated in this research.

ChatGPT adoption and its outcomes

Students who use ChatGPT can use it to plan, clarify, and monitor their learning, supporting self-regulation (Yilmaz and Karaoglan, 2023; Farrokhnia et al., 2024). Thoughtful adoption of AI for learning rather than cheating can also reinforce integrity rather than undermine it (Tlili et al., 2023; Lund and Wang, 2023). Therefore, the authors expect the adoption of ChatGPT. The authors anticipate a positive correlation between ChatGPT adoption and self-regulated learning (H1), academic integrity (H5), and learning engagement (H4).

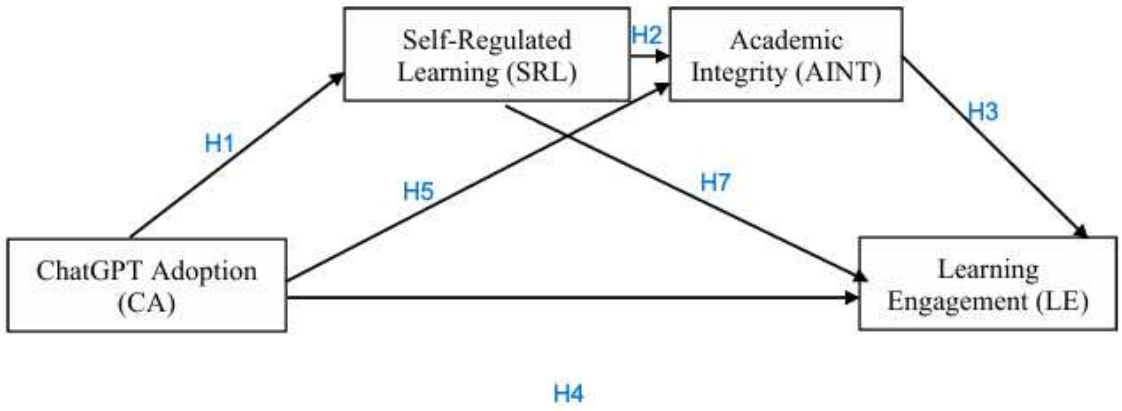
Self-regulation, integrity and engagement

Self-regulated learners are more likely to use tools ethically and remain engaged in challenging tasks (Zimmerman, 2000; Bandura, 1997). Self-regulation is a foundation of integrity because it enables students to plan honest approaches to their work (Almwalad, 2023). In turn, integrity promotes genuine engagement rather than superficial task completion (McCabe, 2001; Cotton et al., 2024). The researchers hypothesised that self-regulated learning is positively related to academic integrity (H2) and learning engagement (H7) and that academic integrity is positively related to learning engagement (H3).

A. Serial mediation and multigroup comparisons

The synthesis of these arguments leads to a serial chain in which ChatGPT's utilisation enhances self-regulated learning, which in turn improves academic integrity, subsequently leading to increased learning engagement (Figure 2). The authors hypothesise serial mediation (H6): Given the documented heterogeneity among undergraduates, the researchers also tested whether the structural relationships differ across gender (H8).

Fig 2: Hypothesised serial mediation model



Serial chain (~~H6~~): CA → SRL → AINT LE. MGA: Gender

Figure 2. Hypothesised serial mediation model linking ChatGPT adoption to learning engagement through self-regulated learning and academic integrity, compared across gender.

Statement of hypotheses

The following hypotheses are stated:

H_1. ChatGPT adoption is positively related to self-regulated learning.

H_2. Self-regulated learning is positively related to academic integrity.

H_3. Academic integrity is positively related to learning engagement.

H4. ChatGPT adoption is positively related to learning engagement.

H_5. ChatGPT adoption is positively related to academic integrity.

H_6. Self-regulated learning and academic integrity serially mediate the adoption–engagement relationship.

H_7. Self-regulated learning is positively related to learning engagement.

H_8. The structural relationships differ across gender.

Methodology

Design

A cross-sectional survey design was adopted. This design was selected because the study's aim was to describe and quantify the strength of association between ChatGPT adoption, self-regulated learning, academic integrity, and learning engagement as they naturally co-occur among final-year undergraduates, rather than to establish that adoption causes changes in the other constructs. Consistent with this aim, all inferential claims in this paper are correlational: the serial-

mediation and multigroup results reported below describe the pattern of statistical association observed within the sample at a single point in the students' academic year, and should not be read as evidence that ChatGPT adoption causally produces the levels of self-regulation, integrity, or engagement reported.

Population

Data from the academic planning units of the various public universities revealed that the population of the study comprised 1,507 final-year undergraduates at the University of Calabar, University of Cross River, and University of Education and Entrepreneurship. All these universities are public institutions in Cross River State, Nigeria.

Sampling technique and sample

The sampling procedure combined proportionate stratification with purposive selection within strata. The population of 1,507 final-year undergraduates was first stratified by university, in proportion to each institution's share of the total population, so that no single institution was over- or under-represented in the achieved sample. Because random selection of individual students was not administratively feasible, given the absence of a unified, up-to-date student registry accessible to the researchers across all three institutions and the constrained data-collection window imposed by students' examination and project schedules, students within each university stratum were then recruited purposively, through research assistants stationed at high-traffic points (lecture halls, libraries, faculty common areas) until each stratum's proportionate quota was filled. This design is consequently better described as stratified-purposive rather than stratified-random sampling, and it is reported as such here rather than as simple random sampling.

The population was restricted to final-year students specifically because this group has accumulated the most sustained exposure to ChatGPT and comparable generative AI tools across their degree program, has had the longest opportunity to develop stable self-regulated learning habits relative to earlier-year students, and is typically closest to independent, high-stakes academic work (research projects, long essays, seminar papers) in which the tension between AI-assisted efficiency and academic integrity is most directly and consequentially encountered. Earlier-year students, by contrast, would have had comparatively limited and more heterogeneous exposure to both ChatGPT and independent scholarly work, making final-year students the theoretically most appropriate, rather than merely the most convenient, population for testing this study's hypotheses. Valid replies were provided by male (n=211) and female (n=241) students, indicating that, despite the purposive element within strata, the achieved sample remained reasonably balanced across the gender groups examined in the multigroup analysis. The achieved sample of 452 exceeds not only the minimum requirement for PLS-SEM estimation of the most complex regression in the model (Hair et al., 2022) but also the sample size of approximately 306 that standard sample-size determination tables recommend for a population of this size at the conventional 95% confidence level (Krejcie & Morgan, 1970), providing two independent bases for judging the sample adequate. Table 1 shows the profile.

Instrument for data collection

The data was obtained using Google Forms for ease of access and participation, which is an online survey called "ChatGPT Adoption, Academic Integrity, and Learning Engagement." The questionnaire contained four sections: Section A contained demographic data, age, and gender and a cover letter stating the aim of the study, confidentiality, and rules of participation. Section B assessed students ChatGPT adoption using statements like "I regularly use ChatGPT to support my academic tasks" and "I consider ChatGPT useful for understanding course material," respectively. Responses were recorded on a five-point Likert scale (1 = strongly disagree to 5 =

agree), together with additional items: I intend to continue using ChatGPT in my studies, I am comfortable integrating ChatGPT into my learning routine, and I use ChatGPT to generate ideas and clarify concepts. Section C examined the self-regulated learning of respondents, using statements like “I set clear goals and plan how to accomplish my academic work," “I monitor my understanding while studying," "I adjust my learning strategies when needed," and so on.

Section D examined the respondents' academic integrity using statements such as “I properly acknowledge sources, including AI-generated content" and “I avoid submitting work that is not genuinely my own. " I use ChatGPT to assist learning rather than to cheat. While section E focused on learning engagement, it included statements such as “I actively participate in my courses and learning activities," “I feel absorbed and interested in my academic work," and “I persist with difficult academic tasks. " Based on the literature and previous studies, 19 questions were first generated, with 4 and 5 items, respectively, used to measure the dimensions of the constructs of ChatGPT adoption, academic integrity, and learning engagement.

Table 1. Demographic profile of respondents (N = 452)

Variable	Category	Frequency	Percent
Gender	Female	241	53.3%
	Male	211	46.7%

Measures and indicators

All constructs in the study were measured reflectively using five-point Likert scales (1 = strongly disagree to 5 = agree) derived from validated instruments. ChatGPT adoption items were adapted from technology-acceptance measures (Davis, 1989; Strzelecki, 2024); self-regulated learning from Pintrich (2004) and Zimmerman (2000); academic integrity from McCabe et al. (2001) and Cotton et al. (2024); and learning engagement from engagement scales (Fredricks et al., 2004; Schaufeli et al., 2002). Each latent variable and its observed indicators are listed in Table 2, and the full measurement structure is as seen in Figure 3.

Item validation

Quantitative validation of the items was performed using an independent panel of five experts in educational technology, educational measurement and evaluation, and educational psychology. The panel was presented with the background study, research objectives, and a first draft of the questionnaire for review. Validation was done on three aspects, namely relevance, precision, and clarity. The dimensions were analysed using the Item Content Validity Index (I-CVI) and Scale Content Validity Index (S-CVI) based on the experts’ recommendations (Polit et al., 2006). Each item was scored by the experts on a 5-point Likert scale.

First, these items were reviewed based on experts’ recommendations and refined to address specific shortcomings to better fit the constructs under investigation. Second, the theoretical relevance and coverage of the construct were prioritized, as removal of such items could lead to gaps in the domain being measured. For instance, some items were needed to describe unique features of the study variables; thus, they were retained to adequately represent the constructs. The approach is in agreement with the advice of Zamanzadeh and Schunk (2011). The goal was to strike a balance between theoretical significance and statistical significance.

After several rounds of revision, 19 items were finalized, consisting of 5 items on ChatGPT adoption, 4 items on self-regulated learning, 5 items on academic integrity, and 5 items on learning

engagement. The retained items showed better clarity, precision, and relevance, which helped the validity of the overall scale and were in line with the objectives of the study.

Data collection procedure

Data collection was carried out by physical and online approaches over a 10-month field period, from December 2025 to March 2026, necessitated by the logistics of coordinating research assistants and reaching final-year students across three institutions during a period that spanned semester breaks and examination windows at each institution. While the study is analysed and reported as a single cross-sectional dataset, the extended field period is acknowledged as a departure from the single-timepoint ideal of cross-sectional designs; the possibility that the perceived usefulness or ease of use of ChatGPT itself shifted over this window, as the tool and student familiarity with it continued to evolve, cannot be ruled out and is noted as a limitation. At each of the three public universities, two research assistants were financially incentivized to collect physical data. The purpose of the study was explained to the research assistants, and they were expected to distribute questionnaires to final-year students of different public universities in Cross River State. A WhatsApp group was created to coordinate operations and communication between researchers and assistants. Of the questionnaires distributed, 452 students returned valid, fully completed responses that were retained for analysis. To prevent duplicate entries, respondents supplied an email address or phone number at the point of submission; these identifiers were used solely for de-duplication, were stored separately from the substantive survey responses, and were not accessible to those coding or analysing the data, so that individual responses to the sensitive academic-integrity items could not be traced back to a named respondent during analysis. The electronic responses were tallied in a .csv file.

Ethical considerations

The study protocol was reviewed and approved by the Research Ethics Committee of the University of Calabar, Calabar, Nigeria (approval number: [UC/25/1879]; date of approval: [4/12/25]), and the study was conducted in accordance with the guidelines and regulations of that committee and with the ethical principles of the Declaration of Helsinki. Participation was voluntary. Before any questionnaire was administered, the research assistants explained to each student the purpose of the study, the voluntary nature of participation, the right to decline or withdraw at any time without academic or other penalty, and the measures taken to keep responses confidential. Verbal informed consent was obtained from every participant before data collection, and only students who gave consent received the questionnaire. Students who completed the online version received the same information in the cover letter at the start of the Google Form. All participants were final-year undergraduates aged 18 years or older. No names were collected, and the contact identifiers used for de-duplication were stored separately from the survey responses.

In this study, SmartPLS 4 was used because it can handle non-variance-based structural equation modeling. SmartPLS is particularly useful for exploratory research and for models with complex relationships or small sample sizes, relative to covariance-based SEM programs such as AMOS or LISREL. It performs quite well in predicting the path coefficients, testing the reliability and confirming the constructs (Hair et al., 2019), even if the data distribution is not normal. It also offers excellent bootstrapping features for significance testing and an intuitive-to-use interface that makes complex statistics accessible. With these characteristics, SmartPLS is a proper tool to analyze latent variables and validate hypothesized models.

Table 2. Latent variables and their measurement indicators

Latent variable	Code	Indicator (measurement item)
ChatGPT Adoption	CA1	I regularly use ChatGPT to support my academic tasks.
	CA2	I find ChatGPT useful for understanding course material.
	CA3	I intend to continue using ChatGPT in my studies.
	CA4	I am comfortable integrating ChatGPT into my learning routine.
	CA5	I use ChatGPT to generate ideas and clarify concepts.
Self-Regulated Learning	SRL1	I set clear goals and plan how to accomplish my academic work.
	SRL2	I monitor my own understanding while studying.
	SRL3	I adjust my learning strategies when needed.
	SRL4	I manage my study time effectively.
Academic Integrity	AINT1	I properly acknowledge sources, including AI-generated content.
	AINT2	I avoid submitting work that is not genuinely my own.
	AINT3	I use ChatGPT to assist learning rather than to cheat.
	AINT4	I uphold honesty in examinations and assignments.
	AINT5	I value integrity even when using AI tools.
Learning Engagement	LE1	I actively participate in my courses and learning activities.
	LE2	I feel absorbed and interested in my academic work.
	LE3	I persist with difficult academic tasks.
	LE4	I invest effort in understanding what I study.
	LE5	I feel energised and motivated in my studies.

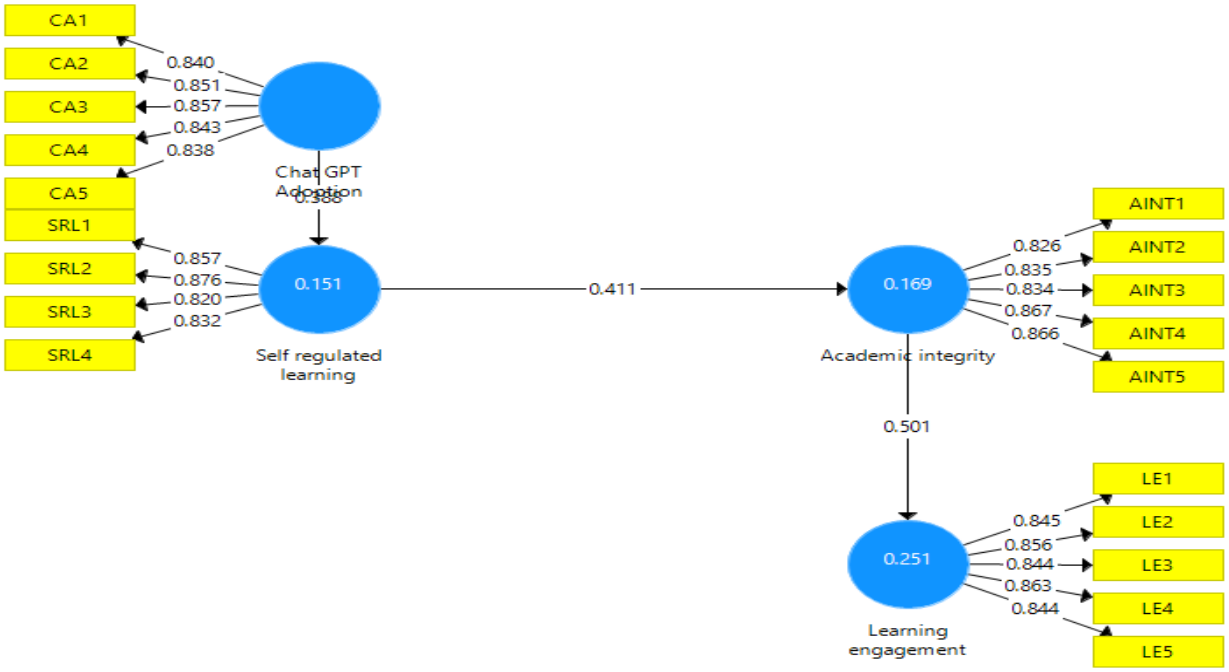


Figure 3. Measurement model showing each latent variable with its reflective indicators and standardised outer loadings; arrows among latent variables show the structural paths.

Analytical strategy

Partial least squares structural equation modelling was chosen because of its adaptability for complicated, prediction-orientated models and non-normal data (Hair et al., 2019; Sarstedt et al., 2011). Analyses were conducted using SmartPLS 4 (Ringle et al., 2022). The measurement model was evaluated using loadings, composite reliability, AVE, the Fornell–Larcker criterion and HTMT (Fornell & Larcker, 1981; Henseler et al., 2015). 5,000 subsamples were bootstrapped for estimating structural routes and specific indirect effects. Based on the MICOM technique and the parametric/Henseler MGA approach (Henseler et al., 2016; Sarstedt et al., 2011), a multigroup analysis by gender was conducted.

Results

Respondent profile

The achieved sample of 452 undergraduates was well distributed across gender, as shown in Figure 4.

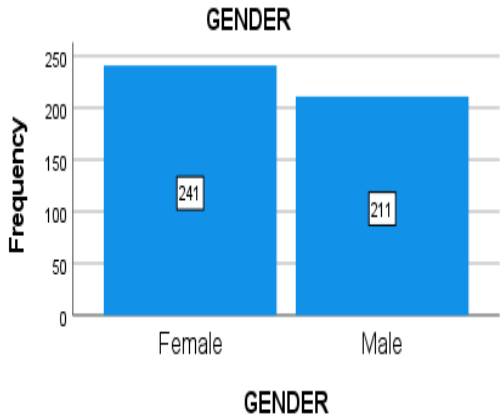


Figure 4. Demographic profile of the sample by gender.

Measurement model

Outer loadings, composite reliability (rhoc), and Cronbach's alpha were above the conventional cutoffs, and AVE was above 0.50 for all constructs, indicating reliability and convergent validity (Hair et al., 2022), as shown in Table 3.

Table 3. Outer loadings, reliability and convergent validity

Construct	Indicator	Loading	α	rho_A	rho_c	AVE
ChatGPT Adoption	CA1	0.840	**0.901**	**0.914**	**0.926**	**0.716**
	CA2	0.851				
	CA3	0.857				
	CA4	0.843				
	CA5	0.838				
Self-Regulated Learning	SRL1	0.857	**0.868**	**0.889**	**0.910**	**0.717**
	SRL2	0.876				
	SRL3	0.820				
	SRL4	0.832				
Academic Integrity	AINT1	0.826	**0.901**	**0.913**	**0.926**	**0.715**
	AINT2	0.835				
	AINT3	0.834				
	AINT4	0.867				
	AINT5	0.866				
Learning Engagement	LE1	0.845	**0.904**	**0.917**	**0.929**	**0.723**
	LE2	0.856				
	LE3	0.844				

Construct	Indicator	Loading	α	rho_A	rho_c	AVE
	LE4	0.863				
	LE5	0.844				

Thresholds: loadings ≥ 0.820; α, rho_A, rho_c ≥ 0.70; AVE ≥ 0.50.

The result of the discriminant validity was confirmed by the Fornell–Larcker criterion (Table 4) and the HTMT values < 0.85 (Table 5). (Henseler et al., 2015).

Table 4. Fornell–Larcker criterion (√AVE on diagonal)

	CA	SRL	AINT	LE
CA	**0.846**			
SRL	0.387	**0.847**		
AINT	0.329	0.412	**0.846**	
LE	0.47	0.45	0.5	**0.85**

Table 5. Heterotrait–monotrait ratio (HTMT)

	CA	SRL	AINT	LE
CA				
SRL	0.437			
AINT	0.363	0.462		
LE	0.52	0.504	0.551	

All HTMT values are below the conservative 0.85 threshold.

Structural model

The result of the structural model revealed that all VIF values for the inner model were less than 3.0, suggesting no concerns about collinearity. The model explained 38.8% of the variance in learning engagement (R^2 = 0.388), 20.4% in academic integrity, and 15.0% in self-regulated learning (Figure 5). The estimates of the paths are presented in Table 6 and Fig. 5.

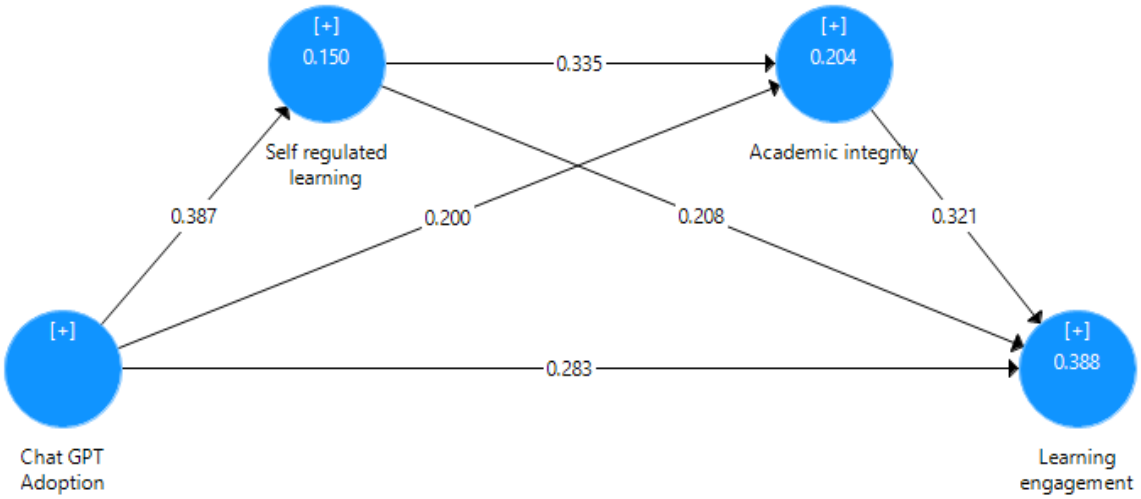


Figure 5. Estimated structural model with standardised path coefficients and R^2 values. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 6. Structural path coefficients and hypothesis tests

Path	β	SE	t	p	Decision
CA → SRL	0.387	0.043	8.905	<0.001	**Supported**
CA → AINT	0.200	0.046	4.376	<0.001	**Supported**
SRL → AINT	0.335	0.046	7.320	<0.001	**Supported**
CA → LE	0.283	0.041	6.924	<0.001	**Supported**
SRL → LE	0.208	0.042	4.919	<0.001	**Supported**
AINT → LE	0.321	0.041	7.730	<0.001	**Supported**

ChatGPT use was a significant positive predictor of self-regulated learning as hypothesized ($\beta = 0.387$, $p < 0.001$; H1 supported). Self-regulated learning was a significant predictor of academic integrity ($\beta = 0.335$; H2 supported) and academic integrity was the best predictor of learning engagement ($\beta = 0.321$; H3 supported). Furthermore, the results showed that the adoption of ChatGPT had a direct impact on engagement ($\beta = 0.283$; H4 Supported) and so did self-regulated learning ($\beta = 0.208$; H7 Supported).

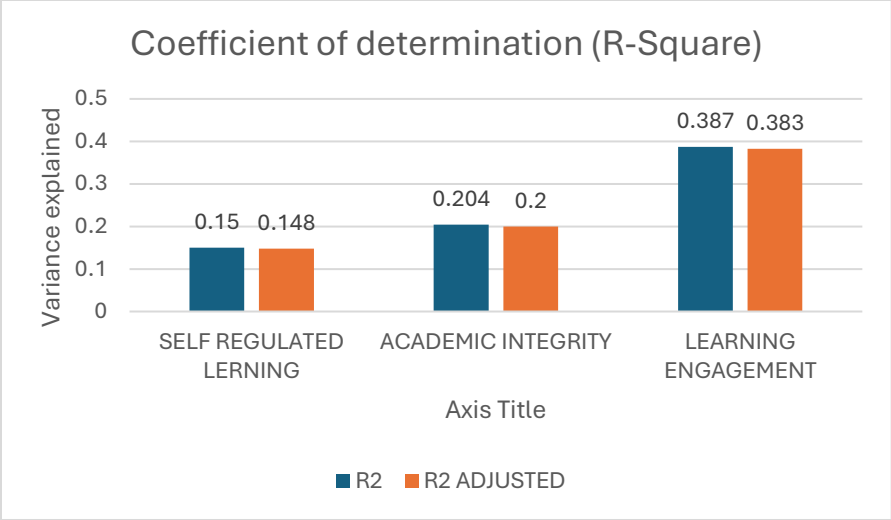


Figure 6. Coefficient of determination (R^2 and adjusted R^2) for the three endogenous constructs.

Mediation analysis

In Table 7 and Figure 7, the indirect effects were tested using bias-corrected bootstrap confidence intervals. The hypothesized four-step serial chain was significant, validating H6. The pattern shows complementing (partial) serial mediation (Hair et al., 2022) since relevant direct effects were also substantial.

Table 7. Specific indirect (serial) effects with 95% bootstrap confidence intervals

Indirect path	Effect	t	CI low	CI high	Sig.
CA → SRL → AINT → LE	0.042	4.915	0.027	0.061	**Yes**
CA → SRL → LE	0.081	4.448	0.048	0.119	Yes
CA → AINT → LE	0.064	4.366	0.038	0.095	Yes
SRL → AINT → LE	0.109	5.736	0.074	0.148	Yes
CA → SRL → AINT	0.130	6.519	0.091	0.171	Yes
SRL → AINT	0.336	8.887	0.261	0.406	Yes

Shaded row is the hypothesised four-step serial mediation chain (H6). An effect is significant when the 95% CI excludes zero.

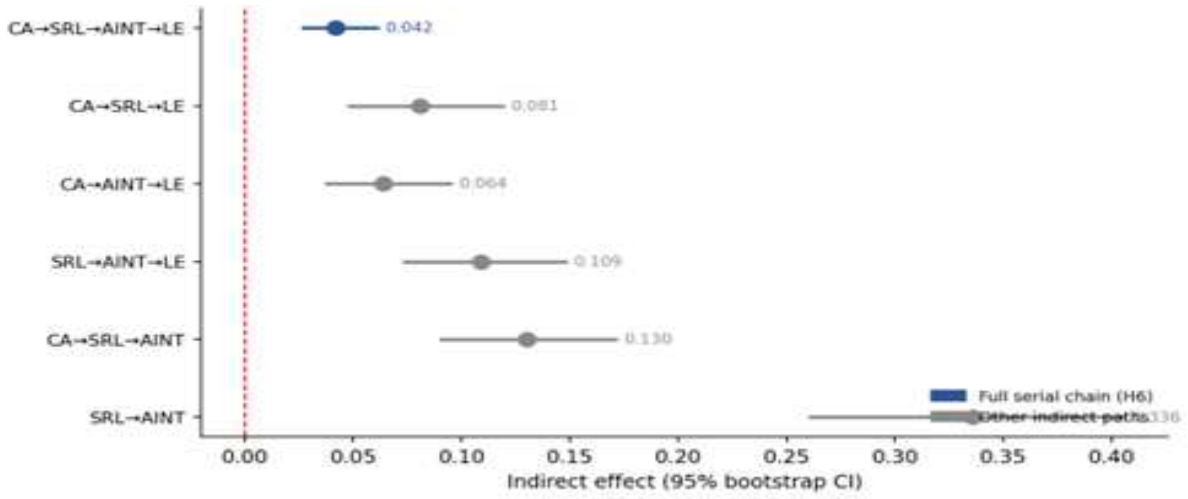


Figure 7. Specific indirect (serial) effects with 95% bootstrap confidence intervals; intervals crossing zero (dashed line) are non-significant.

Multigroup analyses

A multigroup analysis was performed to compare the structural patterns across gender. Figure 8 compares the group-specific coefficients, and Table 7 gives the formal difference tests. Figures 9 and 10 show the full measurement and structural model computed individually for male and female students. A companion analysis of the same dataset, comparing structural patterns across age groups, is reported in a separate paper.

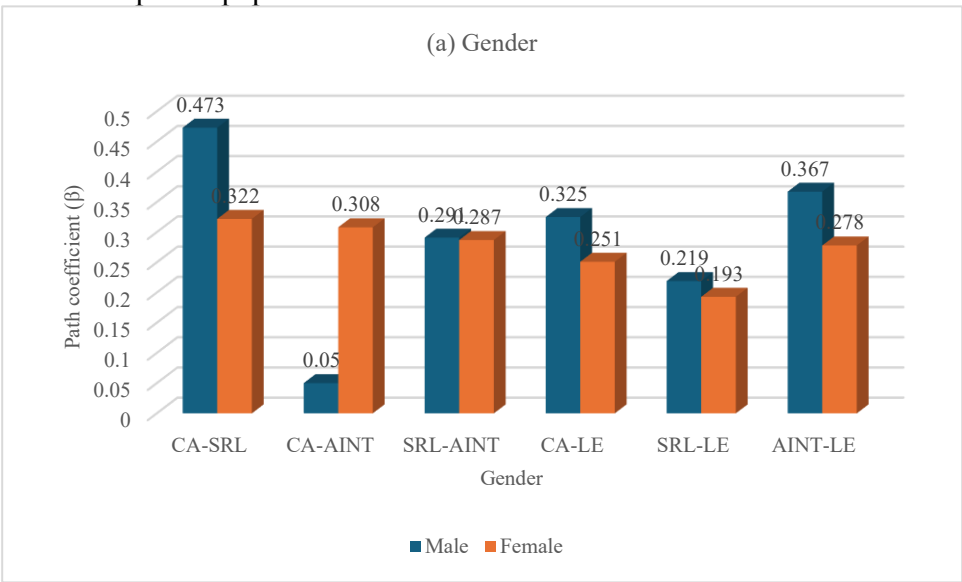


Figure 8. Multigroup path coefficients for gender ($p < 0.05$).

Gender

The result in Table 8 revealed that the adoption–integrity path (CA → AINT) differed significantly by gender, being stronger among female students, while the remaining paths were invariant. H8 was partially supported.

Table 8. Multi-Group Analysis for male and female

Path	β Male	β Female	Diff.	t	p	Sig.
CA->SRL	0.473	0.322	0.151	1.723	0.086	No
CA->AINT	**0.050**	**0.308**	**-0.258**	**2.830**	**0.005**	**Yes**
SRL->AINT	0.291	0.287	0.004	1.602	0.110	No
CA->LE	0.325	0.251	0.074	0.812	0.417	No
SRL->LE	0.219	0.193	0.026	0.369	0.712	No
AINT->LE	0.367	0.278	0.089	1.034	0.302	No

Male n = 211
Female n = 241.
Shaded row indicates a significant difference ($p < 0.05$).

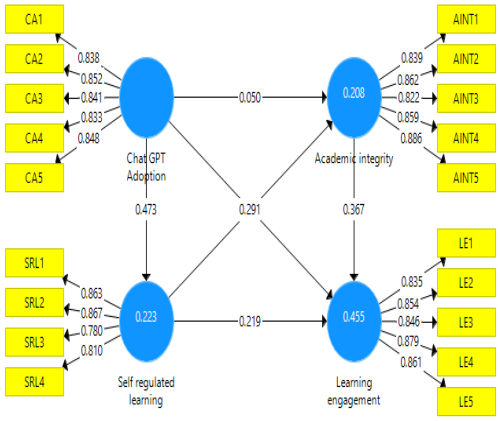


Figure 9: MALE

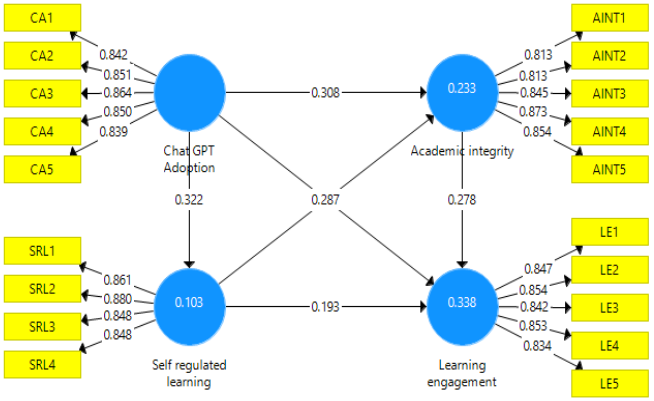


Figure 10: FEMALE

Figure 9 and 10: Multigroup measurement and structural models for male (a) and female (b) students. The adoption → integrity path (CA → AINT) is significantly stronger among female students; all other paths are invariant.

Summary of hypothesis tests

Table 9 consolidates the outcomes of all hypotheses.

Table 9: Summary of hypothesis testing

Hypothesis	Path / comparison	β / effect	p	Decision
H1	CA → SRL	0.387	<0.001	**Supported**
H2	SRL → AINT	0.335	<0.001	**Supported**
H3	AINT → LE	0.321	<0.001	**Supported**
H4	CA → LE	0.283	<0.001	**Supported**
H5	CA → AINT	0.200	<0.001	**Supported**
H7	SRL → LE	0.208	<0.001	**Supported**
H6	CA → SRL → AINT → LE (serial)	0.042	<0.001	**Supported**
H8	Gender differences	—	—	**Partially supported**

Discussion

The findings support an integrated account of how generative-AI adoption shapes learning engagement. ChatGPT adoption promoted self-regulated learning, which strengthened academic integrity, which in turn enhanced engagement—consistent with the view that adoption translates into outcomes through self-regulatory and ethical processes (Venkatesh et al., 2003; Zimmerman et al., 2011). The significant serial chain indicates that the benefit of adoption for engagement is transmitted, in part, through self-regulation and integrity rather than operating only directly (Pintrich, 2004; Bandura, 1997).

These results extend existing scholarship in three ways. First, they connect ChatGPT adoption to engagement through integrity, responding to debates about whether generative AI helps or harms learning (Kasneci et al., 2023). Second, they provide evidence from an under-researched Nigerian public-university context (Michel-Villarreal et al., 2023). Third, the multigroup analysis shows a significant gender difference specifically in the adoption–integrity link, while the remaining structural paths were invariant across gender, underscoring the value of testing demographic moderation rather than assuming it (Sarstedt et al., 2011; Henseler et al., 2016). A companion analysis of the same dataset examines age-group differences separately. This exploration further highlights the importance of understanding how various demographic factors influence interactions with generative AI in educational settings. By exploring these nuances, researchers can better tailor their approaches to enhance learning outcomes across diverse student populations.

Practical implications

Since academic integrity was the strongest single predictor of engagement in this, exceeding both direct paths from adoption and self-regulation, institutions should treat integrity-building as the highest-leverage intervention point in the chain rather than one of several parallel priorities. Concretely, because the measurement items retained here specifically address acknowledging AI-generated content, avoiding AI-generated content, avoiding the submission of non-original work, and using ChatGPT to assist rather than replace independent thought, course-level assessment redesign should require students to submit a brief AI-use disclosure alongside major assignments, stating which sections, if any, involved ChatGPT assistance and how. This approach operationalizes the integrity construct actually measured in this study, rather than relying on a generic honour code that students might disconnect from their specific AI use.

Because self-regulated learning mediated a substantial share of the adoption–engagement relationship (indirect effect via SRL alone = 0.081, nearly double the direct AINT-only path), Cross River State universities should embed brief, structured self-regulation prompts (goal-setting and self-monitoring checklists) directly into AI-supported coursework activities, rather than offering self-regulation training as a separate, generic study-skills workshop divorced from actual ChatGPT use. Because the adoption–integrity path was significantly stronger among female students ($\beta = 0.308$ versus 0.050 for male students, Table 7), targeted orientation sessions on translating ChatGPT use into honest academic practice may plausibly yield larger integrity gains if piloted first with female student cohorts, while male students' comparatively weak adoption–integrity link warrants separate investigation into what non-integrity-mediated pathway is instead driving their engagement, a question this study's design cannot resolve but that institutional data (e.g., disciplinary referral records by gender) could help clarify. Because the remaining structural paths were invariant across gender, the integrity-focused interventions proposed above can be implemented as a single, unified program rather than requiring separate versions for male and female students, with the disclosure mechanism and self-regulation prompts applied uniformly

while the female-first piloting recommendation targets specifically the one path found to differ. This approach not only streamlines the implementation process but also enhances the potential for collective buy-in from all students. By fostering an inclusive environment, the program aims to promote shared accountability and support among peers, ultimately driving greater engagement across the board.

CONCLUSION

This study found that the adoption of ChatGPT through the serial mechanism of self-regulated learning and academic integrity directly and indirectly supports learning engagement among Nigerian undergraduates. This relationship was invariant across gender on all but a single path (adoption–integrity), which was significantly stronger among female students. Based on the technology-acceptance and self-regulation perspectives and applying multigroup PLS-SEM by gender, this study strengthens our knowledge of responsible generative AI integration and offers practical implications for undergraduate education. A companion paper reports the corresponding age-group analysis on the same dataset. These findings highlight the importance of fostering an environment that promotes ethical practices in academic settings, particularly as technology continues to evolve. Future research could further explore how these dynamics change with the introduction of new educational tools and methodologies.

Conflict of interest

The authors hereby declare that there is no conflict of interest.

Clinical Trial Number

Not applicable

Funding declaration

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Ethics, Consent to Participate, and Consent to Publish declarations

Ethics approval: The study protocol was approved by the Research Ethics Committee of the University of Calabar, Calabar, Nigeria (approval number: [UC/25/1879]; date of approval: [4/12/25]). The research was carried out in accordance with the guidelines and regulations of the University of Calabar Research Ethics Committee and the ethical principles of the Declaration of Helsinki.

Consent to participate: Verbal informed consent was obtained from all individual participants included in the study before data collection, after the purpose of the study, the voluntary nature of participation, the right to withdraw at any time without penalty, and the confidentiality of responses had been explained to them. All participants were aged 18 years or older.

Consent to publish: Not applicable. The manuscript does not contain any individual person's data in any form (including images or identifying details).

Data availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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