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Acceptance and use of artificial intelligence for self-directed research learning among postgraduate students in Nigerian public universities

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Abstract
Research competence is a cornerstone of postgraduate education, yet many Nigerian students continue to struggle with essential processes such as literature review, methodological design, and data analysis. While artificial intelligence (AI) holds considerable promise in supporting self-directed research learning (SDRL), its adoption and practical use among postgraduate students in Nigeria remain underexplored. This study addresses that gap by investigating both the acceptance and use of AI tools for SDRL among postgraduate students in Nigerian public universities. Adopting a predictive correlational design, data were collected from 456 students across two institutions using stratified random sampling. Two validated instruments (10-item scales; $\alpha = 0.85$ and $\alpha = 0.87$) were administered both physically and digitally to assess students' acceptance of AI and their actual use of AI for SDRL. Descriptive statistics and linear regression were used to analyse patterns and predict usage based on acceptance. Findings revealed a high level of AI acceptance ($M = 3.30/4.00$), yet a considerably lower level of actual AI usage ($M = 2.26/4.00$) for self-directed research learning. A weak but statistically significant relationship was observed between acceptance and use of AI for self-directed research learning ($R^2 = 0.01$, $\beta = 0.11$, $p < 0.05$), suggesting that acceptance alone does not translate into meaningful engagement. These results highlight a pressing need to move beyond enthusiasm and address practical barriers to AI usage for self-directed research learning, such as limited training opportunities, inadequate mentorship, and infrastructural constraints. Targeted institutional interventions aimed at building AI literacy and integrating AI tools into research support systems could bridge this gap, thereby strengthening postgraduate research capacity and improving learning outcomes in Nigerian higher education.

Keywords Artificial intelligence, Graduate education, Self-directed learning, Technology acceptance, Nigeria

1 Introduction

Research is the most reliable way of advancing knowledge, solving problems, and fostering innovation. It is the cornerstone of progress that enables societies to adapt, grow, and innovate in an ever-changing world. Its importance spans across various fields, including education, science, technology, healthcare, and policy-making [41]. A high level of training is usually required (such as that which can be acquired through postgraduate studies) to produce quality research. Moreover, postgraduate training alone may be insufficient to equip some individuals with sound research skills. In fact, upon the completion of doctoral studies, people undergo several years of postdoctoral training to solidify their research skills. Thus, it is expected that students enrolled in different postgraduate studies take research related courses and activities seriously.

Recent observations give the impression that some postgraduate students in Nigeria face challenges with key research activities. For example, many students struggle to conduct literature reviews, craft sound research methodologies, and select appropriate statistical techniques for data analysis [38, 47]. These challenges are often attributed to a combination of factors, including insufficient training, a weak foundational background [67], limited access to mentorship [53], collaborative opportunities and a weak institutional culture [57]. In many cases, the unavailability of experienced instructors to readily guide postgraduate students in meeting their research needs is seen as a significant obstacle to effective research conduct [68]. Nevertheless, the introduction of advanced large language models, such as ChatGPT-4.1, has begun to transform how students learn and has offered new opportunities for research and self-directed learning from the comfort of their homes.

The Internet has revolutionalised the world and turned it into a global village. Developments in the field of artificial intelligence have further supplemented man with tools to ease the use of the Internet, especially for information search and retrieval [55]. The pervasiveness of AI into different fields, has redefined how postgraduate students should acquire knowledge and skills in research, writing, data analysis, editing and even publication. Research learning is a critical component of the academic journey of postgraduate students. Even during collaborative engagements, research thinking, conceptualisation, design and implementation is often a solitary activity. This implies that scholars would occasionally work in isolation before bringing forth ideas, issues and suggestions for discussion with fellow collaborators.

Since, AI can be used as a companion or a teacher where one is not physically available, postgraduate students can leverage on such opportunities to seek clarification to questions rather than wait for a face-to-face interaction with a more experienced person for guidance. Previous research has documented that AI can be used for self-tutoring on almost any research topic [8]. However, what remains unclear is the extent to which postgraduate students are willing to accept and/or use such technological innovations for self-directed learning. Self-directed research learning (SDRL) refers to the process by which students work independently to gain knowledge that can help them identify research questions, design methodologies, analyse data, interpret results, discuss findings, and contribute to their fields [42]. It has been documented that AI tools, such as data analysis software, literature review assistants, and personalized learning platforms, have the potential to significantly enhance research efficiency, precision, and provide tailored support to students [13, 64].

Despite this great potential, the effectiveness of AI in supporting SDRL may depend on postgraduate students' awareness, acceptance and use of these technologies. Indeed, research indicates that students' familiarity with AI tools, their perceptions of these technologies, and their readiness to integrate them into their learning processes can be important factors that are decisive of the extent to which AI can enhance SDRL outcomes. For instance, a study by Shahzad et al. [63] found that students' awareness of AI tools, particularly ChatGPT, significantly influenced their intention to adopt these technologies in higher education, with perceived ease of use, usefulness, and trust as mediators in this relationship. Similarly, other studies have supported this notion by revealing that awareness of technology and particularly AI, has a direct effect with their acceptance and use of such tools for different purposes [52, 58].

It was along these lines that this exploratory study was undertaken to assess the extent to which postgraduate students are willing to accept and use AI for self-directed research learning and to examine whether acceptance predicts postgraduate students' use of AI for self-directed research learning in public universities in Cross River State, Nigeria. It is important to assess the level of acceptance and use of AI for self-directed research learning among postgraduate students because this population are often exposed to core research principles, ethics and practices in their respective programmes. Supplementing the contents, lessons and experiences gained from their programmes with self-paced AI lessons may be very rewarding in helping them clarify doubts and seek guidance when a teacher may not readily be available. Moreover, the findings of this study can be useful for educators, technology developers, and policymakers to optimize the design and implementation of AI tools that cater to the unique needs of postgraduate researchers [49]. For these reasons, the present study was conceived and executed.

2 Literature review and hypothesis development

2.1 Acceptance of AI for self-directed learning

The use of artificial intelligence (AI) in self-directed learning (SDL) has gained significant attention, especially as students increasingly engage with AI platforms to manage their learning independently and at their own pace [50]. Understanding factors that influence students' acceptance of AI tools is crucial to enhancing their effective integration in higher education.

Several theoretical frameworks have been widely applied to study technology acceptance in educational contexts, including the Technology Acceptance Model (TAM) [23], the Unified Theory of Acceptance and Use of Technology (UTAUT) [70], and Self-Directed Learning (SDL) Theory [40]. These models explain acceptance as influenced by factors such as perceived ease of use, perceived usefulness, social influence, and self-efficacy [4, 31]. Research applying these frameworks to AI tools indicates that postgraduate students' acceptance is positively associated with their beliefs about how AI can facilitate research activities, including information retrieval, writing assistance, and personalized feedback [35, 76].

Empirical studies show that many students demonstrate a willingness to adopt AI-driven platforms for SDL, reporting enhanced motivation and confidence in managing research independently [5, 34]. For instance, Ahmed [2, 26] focused attention on the role of social and peer influences in students' attitudes toward AI, suggesting that acceptance can be reinforced through collaborative and community learning environments.

Furthermore, self-efficacy (the belief in one's ability to use AI tools effectively) has been found as a significant predictor of acceptance, with students who feel more competent displaying greater engagement with AI technologies [43, 62].

Despite these positive findings, there are concerns about AI acceptance. Studies report that students are sometimes apprehensive about the accuracy and reliability of AI-generated content, as well as ethical issues related to data privacy and academic integrity [16, 27]. These concerns can hinder full acceptance and integration of AI tools in SDL, suggesting the need for clear ethical guidelines and institutional policies to support responsible AI use [33, 61].

Contextual factors also affect acceptance levels. Cultural attitudes towards technology, access to adequate infrastructure, and institutional support play critical roles in shaping students' willingness to adopt AI [29, 46]. For example, students in institutions that provide training and digital literacy programs tend to show higher acceptance and more effective use of AI tools [12, 15].

Going ahead, the integration of AI in postgraduate education offers opportunities to enhance SDL by automating routine tasks such as literature reviews and synthesizing research findings, freeing students to focus on critical analysis and interpretation [36]. To maximise these benefits, curriculum reforms incorporating AI literacy are necessary to equip students with the skills needed to critically evaluate AI-generated content and maintain academic rigor [75]. Such comprehensive approaches position AI not as a replacement but as a supportive tool that complements rigorous academic training and prepares students for the evolving demands of research and lifelong learning.

Although several studies reveal a generally positive disposition among students toward AI-supported learning, acceptance levels remain uneven and may be influenced by factors such as ethical concerns, infrastructural disparities, and varying levels of digital readiness [16, 27, 29]. Moreover, some research indicates that while students' express interest in AI tools, this does not always translate to sustained or confident use in self-directed academic contexts, especially when institutional support or training is limited [15, 46]. These observations raise the possibility that overall acceptance, particularly among postgraduate students engaging in self-directed research learning, may not be as widespread as assumed.

H1: Postgraduate students have a generally low level of acceptance of AI for self-directed research learning in universities.

2.2 Use of AI for self-directed learning

The use of AI tools in higher education, particularly for self-directed learning (SDL), has gained substantial attention in recent years (Al-Zahrani & Alasmari [6]; Crompton & Burke [21, 72]). SDL, which empowers learners to independently manage their learning activities [37], is well supported by AI technologies. AI technologies provide an adaptive and personalized learning environment that can enhance SDL by offering tools for information retrieval, knowledge synthesis, and feedback [43]. However, limited research has explored how students perceive the usability and usefulness of AI tools in enhancing satisfaction and shaping attitudes within self-directed learning environments [32].

Recent advancements in artificial intelligence tools such as ChatGPT are reshaping postgraduate research training. Empirical studies indicate that large language models assist students in refining research topics, improving writing, and correcting grammar

[17]. It has been shown that ChatGPT supports students in exploring research questions and managing tasks such as literature reviews, which can strengthen their confidence in research methods [19, 60].

It has been shown that ChatGPT helps reduce the time and effort involved in literature reviews by enabling efficient access to relevant sources, guiding writing structure, and supporting students' adaptation to the research process [3]. In addition, ChatGPT enhances academic writing by improving grammar, aligning with scholarly standards, and offering guidance on research ethics [10, 24]. As self-directed learning becomes more integral to postgraduate education, students are increasingly expected, and sometimes required, to engage with AI tools to support their independent research efforts [56]. Nevertheless, ethical guidelines are necessary to regulate AI use in higher education and maintain scholarly standards [33, 61].

While many students recognize the benefits of AI for personalized learning, concerns persist regarding accuracy, data privacy, and ethical implications. For instance, a study by Chan and Hu [16] found that students appreciated the potential of AI in education but were apprehensive about its reliability and ethical use. Similarly, Farrokhnia et al. [27] reported that although a significant portion of students valued the role of AI in personalized learning, a majority expressed worries about factual inaccuracies, privacy risks, and academic integrity.

Addressing these concerns requires integrating AI with strategies that promote academic integrity. Educators advocate combining AI-assisted learning with digital literacy training to help students engage critically with AI-generated content [12, 15]. Furthermore, Walter [71] emphasizes the need for universities to establish clear policies on AI attribution and to implement mentorship programs that guide students in responsible AI usage, thereby preventing overreliance. For meaningful integration of AI in postgraduate training, institutions should automate routine tasks like literature synthesis [36] and reform curricula to include AI literacy for critical evaluation of AI content [75]. These approaches position AI as a supportive tool, complementing rigorous academic training and preparing students for the evolving research landscape.

Given the growing integration of AI tools in postgraduate education and the emphasis on students' independent engagement with such technologies, it is necessary to assess the extent to which postgraduate students are actively using AI in their self-directed research activities.

H2: Postgraduate students have a low level of AI use for self-directed research learning in universities.

2.3 Relationship between AI acceptance and use

The integration of artificial intelligence (AI) into education has attracted considerable attention in Nigeria, yet the specific link between AI acceptance and its role in fostering self-directed learning (SDL) remains under-investigated. AI-driven tools, such as intelligent tutoring systems (ITS), adaptive learning platforms, and conversational agents, offer learners personalized feedback and guidance, which can support autonomous study behaviors [56]. However, effective integration of these tools for SDL may depend on learners' willingness to adopt and engage with them.

Drawing on established acceptance frameworks, researchers consistently identify perceived usefulness, perceived ease of use, and trust as primary antecedents of behavioural intention toward AI adoption [39, 74]. In a Nigerian context, Esiyok et al. [26] reported that ICT self-efficacy strengthens perceptions of AI chatbot usability, implying that confidence in one's digital skills is a crucial driver of acceptance. Similarly, Saqr et al. (2024) found that self-efficacy reliably predicts learners' intentions to continue using AI-powered e-learning platforms.

Empirical evidence directly linking AI acceptance to SDL outcomes is emerging but still limited. Azevedo et al. [7] observed that when students perceived intelligent tutoring systems as both useful and navigable, they were more likely to employ metacognitive strategies, such as goal-setting and self-monitoring, during independent study sessions. Behforouz and Al Ghaithi [11] examined interactive chatbots in Omani EFL classes and found that higher trust in the chatbot mediated the relationship between perceived system reliability and learner autonomy, leading to increased goal-setting and self-monitoring during self-directed language practice. Similarly, it was noted by Lodge et al. [44] that trust in the interface, including conversational agents, fosters greater willingness to self-regulate in blended language settings.

Regarding AI recommendation engines, Oubalahcen et al. [54] revealed multiple empirical projects showing that recommender systems significantly increase students' self-paced content engagement. Möller et al. [48] reported that students with stronger behavioural intentions to use an AI-driven tutoring assistant accessed self-paced modules 27% more frequently and earned higher exam scores in a distance-learning context. Abdi et al. [1] found that perceived usefulness of an AI-powered e-notes application significantly predicted both behavioural intention and the frequency of independent revision. However, Wang and Li [73] reported that intention to use AI summarization tools predicted key SDL activities, such as creating study plans and seeking additional readings, among students.

Collectively, these findings suggest that learners' acceptance of AI, particularly in terms of perceived usefulness, ease of use, trust, and intention to use, plays a role in predicting the extent to which they engage with AI tools to support self-directed learning.

H3: Postgraduate students' acceptance of AI significantly predicts their use of AI for self-directed research learning in universities.

2.4 Conceptual framework

The conceptual framework for this study combines three theories: the Technology Acceptance Model (TAM; Davis [23], , Self-Directed Learning (SDL) Theory [40], and the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al. [70]. TAM contributes core constructs, perceived usefulness, perceived ease of use, and attitudes, to explain how postgraduate students form intentions to adopt AI tools. SDL Theory places AI adoption within the context of learner autonomy, efficiency, and analytical reasoning, suggesting that AI can serve as a resource for independent research learning. UTAUT adds facilitating conditions, such as institutional training and infrastructure, that affect students' willingness to use AI tools, especially in resource-constrained settings like Nigerian universities. Altogether, these perspectives propose that cognitive acceptance (per TAM) drives AI use, which, in turn, bolsters SDL competencies.

As illustrated in Fig. 1, students' acceptance of AI, which is a product of their perceptions of usefulness and ease of use, directly affects their engagement with AI tools. Engagement is defined in terms of frequency, variety, and purpose of AI use, and it

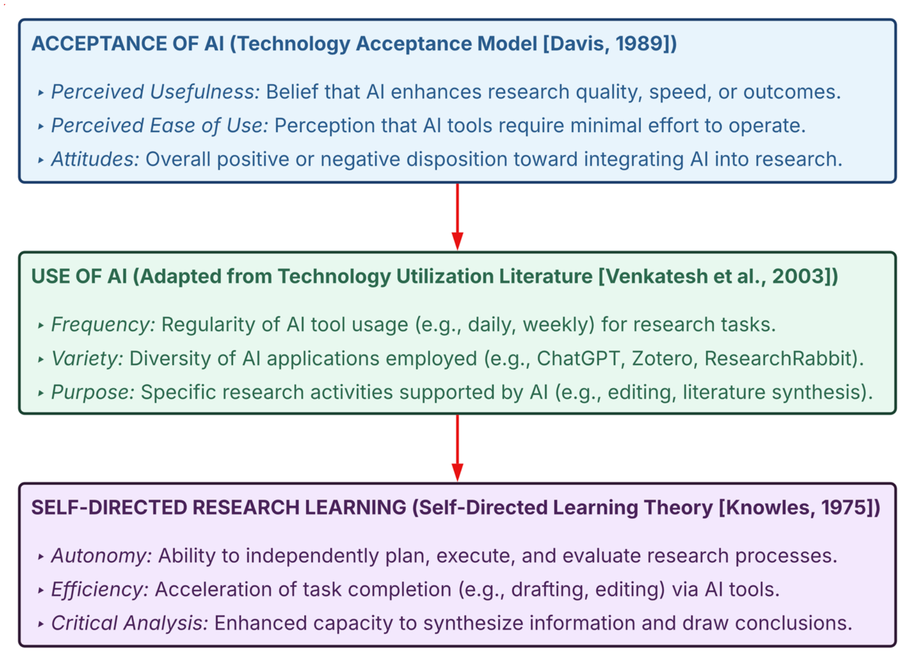

Fig. 1 Conceptual framework developed for this study

mediates the link between acceptance and SDL outcomes (e.g., task autonomy, workflow efficiency, and critical synthesis of information). Facilitating conditions under UTAUT provides the institutional context. That is, when support is lacking, the connection between acceptance and use weakens, whereas when resources and training are available, that connection is strengthened. Thus, the model follows a sequence of acceptance → use → SDL outcomes, with UTAUT revealing how institutional factors either enable or constrain this progression.

Practically, this framework can guide universities, especially those in developing countries such as Nigeria, on creating environments that support AI adoption. By investing in AI infrastructure, offering training programs, and establishing supportive policies, institutions can improve the conditions for AI uptake and, as a result, enhance self-directed learning outcomes. This model is a structural approach to examine the role of AI in research learning among postgraduate students).

3 Methods

This study employed a predictive correlational research design to examine the relationship between postgraduate students' acceptance of artificial intelligence (AI) and their use of AI for self-directed research learning. This design was selected for its capacity to assess both associations between variables and the predictive influence of AI acceptance on usage behaviors [20]. Predictive correlational approaches are widely recognized for identifying factors that drive technology adoption, aligning with the study's goal of informing AI integration strategies in higher education [65].

3.1 Participants

The study drew on a population of 7,600 postgraduate students from two public universities in Nigeria: a federal university with 6,000 students and a state university with 1,600 students. These institutions were deliberately chosen based on their large postgraduate enrolment figures, disciplinary diversity, and representation of both federal and state educational structures relevant to the study's focus.

This study adopted a systematic approach to sample size determination and participant selection to ensure clarity, replicability, and external validity. First, an a priori power analysis was conducted using G*Power version 3.1 program [28] to determine the minimum number of participants required to detect a medium effect size (f^2 = 0.15) [18] at an alpha level of 0.05 and a power level of 0.80. The analysis indicated that at least 160 respondents would be necessary to meet these criteria. To account for possible non-responses, incomplete data and for generalization purposes, the sample size was increased to 480 (three times the original minimum). This conservative adjustment followed recommendations for survey research where response rates cannot be precisely anticipated [25].

Thereafter, a stratified random sampling technique was employed to ensure proportionate representation from the two participating Nigerian universities: a federal university, and a state institution (names withheld for anonymity). Based on institutional enrolment data, the federal university accounted for approximately 79% (N = 6,000) of the total postgraduate student population (N = 7,600), while the state university comprised about 21% (N = 1,600). These proportions were applied to the total sample of 480 students to maintain representativeness: the federal university: $0.79 \times 480 = 379.2$, rounded to 379 participants; the state university: $0.21 \times 480 = 100.8$, rounded to 101 participants. This proportional allocation ensured that each institution's contribution to the final sample reflected its actual share of the postgraduate population [45, 66].

To randomly select participants from each institution, the official student lists, which already contained serial numbers, were used. In Microsoft Excel, the serial numbers for each institution were listed sequentially in one column. Adjacent to these, the = RAND() function was applied to generate a random decimal number for each serial number. The two columns were then sorted in ascending order based on the random numbers, effectively randomising the order of serial numbers. The top 379 serial numbers for the federal university and 101 for the state university were selected as the sample. These serial numbers were then matched to the corresponding students on the official lists to identify the final participants. This process ensured equal selection probability for all eligible students [14]. Any repeated or invalid entries were immediately replaced to maintain the integrity of the randomisation process.

3.2 Instruments and measures

Data were collected using two structured questionnaires adapted from validated technology acceptance frameworks [69]. The *Acceptance of AI Scale* (10 items) assessed attitudes toward AI in academic research (e.g., "AI tools enhance research efficiency") using a 4-point Likert scale (1 = *Strongly Disagree* to 4 = *Strongly Agree*). The *Use of AI Scale* (10 items) measured frequency of AI utilization for self-directed learning (e.g., "I use AI to gather research materials") on a 4-point frequency scale (1 = *Never* to 4 = *Always*). Items were derived from literature on AI in education [75] and refined through expert consultations. Pilot testing (n = 40) confirmed readability and relevance.

Content validity was established via reviews by three experts in educational technology and research methodology, ensuring alignment with theoretical constructs [59].

Face validity was confirmed through participant feedback during piloting. Internal consistency, evaluated using Cronbach's alpha, yielded strong reliability coefficients: $\alpha = 0.85$ (Acceptance of AI) and $\alpha = 0.87$ (Use of AI for self-directed research learning), exceeding the threshold of 0.70 for acceptable reliability [51]. These results affirm the instruments' internal consistency for measuring the variables of the study [22].

3.3 Data collection and analysis

Ethical approval was secured from both universities' Institutional Review Boards, adhering to the Belmont Report principles. Participants were recruited during postgraduate seminars and workshops, with informed consent emphasizing voluntary participation and confidentiality. Questionnaires were distributed physically and electronically (Google Forms) to maximize accessibility [25]. A 95% response rate ($n = 456$) was achieved through follow-ups and reminders, consistent with high-response survey strategies [9]. Data collection was concluded within two weeks to minimize temporal confounding.

Descriptive statistics (means, standard deviations) summarized AI acceptance and usage levels. One sample-test was used to test the first two hypotheses of this study, whereas simple linear regression in SPSS version 27 and tested the predictive relationship between acceptance (independent variable) and usage (dependent variable). Assumptions of normality, linearity, and homoscedasticity were verified in line with recommended practice [65]. Results were interpreted using standardized beta coefficients (β), R^2 values, and significance thresholds ($p < 0.05$). A p-value below 0.05 indicated rejection of the null hypothesis, signifying a statistically significant predictive relationship [30].

4 Results

4.1 Hypothesis 1

Postgraduate students have a generally low level of acceptance of AI for self-directed research learning in universities. As shown in Table 1, the overall mean score was 3.30 (SD = 0.74), which is higher than the benchmark mean of 2.50. This indicates that postgraduate students generally have a positive attitude towards using AI for self-directed research learning. All ten items in the analysis had mean scores above the benchmark, suggesting consistent agreement with statements regarding the acceptance of AI for learning.

The item with the highest mean score was *"I am enthusiastic about adopting AI to assist with learning advanced research techniques"* (M = 3.78, SD = 0.43), indicating that students are particularly excited about using AI to learn more complex aspects of research. Students also showed strong agreement with using AI as a reliable alternative to traditional guidance (M = 3.70, SD = 0.87) and as a helpful tool to clarify difficult research topics (M = 3.50, SD = 1.23). These findings suggest that many students find AI tools trustworthy and effective for addressing specific research challenges.

However, the item with the lowest mean score, *"I am very open to using AI to learn about research concepts in the absence of a teacher"* (M = 2.54, SD = 0.11), suggests that some students prefer to combine AI with traditional teacher-led learning. While they appreciate the value of AI, they may not yet see it as a complete replacement for human instruction.

Table 1 Mean rating and standard deviation of postgraduate students' acceptance of AI for self-directed research learning

SN	Items	Mean	SD	Remark
1	I am very open to using AI to learn about research concepts in the absence of a teacher.	2.54	0.11	High
2	I am willing to use AI to enhance my knowledge of research acquired from lectures.	2.60	0.23	High
3	I find it acceptable to rely on AI tools to clarify complex research topics.	3.50	1.23	High
4	I am motivated to use AI to supplement my learning in areas where I need improvement.	3.23	0.98	High
5	I consider AI tools a dependable alternative to traditional research guidance.	3.70	0.87	High
6	I am comfortable exploring new AI tools to help me understand research methodologies.	2.67	0.34	High
7	I am enthusiastic about adopting AI to assist with learning advanced research techniques.	3.78	0.43	High
8	I am willing to replace certain manual research tasks with AI-assisted solutions.	3.45	0.69	High
9	I am open to using AI to acquire skills in data analysis without direct supervision.	3.30	1.22	High
10	I am interested in leveraging AI to deepen my understanding of academic writing and research ethics.	3.45	0.65	High
	Overall	3.30	0.74	High

Criterion mean = 2.50

Table 2 One-sample t-test result summary showing the level of postgraduate students' acceptance of AI for self-directed research learning

Statistic	Value
Sample mean (M)	3.3
Standard deviation (SD)	0.74
Population mean (μ)	2.5
Sample size (N)	456
t-Statistic (t)	23.09
Degrees of freedom (df)	455
p-Value (p)	<0 0.001

A one-sample t-test was performed to compare the sample mean level of postgraduate students' acceptance of AI for self-directed research learning (M = 3.30, SD = 0.74) with the hypothesised population mean (μ = 2.50). As shown in Table 2, the result revealed a statistically significant difference between the sample and population means, $t(455) = 23.09$, $p < 0.001$. The sample mean of 3.30 is significantly higher than the hypothesised mean of 2.50. Therefore, the null hypothesis that postgraduate students have a generally low level of acceptance of AI for self-directed research learning in universities is rejected. This suggests that students demonstrate a significantly high level of acceptance of AI for self-directed research purposes.

4.2 Hypothesis 2

Postgraduate students have a low level of AI use for self-directed research learning in universities. As presented in Table 3, the overall mean score was 2.26 (SD = 0.85), which is below the criterion mean of 2.50. This result indicates that, on average, postgraduate students demonstrate a low level of AI use for self-directed research learning. Among the ten items analysed, only three recorded mean scores above the criterion mean, suggesting that students occasionally use AI for specific academic tasks.

Table 3 Mean rating and standard deviation of postgraduate students' use of AI for self-directed research learning

SN	Items	Mean	SD	Remark
	How often do you:			
1	Use AI tools to understand new research concepts without seeking assistance from a lecturer?	1.34	0.32	Low
2	Rely on AI applications to improve my understanding of research methodologies?	2.45	0.41	Low
3	Use AI to review and clarify lecture content related to research topics?	2.65	1.31	Low
4	Use AI to assist in designing and conducting research experiments?	3.03	2.04	High
5	Depend on AI to generate summaries for articles on research topics?	2.53	0.33	High
6	Use AI to practice applying research concepts through exercises?	1.87	1.03	Low
7	Rely on AI to create outlines for research proposals?	2.67	0.56	High
8	Use AI tools to correct grammatical errors in my academic writing?	2.32	0.46	Low
9	Use AI platforms to explore alternative solutions to research challenges	1.72	0.80	Low
10	Depend on AI to gain deeper understanding of unfamiliar research technique?	2.01	1.22	Low
	Overall	2.26	0.85	Low

Criterion mean = 2.50

Table 4 One-sample t-test results summary showing the level of postgraduate students' use of AI for self-directed research learning

Statistic	Value
Sample mean (M)	2.26
Standard deviation (SD)	0.85
Population mean (μ)	2.5
Sample size (N)	456
t-Statistic (t)	-6.03
Degrees of freedom (df)	455
p-Value (p)	< 0.001

The item with the highest mean score was *"Use AI to assist in designing and conducting research experiments"* (M = 3.03, SD = 2.04), indicating that students are more inclined to apply AI to practical and technical aspects of research. Other relatively high-scoring items include *"Use AI to create outlines for research proposals"* (M = 2.67, SD = 0.56) and *"Depend on AI to generate summaries for articles on research topics"* (M = 2.53, SD = 0.33), which reflect moderate use of AI for planning and content processing.

Conversely, several items recorded low mean scores, pointing to infrequent use of AI in core learning activities. For example, *"Use AI tools to understand new research concepts without seeking assistance from a lecturer"* (M = 1.34, SD = 0.32) and *"Use AI platforms to explore alternative solutions to research challenges"* (M = 1.72, SD = 0.80) had the lowest scores. These findings suggest that many students still prefer traditional or human-mediated approaches to learning complex research concepts. Similarly, reliance on AI for grammar correction (M = 2.32, SD = 0.46) and for practicing the application of research concepts (M = 1.87, SD = 1.03) was reported to be low.

A one-sample t-test was conducted to compare the observed mean of postgraduate students' use of AI for self-directed research learning (M = 2.26, SD = 0.85) with the criterion mean (μ = 2.50). As shown in Table 4, the result revealed a statistically significant difference, $t(455) = -6.03$, $p < 0.001$. Since the sample mean is significantly lower than the hypothesised population mean, the null hypothesis that "postgraduate students have a low level of AI use for self-directed research learning in universities" is accepted. This

Table 5 Simple linear regression summary showing the prediction of postgraduate students' use of AI for self-directed research learning from their acceptance of AI ($N=456$)

R	$\boldsymbol{R^2}$		**Adj.** $\boldsymbol{R^2}$	**SE**	
0.11	0.01		0.01	8.91	
Source	*Df*	*SS*	*MS*	*F*	*p*
Regression	1	425.06	425.06	5.35	0.021
Residual	454	36059.60	79.43		
Total	455	36484.66			
Predictor	*B*	*SE*	*t*	*p*	
Intercept	23.00	1.23	18.73	0.000	
Acceptance of AI	0.11	0.05	2.31	0.021	

indicates that while students may accept AI conceptually, actual usage for independent research tasks remains relatively low.

4.3 Hypothesis 3

Postgraduate students' acceptance of AI significantly predicts their use of AI for self-directed research learning in universities.

A simple linear regression analysis was conducted to examine whether postgraduate students' acceptance of artificial intelligence (AI) significantly predicts their use of AI for self-directed research learning. Results presented in Table 5 indicated a weak positive relationship between acceptance and use of AI for self-directed research learning ($R=0.11$), with the model explaining only 1% of the variance in students' use of AI ($R^2 = 0.01$, Adjusted $R^2 = 0.01$). The standard error of the estimate was 8.91, indicating substantial unexplained variability in the model.

Despite the weak association, the regression model was statistically significant, $F(1, 454)=5.35$, $p=0.021$, suggesting that acceptance of AI significantly contributes to predicting students' use of AI for self-directed research learning. The unstandardized regression coefficient ($B=0.11$, $SE=0.05$) was also statistically significant, $t(454)=2.31$, $p=0.021$. This indicates that for every one-unit increase in acceptance, students predicted use of AI increases by 0.11 units, holding other factors constant.

The regression equation is:

$$\text{Use} = 23.00 + 0.11\ (\text{Acceptance}) + 0.05 \tag{1}$$

Given that the p-value is less than 0.05, the null hypothesis, which states that acceptance of AI does not significantly predict its use for self-directed research learning, is rejected. Therefore, the alternative hypothesis is supported, implying tghat postgraduate students' acceptance of AI significantly predicts their use of AI for self-directed research learning, although the strength of this predictive relationship is weak.

5 Discussion

5.1 Acceptance of AI for self-directed research learning

Postgraduate students in this study reported a high level of acceptance of AI for self-directed research learning, significantly exceeding the benchmark mean. These findings align with Technology Acceptance Model (TAM) principles, which posit that perceived usefulness and ease of use strongly influence users' intention to adopt new technologies [23, 70]. In particular, students' enthusiasm for using AI to learn advanced research techniques and their perception of AI as a reliable alternative to traditional guidance reflect high perceived usefulness, an established predictor of technology acceptance in educational settings [4, 35].

Moreover, strong agreement with the statement that AI helps clarify complex research topics suggests that students appreciate the capacity of AI to provide just-in-time informational support, a key component of self-directed learning (SDL) theory [40, 50]. This finding echoes earlier evidence that self-efficacy correlates with greater acceptance and engagement [43, 62]. Nevertheless, the relatively lower mean score for using AI without any teacher involvement indicates that many students still prefer combining AI with instructor input, rather than relying on AI alone. Such caution may stem from concerns about the accuracy and reliability of AI-generated content, as well as ethical considerations surrounding data privacy and academic integrity [16, 27].

Contextual factors may have likely influenced these attitudes. Institutions offering AI training and digital literacy support tend to foster higher acceptance and more confident use of AI platforms [12, 15, 46]. In environments where such support is lacking, students who acknowledge the benefits of AI may still hesitate to depend on it fully, fearing misapplication or ethical pitfalls [33, 61]. This implies that there is need for clear institutional policies and curriculum reforms that integrate AI literacy with ethical guidelines [36, 75]. By equipping students with critical evaluation skills and frameworks for responsible AI use, universities can mitigate apprehensions and encourage more autonomous engagement.

Empirical evidence also indicates that social influences and collaborative learning are important factors influencing AI acceptance [2, 26]. Peer interactions and community-based learning environments reinforce positive attitudes, suggesting that fostering collaborative AI experiences may further elevate acceptance levels. Additionally, while students recognize the utility of AI for research-related tasks, actual adoption may remain uneven if infrastructural disparities and differing levels of digital readiness persist [15, 29].

Thus, even though postgraduate students in this sample had significantly high acceptance of AI for self-directed research learning, their preference for blended approaches and their ethical and reliability concerns suggest that acceptance alone does not guarantee independent use. Future research should explore how training, institutional support, and infrastructural enhancements can translate positive attitudes into sustained, effective AI engagement. Such efforts will be essential to position AI as a complementary tool that enhances, rather than replaces, rigorous academic training and lifelong learning.

5.2 Use of AI for self-directed research learning

Despite the high level of acceptance earlier reported, postgraduate students in this study reported infrequent use of AI tools for self-directed research learning, a finding at odds with the potential of AI to facilitate independent scholarly inquiry [37]. Although participants occasionally drew on AI to support practical tasks, such as designing experiments, outlining proposals, and summarizing articles, they rarely relied on AI to grasp new concepts without instructor guidance or to explore alternative solutions to research challenges. This selective engagement implies that, despite recognizing the utility of AI for specific research activities, students remain reluctant to embed it within the core processes of self-directed learning [21, 32].

Large language models like ChatGPT have been shown to streamline literature reviews and enhance writing proficiency [3, 17, 19]. For example, the capacity of ChatGPT to retrieve and synthesize pertinent sources reduces cognitive load in early research stages [3], while its guidance on grammar and academic conventions supports scholarly writing development [10, 24]. Nevertheless, the present findings align with the concerns reported by Chan and Hu [16, 27] that postgraduate learners often question the reliability of AI and express ethical reservations, particularly around data privacy and academic integrity. Such apprehensions may explain why students restrict AI to auxiliary tasks rather than leverage it for independently mastering complex research techniques. This strengthens the importance of fostering critical evaluation skills when integrating AI [12, 15].

Institutional support plays a significant role in influencing how students adopt and use AI. When universities integrate AI literacy into curricula and provide digital support, students exhibit greater confidence and more consistent use of AI platforms [12]; Cardon et al., [15, 46]. In contrast, in environments lacking structured AI training or clear policies on responsible use, students revert to traditional, human-mediated strategies [33, 61]. These patterns align with arguments by Imran and Almusharraf [36, 75] that embedding AI ethics and critical evaluation into postgraduate programs is essential to bridge the gap between positive attitudes and substantive utilization.

Collaborative and social dimensions of learning also appear underutilized. Research by Ahmed [2, 26] discovered the role of peer influence and community-based projects in reinforcing students' willingness to experiment with AI tools. In the present sample, few students turned to AI platforms for co-constructing knowledge or simulating peer feedback. These activities are shown to bolster both engagement and self-efficacy [43, 62]. Incorporating AI-focused group assignments or mentorship programs could therefore cultivate a culture of shared exploration, reducing individual apprehension and fostering deeper integration of AI into self-directed learning. Finally, infrastructural disparities may further limit AI engagement [29]. Without reliable access to high-speed internet, up-to-date software, or dedicated AI workspaces, postgraduate students cannot fully harness the benefits of AI [46].

Therefore, efforts must be made to address these logistical challenges alongside pedagogical reforms that can create a more equitable and effective AI-supported research environment. Although postgraduate students recognize the advantages of AI for accomplishing research tasks, their overall use remains sporadic. To translate favorable attitudes into sustained, autonomous practice, universities should implement comprehensive AI literacy curricula, establish clear ethical guidelines, and create collaborative opportunities that will demystify the role of AI in scholarly work. These measures will empower students to move beyond peripheral use and integrate AI as a substantive enabler of self-directed research.

5.3 Acceptance and use of AI for self-directed research learning

This study found that postgraduate students' acceptance of artificial intelligence (AI) significantly predicts their use of it for self-directed research learning. Although the relationship was statistically significant, it was weak, suggesting that acceptance contributes to students' engagement with AI but is not the only factor influencing its use in independent academic work. This finding aligns with earlier research indicating that learners' willingness to adopt AI technologies influences how they engage with these tools in educational settings. Studies on technology acceptance frameworks consistently identify perceived usefulness, perceived ease of use, and trust as major antecedents of behavioural intention toward AI adoption [39, 74]. Moreover, Esiyok et al. [26] found that students with higher digital confidence are more likely to perceive AI tools as usable and valuable. This reinforces the idea that acceptance is shaped not only by attitude but also by readiness and competence, which may explain its predictive effect in this context.

Although empirical links between AI acceptance and self-directed learning (SDL) are still developing, the present findings are consistent with related studies. Azevedo et al. [7] found that students who regarded intelligent tutoring systems as useful and easy to navigate were more likely to engage in SDL behaviours such as goal-setting and self-monitoring. Behforouz and Al Ghaithi [11] similarly reported that trust in chatbots was associated with increased learner autonomy and use of self-regulation strategies. These studies suggest that students who accept AI are more likely to apply it in managing their independent learning. Other studies further confirm that acceptance plays a role in students' use of AI-supported learning tools. Abdi et al. [1] showed that students who valued the usefulness of AI-based e-notes used them more frequently during independent study. These patterns support the view that acceptance fosters more active and autonomous engagement with AI during learning.

However, the weak strength of association in the present study indicates that acceptance alone is insufficient to explain students' use of AI for self-directed research learning. Other variables such as institutional access to AI tools, curriculum integration, digital infrastructure, and research skill levels may also influence usage. Möller et al. [48] noted that students were more likely to use AI tools when they were embedded in structured learning environments with clear academic goals and guidance. This suggests that beyond acceptance, supportive conditions are necessary to sustain meaningful use of AI in independent research learning. Thus, the present study provides evidence that postgraduate students' acceptance of AI predicts their use of such tools for self-directed research learning. Yet, the modest correlation suggests the need for institutions to adopt a wide range of strategies. Encouraging positive attitudes is essential, but this should be complemented with practical exposure, digital support systems, and integration of AI tools into the research learning process to enhance students' autonomy and academic engagement.

5.4 Limitations and future research directions

Although this study has provided useful evidence about postgraduate students' acceptance and use of artificial intelligence (AI) for self-directed research learning, several limitations are hereby acknowledged. First, the sample was drawn from only two public universities, which may limit the generalisability of the findings to other institutional contexts, particularly private or non-Nigerian institutions with different technological infrastructures or pedagogical orientations. Second, the study focused exclusively on two variables (acceptance and use), while excluding other relevant factors such as digital literacy, prior experience with AI tools, institutional support, and research self-efficacy, all of which may influence students' use of AI. Thirdly, the reliance on self-reported data has the potential to introduce response bias. This is because participants may have overstated their use or acceptance of AI due to perceived expectations or social desirability, especially given the growing academic discourse surrounding AI in education. Moreover, the cross-sectional nature of the study also limits the ability of this study to infer causal relationships between acceptance and usage.

Therefore, based on the limitations of this study, future studies should consider adopting a more comprehensive framework that incorporates other predictors, such as digital competence, access to AI resources, and the role of faculty or peer influence in postgraduate students' use of AI for self-directed research learning. The use of longitudinal designs could also enable researchers to examine how acceptance and usage of AI for self-directed research learning evolve over time. In addition, expanding on this research to cover more institutions and disciplines would also strengthen the external validity of this study.

Despite these limitations, the present study has contributed meaningfully to the growing literature on AI in higher education. The significant relationship between acceptance and use of AI for self-directed research learning, although modest, is important for policymakers and institutions of higher learning to address the attitudinal and contextual factors facilitate or inhibit the effective integration of AI into the academic research endeavours of postgraduate students. Therefore, the findings of this study have provided the foundation for interventions, institutional policies, and curriculum enhancements that support students in navigating self-directed learning in AI-mediated environments to be developed and implemented.

6 Conclusion

This study examined postgraduate students' acceptance and use of artificial intelligence (AI) for self-directed research learning in Nigeria. The results show a clear difference between the students' generally high acceptance of AI and their relatively limited use of the technology for independent research purposes. While many students acknowledge that AI can assist with academic writing, help explain complex research ideas, and support data analysis, several factors appear to restrict its practical application. These factors include limited training opportunities, infrastructural challenges, and ongoing ethical concerns. A significant positive relationship was found between acceptance and use, suggesting that students who are more receptive to AI tend to engage with it more frequently in their research. This relationship points to the need for institutional efforts that not only promote awareness but also create the conditions necessary for students to confidently and effectively use AI in academic work. Improving acceptance alone may not be sufficient unless supported by measures that make the use of AI feasible and beneficial.

Beyond the immediate context, this research contributes to broader discussions about integrating AI responsibly into higher education. The findings call for strategies that consider the specific needs and limitations of the local environment. In resource-constrained settings such as Nigeria, it is essential to build institutional capacity through targeted training, ensure access to relevant AI platforms, and embed AI literacy into research curricula. These steps can help bridge the gap between student interest and practical engagement. AI has the potential to enrich research learning experiences and foster greater academic independence. However, realising this potential requires more than access to tools; it involves thoughtful, ethical, and context-aware educational practices. With appropriate support systems, postgraduate students in Nigeria and similar environments can move from recognising AI's value to using it meaningfully as part of their academic development and innovation.

Supplementary Information

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Supplementary Material 1

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Author contributions
V.J.O.: Conceptualization, methodology, data analysis, manuscript writing, and revisions. C.O.C.: Data analysis, data collection, manuscript drafting, literature review, and revisions. V.U.A.: Conceptualization, data interpretation, data collection, and manuscript review. T.J.O.: Data collection, manuscript drafting, and revisions. J.O.O.: Study design, data collection, and manuscript revisions. I.J.E.: Critical feedback on manuscript, revisions, and overall manuscript review.

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Data availability
The data are available on request from the corresponding author.

Declarations

Ethics approval
Ethical approval for this study was obtained from the Ethics Committee of University of Calabar, with approval number UC/IRB/2024/053.

Consent to participate
All participants gave their consent to engage in this study, and there was a clear understanding between the researchers and the participants that the data collected from them would only be aggregated without revealing their identities. All the personal data of respondents were treated following the Safe Harbour principles.

Consent to publish
Participants were informed about the purpose of the study and agreed to the publication of anonymised responses.

Competing interests
The authors declare no competing interests.

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