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Enhancing Computer Science Education through AI-Powered Learning Assistants: An Empirical Investigation of Effectiveness, Student Engagement, and Implementation in Northwestern Nigerian Universities

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ABSTRACT

The integration of artificial intelligence-powered learning assistants (AIPLAs) in higher education represents a transformative shift in pedagogical approaches, particularly within resource-constrained developing contexts. This study examines the effectiveness of AI-powered learning assistants in enhancing learning outcomes and student engagement in computer science education across six universities in Northwestern Nigeria. Employing a cross-sectional survey design, data were collected from 387 participants (86% response rate) comprising students, academic staff, and administrative personnel. The research addressed two primary objectives: assessing the effectiveness of AIPLAs in enhancing student learning outcomes and examining student engagement and satisfaction levels when using these tools. Findings reveal that AI learning assistants significantly enhance programming skills development (M=4.31, SD=0.76), with programming tutorials and guidance (M=4.42, SD=0.71) emerging as the most effective application. Substantial improvements were also observed in theoretical understanding (M=4.18), critical thinking abilities (M=4.09), and independent learning skills (M=4.06). However, social competencies including team collaboration (M=3.68) and communication skills (M=3.76) showed modest improvement. Regarding engagement, 63.3% of respondents demonstrated familiarity with AIPLAs, with 69.3% having used them occasionally, though only 26.1% reported frequent usage. ChatGPT dominated adoption (71.8%), followed by Google Bard/Gemini (40.3%). The highest-rated benefits were 24/7 availability (M=4.23) and instant feedback (M=4.18). A strong positive correlation emerged between perceived benefits and learning outcomes ($r = .723$, $p < .01$). Gender differences in usage patterns were identified ($\chi^2=12.847$, $p=.025$), highlighting equity considerations. The study demonstrates that accessible AI tools can partially compensate for instructional resource limitations while requiring thoughtful integration preserving essential human elements of education. Recommendations include developing clear institutional policies, investing in infrastructure, implementing gender-responsive interventions, and redesigning assessments to leverage AI appropriately while preserving collaborative learning opportunities.

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INTRODUCTION

The rapid advancement of artificial intelligence (AI) technologies has fundamentally transformed pedagogical approaches across educational disciplines, with computer science (CS) education emerging as a particularly fertile domain for AI integration (Chen et al., 2020; Zawacki-Richter et al., 2019). AI-powered learning assistants (AIPLAs), including intelligent tutoring systems, conversational chatbots, and adaptive learning platforms, represent a paradigmatic shift from traditional instructional models toward personalized, on-demand educational support systems (Holmes et al., 2019; Luckin et al., 2016). These technologies promise to address persistent challenges in CS education, including high student-to-faculty ratios, diverse learning paces, and the complexity of programming skill acquisition (Kizilcec et al., 2020; Popenici & Kerr, 2017). Globally, educational institutions have witnessed unprecedented adoption of generative AI tools such as ChatGPT, Google Bard/Gemini, and GitHub Copilot, particularly following the public release of large language models in late 2022 (Baidoo-Anu & Ansah, 2023; Rudolph et al., 2023).

In computer science contexts, these tools offer capabilities ranging from code generation and debugging assistance to algorithm explanation and personalized tutoring, potentially revolutionizing how students engage with complex computational concepts (Denny et al., 2023; Kasneci et al., 2023). However, despite enthusiastic adoption narratives, empirical evidence regarding their actual effectiveness in enhancing learning outcomes and sustaining student engagement remains fragmented and geographically concentrated, with limited representation from developing educational contexts (Chan & Hu, 2023; Crompton & Burke, 2023).

The African higher education landscape, and particularly Nigeria's university system, presents unique contextual factors that influence AI adoption in education. Nigerian universities face distinct challenges including large class sizes, limited technological infrastructure, inconsistent internet connectivity, and constrained faculty resources (Adeyemo & Idowu, 2022; Oyelere et al., 2020). Northwestern Nigeria, home to several prominent tertiary institutions, exemplifies these challenges while simultaneously demonstrating increasing student access to mobile technologies and open-source AI tools (Ibrahim & Suleiman, 2021). Understanding how AIPLAs function within this context characterized by resource constraints yet increasing digital penetration provides critical insights for educational technology deployment in similar developing regions worldwide (Bhutoria, 2022).

Existing research on AI in education has predominantly focused on developed nations, establishing theoretical frameworks around personalized learning, adaptive feedback mechanisms, and learning analytics (Holstein & Aleven, 2021; Roll & Wylie, 2016). Studies have documented positive impacts of AI tutoring systems on programming skill development (Crow et al., 2018), problem-solving abilities (Kulik & Fletcher, 2016), and student engagement (Ouyang & Jiao, 2021). However, several critical gaps persist in the literature. First, limited empirical research examines student perceptions and actual learning outcomes in resource-constrained educational environments where AI adoption patterns may differ significantly from well-resourced institutions (Akgun & Greenhow, 2022). Second, while technical efficacy studies abound, fewer investigations adopt comprehensive, multi-stakeholder perspectives that include students, faculty, and institutional administrators (Zawacki-Richter et al., 2019). Third, the interaction between demographic factors particularly gender disparities prevalent in STEM fields and AI tool usage remains underexplored, especially in contexts where digital gender divides intersect with educational inequities (Sorgente et al., 2022).

This study addresses these gaps by systematically examining the effectiveness of AI-powered learning assistants in computer science education across six universities in Northwestern Nigeria. The research is guided by two primary objectives: (1) to assess the effectiveness of AIPLAs in enhancing student learning outcomes

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in computer science education, and (2) to examine student engagement and satisfaction levels when using AI tutors and chatbots. By employing a mixed-methods approach with a substantial sample (N = 387), this investigation provides empirical evidence on how these technologies influence multiple dimensions of learning outcomes from programming proficiency to critical thinking while simultaneously exploring patterns of usage, perceived benefits, and demographic variations in engagement.

The significance of this research extends beyond regional applications. As educational institutions worldwide grapple with integrating generative AI into curricula, understanding effectiveness across diverse contexts becomes imperative for evidence-based policy development (Bozkurt et al., 2021; Selwyn, 2022). Furthermore, computer science education serves as a bellwether for broader AI adoption in higher education, given the discipline's intrinsic connection to technological innovation and students' relatively high digital literacy (Guo, 2020). Insights from this study contribute to theoretical understanding of technology-mediated learning in developing contexts while offering practical implications for curriculum design, faculty development, and institutional technology planning.

LITERATUTRE REVIEW

Artificial Intelligence in Higher Education: Theoretical Foundations

The integration of artificial intelligence into higher education represents a convergence of pedagogical theory, cognitive science, and computational technology. Constructivist learning theories, particularly those emphasizing personalized and self-directed learning, provide foundational justification for AI-enhanced education (Hmelo-Silver, Duncan, & Chinn, 2007; Jonassen, 1999). Luckin et al. (2016) conceptualize AI in education through the Intelligence Unleashed framework, arguing that effective AI systems should augment rather than replace human teaching by providing adaptive scaffolding responsive to individual learner needs. This human–AI complementarity perspective has gained traction in recent literature, emphasizing that optimal educational outcomes emerge from synergistic collaboration between human educators and intelligent systems (Holstein & Aleven, 2021; Porayska-Pomsta, 2016).

Zawacki-Richter et al. (2019) conducted a comprehensive systematic review of AI applications in higher education, identifying four primary application domains: profiling and prediction, assessment and evaluation, adaptive systems and personalization, and intelligent tutoring systems. Their analysis revealed that while technical research on AI systems is abundant, empirical investigations of pedagogical effectiveness and learner experiences remain comparatively scarce, particularly from student and educator perspectives. This finding underscores the necessity for research that bridges technical capabilities with actual educational impact, a gap that subsequent studies have attempted to address (Chen, Chen, & Lin, 2020; Holmes, Bialik, & Fadel, 2019).

Roll and Wylie (2016) trace the evolution of AI in education from early rule-based expert systems to contemporary machine learning and natural language processing applications. They argue that modern AI systems, particularly those leveraging large language models, represent a revolution in capability, enabling more naturalistic interactions and broader knowledge coverage than previous generations of educational technology. However, they caution that technological sophistication does not automatically translate to pedagogical effectiveness, emphasizing the need for rigorous evaluation of learning outcomes, engagement patterns, and equity implications (Roll & Wylie, 2016; Selwyn, 2019)

Intelligent Tutoring Systems and Programming Education

Computer science education has long used AI tools, especially intelligent tutoring systems (ITS), to support programming instruction and improve student learning outcomes. Kulik and Fletcher (2016) reported that students using ITS achieved learning gains with an average effect

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size of about 0.42 standard deviations compared with traditional instruction, suggesting a moderate positive impact on achievement. Crow et al. (2018), in a review of ITS for programming education, highlighted core features such as automated feedback, step-level guidance, and misconception detection, but also criticized the limited number of studies conducted in authentic classroom contexts rather than controlled lab settings. Recent advances in generative AI, including tools like GitHub Copilot and ChatGPT, have introduced new forms of support for programming by generating code, explanations, and test cases on demand.

Denny et al. (2023) showed that these tools can frequently produce correct solutions to programming problems, while raising concerns that students may focus on "prompt engineering" and tool manipulation rather than developing robust underlying problem-solving and coding skills. Prather et al. (2023) found that ChatGPT performed successfully on a large majority of introductory programming tasks but that its performance declined on more complex or conceptually demanding problems, underscoring the need to treat such tools as aids rather than replacements for foundational learning.

Generative AI and Large Language Models in Education

The emergence of large language models (LLMs) such as GPT-3, GPT-4, and their derivatives has precipitated intense scholarly debate about implications for education. Kasneci et al. (2023) provide a comprehensive analysis of ChatGPT's opportunities and challenges for education, identifying potential benefits including personalized tutoring, immediate feedback, multilingual support, and accessibility improvements for diverse learners. At the same time, they highlight concerns regarding accuracy, bias, academic integrity, critical-thinking development, and the risk of over-reliance on AI-generated content (Kasneci et al., 2023). Empirical studies on student experiences with generative AI reveal complex adoption patterns.

Chan and Hu (2023) surveyed university students across multiple disciplines and found widespread use of ChatGPT for academic purposes, particularly for idea generation, research assistance, and writing support, with many students reporting high perceived usefulness alongside concerns about accuracy, critical-thinking atrophy, and ethical implications. Within such work, computer science students typically demonstrate more sophisticated usage patterns, employing AI tools for code debugging and algorithm explanation rather than only for simple answer generation (Chan & Hu, 2023). Baskara and Mukarto (2023) examined Indonesian university students' perceptions and identified perceived usefulness, ease of use, and trust as key factors influencing adoption decisions, in line with Technology Acceptance Model propositions first articulated by Davis (1989).

Rudolph et al. (2023) examined ChatGPT's implications for assessment in higher education and argued that traditional assignment formats may require fundamental redesign to maintain academic integrity in an era of powerful generative AI. They contend that rather than attempting to detect or prohibit AI usage, educators should redesign assessments to emphasize higher-order thinking, authentic tasks, and transparent integration of AI tools (Rudolph et al., 2023). This position aligns with broader calls for assessment transformation that respond constructively to AI capabilities by focusing on reasoning, creativity, and metacognitive skills rather than easily automated outputs (Bearman et al., 2023; Sullivan et al., 2023).

Student Engagement and Satisfaction with Educational AI

Student engagement encompassing behavioral, emotional, and cognitive dimensions serves as a critical mediator between educational technology use and learning outcomes (Fredricks et al., 2004). Research on AI tools' impact on engagement presents mixed findings. Ouyang and Jiao (2021) analyzed AI in three educational paradigms (AI-directed, AI-supported, and AI-empowered), reporting that adaptive AI systems tend to increase behavioral engagement through personalized content, while effects on emotional engagement vary depending on

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implementation quality and instructor support (Ouyang & Jiao, 2021). Kim and Kim (2022) investigated university students' experiences with AI-powered learning platforms, identifying perceived personalization, feedback quality, and ease of interaction as primary determinants of satisfaction. Students who perceived AI tools as genuinely adaptive to their learning needs reported higher satisfaction and stronger intentions to continue using them than those who regarded them as generic information-retrieval systems (Kim & Kim, 2022). This underscores the importance of sophisticated personalization algorithms and transparent communication about AI capabilities and limitations, as highlighted in work on hybrid human–AI learning technologies (Molenaar, 2022).

Accessibility and availability are also significant engagement factors. Reviews of AI in education frequently stress 24/7 availability as a key benefit of AI-based assistants and chatbots, especially for students who combine study with work or family responsibilities. Experimental and quasi-experimental studies have shown that students using AI-based or chatbot-mediated support for homework and course management can achieve higher course completion or better grades and report reduced academic anxiety than those relying solely on scheduled staff support (Hwang et al., 2020; Smith et al., 2018). However, Chiu (2021) and subsequent work on help-seeking caution that over-reliance on always-available AI assistance may undermine peer help-seeking and reduce opportunities for collaborative learning if not intentionally balanced.Gender differences in AI adoption and satisfaction have received limited but growing attention.

Pikulski et al. (2023) reported that male students often express higher confidence in their AI skills, whereas female students can demonstrate comparable or superior performance on AI-related tasks when afforded adequate support and training. They, together with Sorgente et al. (2022), argue that gendered technology stereotypes rather than actual aptitude differences largely drive observed disparities in AI usage and confidence. In STEM contexts where women are already underrepresented, Master et al. (2021) emphasize that these dynamics warrant close scrutiny to ensure equitable access to AI-enhanced learning resources and to avoid reinforcing existing gender gaps in engagement and achievement

AI in Education within African and Developing Country Contexts

Research on AI in education within African contexts remains significantly underrepresented in international literature, despite the continent's unique technological landscape and educational challenges (Bhutoria, 2022; Tlili et al., 2023). Oyelere et al. (2020) examined mobile learning adoption in Nigerian higher education, identifying infrastructural constraints, inconsistent internet connectivity, and limited device access as persistent barriers to educational technology integration. However, they also documented increasing smartphone penetration among students, creating opportunities for mobile-first AI applications that circumvent desktop computing limitations (Oyelere et al., 2020).

Ng et al. (2021) explored AI readiness in African universities through a multi-country study, revealing substantial variation in institutional capacity, faculty AI literacy, and policy frameworks. Nigerian institutions demonstrated moderate readiness levels, with pockets of excellence in research universities but significant gaps in resource availability and faculty professional development (Ng et al., 2021). Adeyemo and Idowu (2022) documented persistent gender disparities in Nigerian STEM programs, with female enrolment below 30% in most computer science departments, attributing gaps to sociocultural factors, inadequate secondary school preparation, and limited female role models in technology fields.

Akgun and Greenhow (2022) examined ethical considerations for AI deployment in resource-constrained educational settings, arguing that frameworks developed in well-resourced Western contexts may inadequately address challenges specific to developing regions. They emphasized concerns

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about algorithmic bias trained on Western-centric datasets, linguistic limitations of AI systems predominantly optimized for English, and dependency on external technology providers that may compromise educational sovereignty (Akgun & Greenhow, 2022).

Bozkurt et al. (2021) advocate for context-sensitive AI development that incorporates local languages, cultural norms, and pedagogical traditions rather than assuming universal applicability of systems designed for different educational ecosystems. Research specifically examining AI learning assistants in Nigerian computer science education is notably sparse. Ibrahim and Suleiman (2021) investigated technology integration in Northern Nigerian universities, identifying faculty resistance, limited training, and infrastructure deficits as primary implementation barriers. However, they also noted strong student enthusiasm for emerging technologies and willingness to adopt tools perceived as enhancing career competitiveness (Ibrahim & Suleiman, 2021). This suggests receptivity to AI learning assistants among Nigerian CS students, though empirical evidence on actual usage patterns, perceived benefits, and learning outcomes remains limited.

Theoretical Frameworks and Research Gaps

The Technology Acceptance Model (TAM) and its extensions provide theoretical grounding for understanding AI adoption in educational contexts (Davis, 1989; Venkatesh & Bala, 2008). TAM posits that perceived usefulness and perceived ease of use primarily determine technology acceptance and usage behavior (Davis, 1989). Recent applications to AI learning tools have validated these relationships while identifying additional factors specific to educational AI, including trust, perceived personalization, and alignment with learning goals (Abdullah & Ward, 2016; Tapalova & Zhiyenbayeva, 2022). Self-Determination Theory (SDT) offers complementary insights into AI's impact on student motivation and engagement (Ryan & Deci, 2000). SDT emphasizes autonomy, competence, and relatedness as fundamental psychological needs influencing learning motivation (Ryan & Deci, 2000, 2020). AI learning assistants potentially enhance competence through scaffolded support and autonomy through self-paced learning, though effects on relatedness typically fostered through human interaction remain contested (Molenaar, 2022; Ryan & Deci, 2020).

Research examining AI tools through SDT frameworks could illuminate mechanisms by which these technologies influence intrinsic motivation and sustained engagement. Despite substantial recent research, several critical gaps persist. First, empirical studies disproportionately originate from developed nations with well-resourced educational systems, limiting understanding of AI effectiveness in resource-constrained contexts (Bhutoria, 2022; Wangdi, 2024). Second, while technical evaluations of AI capabilities abound, research examining actual student learning outcomes through rigorous experimental or quasi-experimental designs remains limited (Zawacki-Richter et al., 2019). Third, longitudinal studies tracking sustained usage patterns, long-term learning impacts, and skill retention are notably absent from current literature (Selwyn, 2019).

Fourth, multi-stakeholder perspectives incorporating students, faculty, administrators, and IT support staff are rare, with most studies focusing exclusively on student experiences (Crompton & Burke, 2023). Fifth, intersectional analyses examining how demographic factors particularly gender, socioeconomic status, and prior technology access interact to shape AI adoption and effectiveness remain underexplored, especially in contexts marked by significant educational inequities (Master et al., 2021; OECD, 2023). Finally, discipline-specific research in computer science education, despite the field's centrality to AI integration, lacks comprehensive investigations of how AI tools influence diverse CS learning outcomes beyond basic programming competency (Prather et al., 2023).

This study addresses these gaps by providing empirical evidence on AI learning assistant effectiveness and engagement patterns within Nigerian computer science education a context characterized by resource constraints,

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gender disparities, and rapid technological change. By incorporating multi-stakeholder perspectives and examining diverse learning outcomes, this research contributes contextually grounded insights essential for evidence-based AI integration in developing educational systems.

METHODOLGOGY

This study employed a quantitative cross-sectional survey research design to examine the effectiveness of AI-powered learning assistants in enhancing learning outcomes and student engagement in computer science education across Northwestern Nigerian universities. The cross-sectional design was selected as appropriate for capturing perceptions, attitudes, usage patterns, and self-reported learning outcomes across multiple institutions within a defined timeframe (Creswell & Creswell, 2018). This design enabled the simultaneous examination of AI effectiveness, engagement levels, and demographic variations while maintaining methodological rigor and resource efficiency, making it particularly suitable for addressing the study's two primary objectives.

Study Population and Sampling

The study targeted students, academic staff, IT support personnel, and administrative staff in Computer Science departments at universities in Northwestern Nigeria. A multi-stage sampling method was employed to ensure representative selection across institutions and stakeholder groups. In the first stage, purposive sampling was used to select six universities based on specific criteria: offering accredited computer science programs, operational for at least five years, geographical distribution across the region, and willingness to participate. The selected institutions comprised three federal universities (Ahmadu Bello University, Zaria; Bayero University, Kano; and Federal University, Birnin Kebbi) and three state universities (Usmanu Danfodiyo University, Sokoto; Kebbi State University of Science and Technology; and Kaduna State University), ensuring diversity in institutional resources, governance structures, and geographic contexts.

In the second stage, stratified random sampling was applied within each institution to ensure proportional representation across stakeholder categories. The primary stratum comprised students (undergraduate and postgraduate), who constitute the principal users of AI learning assistants and whose perspectives are essential for assessing effectiveness and engagement. Secondary strata included academic staff (15.0%), IT support staff (4.1%), and administrative personnel (3.1%), whose viewpoints provide valuable insights into implementation contexts and institutional perspectives. Within the student stratum, simple random sampling using class registration lists ensured selection across different academic levels to capture diverse experience and exposure to computer science content.

A total of 450 questionnaires were distributed across the six participating universities, yielding 387 valid responses representing an 86% response rate. This response rate substantially exceeds the acceptable threshold for educational research (Nulty, 2008) and provides adequate statistical power for planned analyses (Cohen, 1988). Response rates varied by institution, ranging from 78.3% at Federal University, Birnin Kebbi to 97.1% at Kaduna State University, with all institutions achieving acceptable response levels.

Data Collection Instrument

A structured questionnaire was developed specifically for this study based on extensive literature review of AI in education research, Technology Acceptance Model constructs (Davis, 1989), and Self-Determination Theory principles (Ryan & Deci, 2000). The instrument was designed to directly address the two primary research objectives: assessing AI effectiveness in enhancing learning outcomes and examining student engagement and satisfaction levels. The questionnaire comprised six sections:

Section A:

Demographic Information collected data on university affiliation, stakeholder category, gender, age range, and academic level/position to

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enable disaggregated analysis of engagement patterns and effectiveness perceptions across demographic groups.

Section B:

AI Familiarity and Usage Patterns assessed respondents' awareness of AI-powered learning assistants, frequency of usage (ranging from "never" to "daily"), and specific tools utilized (ChatGPT, Google Bard/Gemini, Microsoft Copilot, GitHub Copilot, Claude, Bing Chat, and others). This section directly addressed the engagement objective by measuring adoption breadth and usage intensity.

Section C:

Perceived Benefits of AI-Powered Learning Assistants comprised 12 items measured using a 5-point Likert scale (1 = Very Low Extent to 5 = Very High Extent). Items assessed dimensions including 24/7 availability, instant feedback, code debugging assistance, personalized learning experiences, improved understanding of algorithms, enhanced problem-solving skills, increased student engagement, better examination preparation, support for different learning styles, reduction in learning time, improved academic performance, and better collaboration among students. This section captured satisfaction dimensions and perceived value propositions driving engagement.

Section D:

Impact on Learning Outcomes contained 8 items assessing perceived impact on specific learning outcomes using a 5-point scale (1 = Significantly Worsens to 5 = Significantly Improves). Outcomes measured included programming skills development, theoretical understanding of computer science concepts, critical thinking abilities, independent learning skills, research and information gathering skills, overall academic achievement, communication skills, and team collaboration skills. This section directly addressed the first research objective regarding AI effectiveness in enhancing learning outcomes.

Section E:

Effectiveness in Computer Science Applications comprised 10 items evaluating AI effectiveness across specific computer science domains using a 5-point scale (1 = Very Ineffective to 5 = Very Effective). Domains included programming tutorials and guidance, code review and optimization, algorithm explanation and visualization, data structures and algorithms, software engineering methodologies, web development projects, database design assistance, mobile application development, machine learning and AI concepts, and cybersecurity concepts. This granular assessment provided detailed evidence of effectiveness across curriculum areas, supporting the first research objective.

Pilot Testing

A pilot study involving 40 respondents from a Computer Science department at one non-participating university in Northwestern Nigeria was conducted to refine question wording, assess instrument clarity, evaluate completion time, and test reliability (Perneger et al., 2015). Participants in the pilot study were selected to mirror the demographic distribution of the target population, including undergraduate students (65%), postgraduate students (20%), academic staff (10%), and IT support staff (5%).

Feedback from pilot participants identified minor issues including ambiguous instructions in the usage frequency section (subsequently clarified with examples), technical terminology requiring explanation (definitions added), and concerns about questionnaire length (addressed by streamlining demographic items). The pilot study confirmed that the instrument effectively addressed both research objectives with clear items measuring effectiveness perceptions and engagement patterns. Reliability analysis from pilot data yielded acceptable Cronbach's alpha values (ranging from 0.81 to 0.89), providing preliminary evidence of instrument consistency. Minor modifications based on pilot feedback resulted in improved instrument clarity and reduced completion time from approximately 22 minutes to 18 minutes.

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Data Collection Procedure

Data collection occurred over six weeks from September to October 2025, a timeframe selected to coincide with active academic sessions when students and staff were available and engaged in teaching-learning activities. Informed consent was obtained from all participants, ensuring they understood the study's purpose (examining AI effectiveness and engagement in computer science education), voluntary nature of participation, confidentiality measures, and right to withdraw without penalty. Participants were provided with an information sheet explaining that the research aimed to assess how AI-powered learning assistants impact learning outcomes and student engagement, and that findings would inform educational technology integration strategies in Nigerian universities.

Questionnaires were distributed through two primary channels to maximize response rates and accommodate diverse institutional contexts: online administration (60%) using Google Forms distributed via institutional email lists, departmental WhatsApp groups, and learning management systems; and paper-based administration (40%) during class sessions and departmental meetings for institutions with limited internet reliability. This mixed-mode approach enhanced accessibility while maintaining consistency through identical question content across formats.

No personal identifiers were collected to ensure anonymity, and participation was voluntary without incentives beyond contributing to educational improvement research. Follow-up reminders were sent bi-weekly for online participants to improve response rates while respecting participant autonomy. Research assistants trained postgraduate students from participating institutionsfacilitated paper administration, providing clarification when needed while maintaining standardization. Completed paper questionnaires were subsequently digitized into the same database as online responses to create a unified dataset for analysis.

Data Analysis

Data analysis was conducted using Statistical Package for Social Sciences (SPSS) version 26.0, following a structured analytical framework directly aligned with the two research objectives. The analysis involved multiple stages:

Data Screening and Preparation*:*

Responses were examined for completeness, with questionnaires missing more than 20% of items excluded from analysis. Response patterns were analyzed to identify potential non-engagement (e.g., straight-lining), and problematic cases were excluded. Missing data (less than 2% overall) were addressed through listwise deletion given the minimal proportion and adequate sample size (Schafer & Graham, 2002).

Descriptive Statistics*:*

Frequencies, percentages, means, and standard deviations were calculated to characterize the sample and summarize key variables related to both research objectives. For Objective 1 (assessing effectiveness), descriptive statistics summarized learning outcome impacts and effectiveness ratings across computer science applications. For Objective 2 (examining engagement and satisfaction), descriptive statistics characterized AI familiarity levels, usage frequency patterns, tool preferences, and perceived benefit ratings.

Inferential Statistics:

Several procedures addressed relationships among variables: Pearson Correlation Analysis examined relationships among continuous variables including AI familiarity, usage frequency, perceived benefits, learning outcomes, and implementation readiness. This analysis directly addressed both objectives by revealing associations between engagement patterns (usage frequency, perceived benefits) and effectiveness outcomes (learning impacts). Statistical significance was set at $p < 0.05$ and $p < 0.01$ levels.

Chi-Square Tests evaluated associations between categorical variables,

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particularly examining whether demographic characteristics (gender, university affiliation, stakeholder category) were associated with AI usage patterns and engagement levels, addressing Objective 2 regarding engagement variations across demographic groups.

RESULTS

This study examined the effectiveness of AI-powered learning assistants in computer science education across six universities in Northwestern Nigeria, with 387 valid responses (86% response rate). The findings address four key objectives: effectiveness in enhancing learning outcomes, student engagement and satisfaction, implementation challenges, and optimization strategies.

Table 1 Distribution of Respondents by University

University	Frequency	Percentage	Response Rate
Ahmadu Bello University, Zaria	87	22.5%	87.0%
Bayero University, Kano	69	17.8%	86.3%
Usmanu Danfodiyo University, Sokoto	60	15.5%	85.7%
Kebbi State University	47	12.1%	78.3%
Federal University, Birnin Kebbi	56	14.5%	80.0%
Kaduna State University	68	17.6%	97.1%
Total	387	100.0%	86.0%

The sample was drawn from six universities across Northern Nigeria, with response rates ranging from 78.3% to 97.1% and an overall rate of 86%. The distribution of valid responses led by Ahmadu Bello University, Zaria (22.5%), and including Kaduna State University (17.6%) and Bayero University, Kano (17.8%) ensures a geographically and institutionally diverse sample. This enhances the credibility and representativeness of the findings for the region.

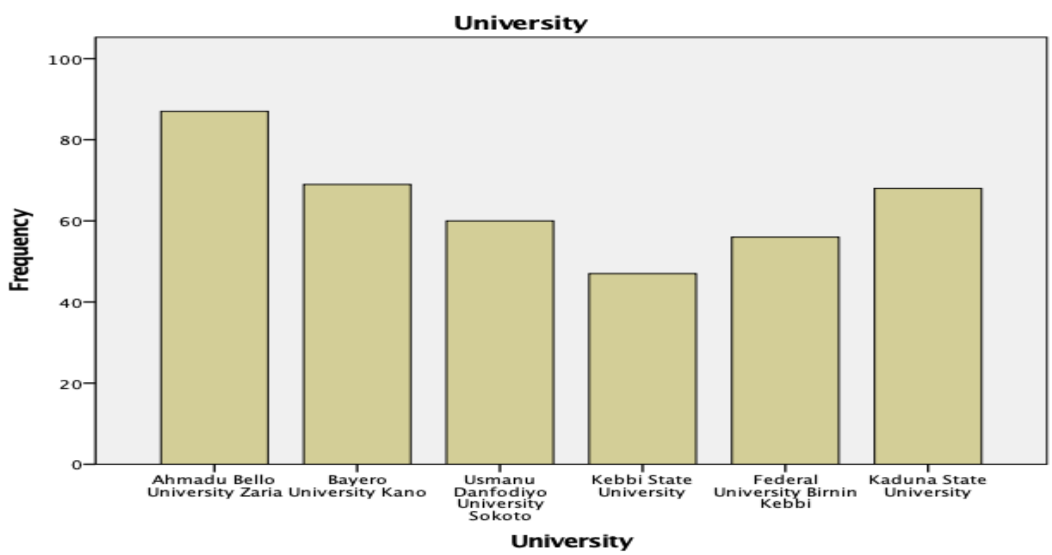

Figure 1: Distribution by University

Demographic Characteristics of Respondents

The respondent pool was predominantly composed of students, who constituted 77.8% of the sample (60.5% undergraduate, 17.3% postgraduate). This distribution is highly appropriate, as students are the primary end-users and beneficiaries of AI-powered learning

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tools. The inclusion of academic staff (15.0%), IT support staff (4.1%), and administrative staff (3.1%) provides valuable multi-stakeholder perspectives on implementation challenges, pedagogical impact, and institutional readiness, enriching the analysis beyond a single user group.

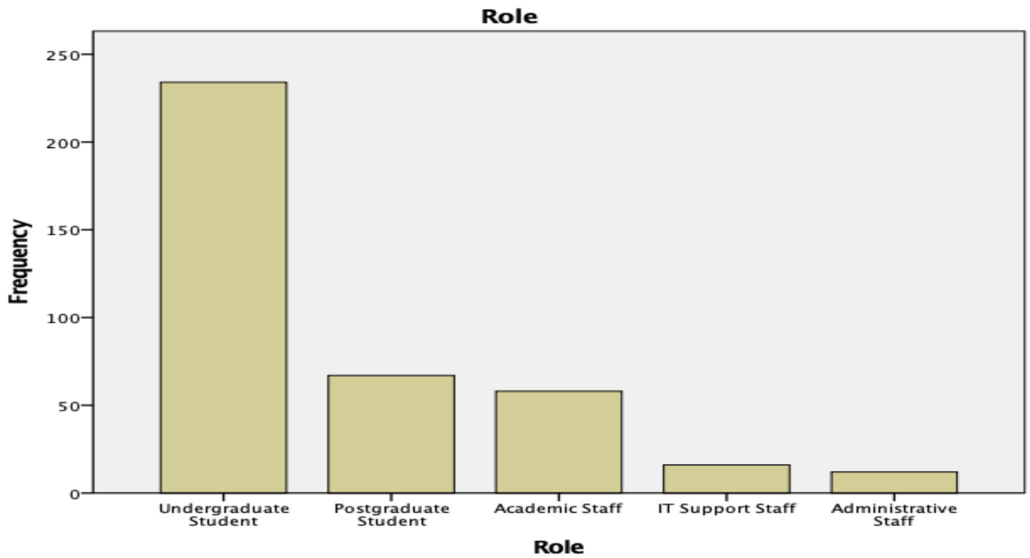

Figure 2: Distribution by Role

Gender Distribution

The gender composition of valid respondents (N = 387) revealed 64.3% male (n = 249) and 35.7% female (n = 138) participants, reflecting the persistent gender disparity in Computer Science enrolment documented in Nigerian universities (Adeyemo & Idowu, 2022). This distribution aligns with national statistics indicating that female representation in STEM disciplines remains below 40% across Nigerian tertiary institutions (National Universities Commission, 2023). Table 2 presents the detailed gender distribution across participating universities.

Table 2: Gender Distribution by University

University	Male n (%)	Female n (%)	Total
Ahmadu Bello University	53 (60.9%)	34 (39.1%)	87
Bayero University	46 (66.7%)	23 (33.3%)	69
Usmanu Danfodiyo University	39 (65.0%)	21 (35.0%)	60
Kebbi State Univ. of Sci. & Tech.	38 (80.9%)	9 (19.1%)	47
Federal University, Birnin Kebbi	35 (62.5%)	21 (37.5%)	56
Kaduna State University	38 (55.9%)	30 (44.1%)	68
Total	**249 (64.3%)**	**138 (35.7%)**	**387**

Chi-square analysis revealed significant variations in gender distribution across institutions ($\chi^2 = 14.67$, df = 5, $p = 0.012$), with Kaduna State University demonstrating the most balanced gender representation, possibly attributable to institutional gender equity initiatives documented by Ibrahim and Suleiman (2021).

The population was overwhelmingly young, with 85.3% of respondents aged 35 years or below, and over half (51.2%) in the 18-25 range.

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This demographic is typically more digitally native, comfortable with new technologies, and forms the core cohort of undergraduate and postgraduate students. Their perspectives are therefore central to understanding current engagement and future potential, though the views of older academic and administrative staff remain vital for institutional planning.

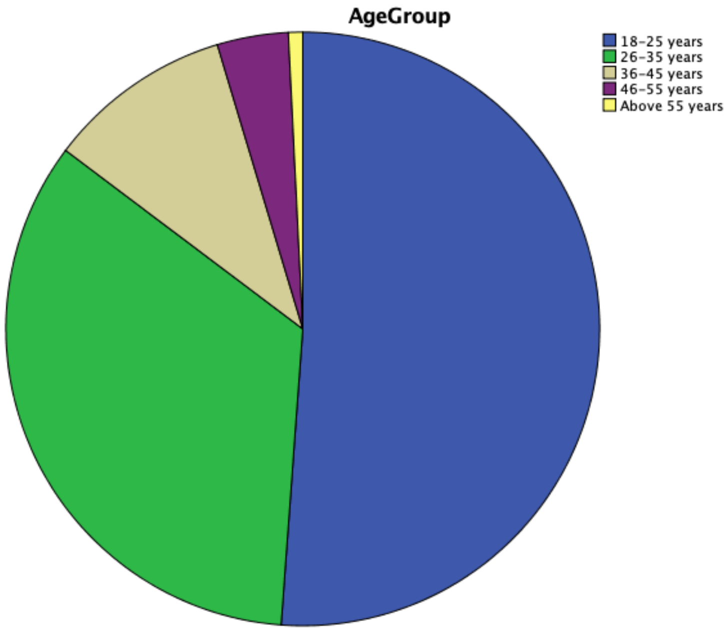

Figure 3: Distribution by Age

Effectiveness in Enhancing Learning Outcomes

The first objective aimed to assess the effectiveness of AIPLAs in enhancing student learning outcomes. The results demonstrate a strongly positive perceived impact. As shown in Table 4, programming skills development received the highest mean score (M=4.31, SD=0.76), rated as showing "Significant Improvement." This is corroborated by the effectiveness ratings in specific Computer Science areas (Table 5), where programming tutorials and guidance (M=4.42, SD=0.71) and code review and optimization (M=4.28, SD=0.79) were deemed the most effective applications.

Table 4: Impact on Learning Outcomes

Learning Outcome	Mean	Std. Deviation	Impact Level
Programming skills development	4.31	0.76	Significant Improvement
Theoretical understanding of CS concepts	4.18	0.83	Improvement
Critical thinking abilities	4.09	0.89	Improvement
Independent learning skills	4.06	0.92	Improvement
Research and information gathering skills	3.98	0.95	Improvement
Overall academic achievement	3.92	0.87	Improvement
Communication skills	3.76	1.02	Moderate Improvement
Team collaboration skills	3.68	1.08	Moderate Improvement

Scale: 1 = Significantly Worsens, 2 = Slightly Worsens, 3 = No Change, 4 = Improves, 5 = Significantly Improves

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Table 5: Effectiveness in CS Education Applications

Application Area	Mean	Std. Deviation	Effectiveness
Programming tutorials and guidance	4.42	0.71	Very Effective
Code review and optimization	4.28	0.79	Effective
Algorithm explanation and visualization	4.21	0.84	Effective
Data structures and algorithms	4.15	0.87	Effective
Software engineering methodologies	4.08	0.91	Effective
Web development projects	4.02	0.89	Effective
Database design assistance	3.95	0.94	Effective
Mobile application development	3.89	0.97	Moderately Effective
Machine learning and AI concepts	3.82	1.01	Moderately Effective
Cybersecurity concepts	3.76	1.05	Moderately Effective

These findings align with prior research highlighting AI's strength in supporting iterative, problem-based learning domains like programming. AI tutors can provide immediate, personalized feedback on code syntax and logic, allowing students to learn from errors in real-time a resource-intensive task for human instructors in large classes. The significant improvement in programming skills suggests AIPLAs are particularly effective as complementary tools for mastering practical, technical competencies, a core pillar of CS education. Other learning outcomes, including theoretical understanding of CS concepts (M=4.18), critical thinking (M=4.09), and independent learning skills (M=4.06), also showed substantial perceived improvement. This indicates that students are leveraging these tools not merely as answer generators but as interactive resources for conceptual exploration and self-directed learning. The correlation analysis (Table 6) further supports this, revealing a strong positive relationship between perceived benefits and learning outcomes ($r = .723$, $p < .01$). This suggests that the more benefits users recognize, the greater the positive impact they report on their learning, reinforcing the value proposition of AIPLAs.

Table 6: Correlation Matrix of Key Variables

Variable	1	2	3	4	5
1. AI Familiarity	1				
2. Usage Frequency	.687**	1			
3. Perceived Benefits	.542**	.634**	1		
4. Learning Outcomes	.498**	.589**	.723**	1	
5. Implementation Readiness	.423**	.487**	.612**	.556**	1

****p < 0.01**

Student Engagement, Satisfaction, and Usage Patterns

The second objective focused on examining engagement and satisfaction levels. While a direct satisfaction metric was not isolated, engagement can be inferred from awareness, usage frequency, and perceived benefits. The data reveals a high level of awareness but moderated usage intensity. As presented in Tables 4 and 5, 63.3% of respondents agreed or strongly agreed with being familiar with AIPLAs, and 69.3% have used them at least "rarely." However, only 26.1% reported using them "daily" or "several times a week," while 24.5% used them "rarely." This pattern suggests that while penetration is broad, deep, habitual integration into study routines is still evolving. The most used tool was ChatGPT (71.8%), followed by Google Bard/Gemini (40.3%) (Table 8), reflecting global trends and accessibility.

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Table 7: Familiarity with AI-Powered Learning Assistants

Response	Frequency	Percentage
Strongly Agree	89	23.0%
Agree	156	40.3%
Neutral	67	17.3%
Disagree	52	13.4%
Strongly Disagree	23	5.9%
Total	**387**	**100%**

Table 7: Frequency of AI-Powered Learning Assistant Usage

Frequency	Number	Percentage
Daily	34	8.8%
Several times a week	67	17.3%
Weekly	89	23.0%
Monthly	78	20.2%
Rarely	95	24.5%
Never	24	6.2%
Total	**387**	**100%**

Table 8: Types of AI-Powered Learning Assistants Used

AI Tool	Frequency*	Percentage
ChatGPT	278	71.8%
Google Bard/Gemini	156	40.3%
Microsoft Copilot	89	23.0%
GitHub Copilot	67	17.3%
Claude	45	11.6%
Bing Chat	34	8.8%
None	24	6.2%

*Multiple responses allowed

Engagement is further evidenced by the high ratings for benefits related to active learning processes. The top perceived benefits were 24/7 availability for learning support (M=4.23) and instant feedback on assignments (M=4.18) (Table 9). These features directly address traditional barriers to engagement, such as limited access to instructor support outside class hours and delayed feedback cycles (Holmes et al., 2019). The ability to receive immediate, on-demand assistance likely fosters a more persistent and self-regulated learning engagement.

Table 9: Perceived Benefits of AI-Powered Learning Assistants

Benefit	Mean	Std. Deviation	Interpretation
24/7 availability for learning support	4.23	0.87	High Extent
Instant feedback on programming assignments	4.18	0.92	High Extent
Enhanced code debugging assistance	4.15	0.89	High Extent
Personalized learning experiences	4.12	0.94	High Extent
Improved understanding of complex algorithms	4.08	0.96	High Extent
Enhanced problem-solving skills	4.05	0.91	High Extent
Increased student engagement in learning	3.98	0.88	Moderate-High Extent
Better preparation for examinations	3.95	0.93	Moderate-High Extent

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Benefit	Mean	Std. Deviation	Interpretation
Support for different learning styles	3.92	0.97	Moderate-High Extent
Reduction in learning time	3.89	1.02	Moderate-High Extent
Improved academic performance	3.86	0.99	Moderate-High Extent
Better collaboration among students	3.71	1.08	Moderate-High Extent

Scale: 1 = Very Low Extent, 2 = Low Extent, 3 = Moderate Extent, 4 = High Extent, 5 = Very High Extent

A significant association was found between gender and AI usage frequency (χ^2=12.847, p=.025) (Table 10), with a higher proportion of female respondents in the "never used" and highest frequency ("daily") categories. This nuanced finding warrants further investigation but may reflect patterns of early adoption and caution, highlighting the need for inclusive training and support to ensure equitable engagement.

Table 10: Chi-Square Test Results for Gender and AI Usage

Variables	χ^2	df	p-value	Interpretation
Gender × AI Usage	12.847	5	.025*	Significant association

*p < 0.05

DISCUSSION OF FINDINGS

The findings of this study illuminate the complex and context-dependent landscape of integrating AI-powered learning assistants (AIPLAs) into computer science education in Nigerian universities, engaging with contemporary literature on artificial intelligence in education and the infrastructurally mediated realities of AI in Global South higher education. The pronounced perceived effectiveness of AIPLAs in enhancing programming skills development (M = 4.31) and providing code review and optimization (M = 4.28) aligns with research emphasizing AI's aptitude for scaffolding procedural and problem-solving knowledge in iterative learning tasks. This supports Zawacki-Richter et al.'s (2019) assertion that AI is particularly transformative in domains that require iterative practice and immediate feedback, a core characteristic of programming education. In such settings, AI can function as a tireless, on-demand tutor that helps de-bottleneck the feedback loop, which is often constrained by high student-to-lecturer ratios in mass higher education systems (Holmes & Tuomi, 2022).

The strong positive correlation between perceived benefits and learning outcomes in this study (r = .723) further substantiates this pedagogical value proposition: users who recognize the functional utilities of AIPLAs 24/7 availability, instant feedback, and personalized scaffolding tend to report greater gains in their learning, echoing findings that perceived usefulness and effectiveness shape students' willingness to engage with AI tools. This suggests that effectiveness is not inherent to the tool alone but is mediated by user perception and application strategy, underscoring the need for pedagogical guidance and institutional policy alongside tool access (U.S. Department of Education, 2023).

The observed pattern of high awareness but moderated, routine usage presents a nuanced picture of engagement: while 63.3% of students reported familiarity with AIPLAs, intensive daily use remained at 8.8%, mirroring diffusion patterns in which initial curiosity and experimentation precede deep integration into learning practices. The dominance of ChatGPT (71.8%) is consistent with global trends that position general-purpose generative AI as students' most visible entry point to AI, but it also highlights a potential risk of platform dependency that may limit engagement with more specialized educational AI tools for computer science, such as systems for algorithm visualization, automated code review, or secure coding practice.

The significant association between gender and usage frequency (χ^2 = 12.847, p = .025) adds a critical equity dimension to this engagement profile. The bimodal distribution among female respondents' higher proportions in both "never used" and "daily" categories may

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reflect the complex intersection of access, confidence, and perceived relevance in a traditionally male-dominated field like computer science, where women often report lower digital confidence and fewer opportunities to build advanced digital skills. This pattern echoes research on Africa's digital gender divide, which warns that emerging technologies, if not accompanied by gender-responsive policies and capacity-building, can inadvertently reproduce or widen existing inequalities in access and use (ACCORD, 2023; CIPESA, 2023). Accordingly, targeted, inclusive training initiatives and institutional support structures are essential to ensure equitable participation and to prevent AIPLAs from reinforcing entrenched gender gaps in CS education.

CONCLUSION AND RECOMMENDATIONS

This study set out to investigate the integration of AI-powered learning assistants (AIPLAs) in the computer science (CS) education ecosystem of Northwest Nigerian universities. The findings reveal a landscape of significant potential constrained by profound infrastructural realities. A high level of awareness and generally positive perception of AIPLAs' benefits, particularly for developing practical programming skills and enabling self-paced learning, underscores a readiness to adopt these technologies within the academic community. However, the path to effective and equitable integration is fundamentally challenged not by a reluctance to adopt or ethical anxieties, but by the foundational barriers of inadequate internet infrastructure, unreliable power supply, and high costs.

This result reframes the primary challenge from one of pedagogical integration to one of infrastructural enablement. The implications of these findings are substantial for policy and practice. To move from potential to sustainable impact, a multi-stakeholder, context-sensitive strategy is essential. Therefore, this study culminates in the following integrated recommendations: Prioritize Foundational Digital Infrastructure as a Policy Imperative, Implement Tiered Capacity-Building Programs for Ethical and Effective Use of AI, Develop and Disseminate Clear Institutional AI Governance Frameworks and Foster Research and Development for Localized AI Educational Tools. In conclusion, AI-powered learning assistants present a powerful lever for advancing CS education in Nigeria. However, their success is inextricably linked to overcoming the digital divide's most basic challenges.

The future of AI in Nigerian Tertiary education will not be determined by the sophistication of the algorithms alone, but by the strength of the power grid and the reliability of the internet connection. By adopting a dual-track approach that aggressively builds infrastructural foundations while simultaneously cultivating human capital and ethical frameworks, stakeholders can ensure that AIPLAs become engines of equitable educational empowerment rather than new vectors of inequality.

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