Journal of Future Artificial Intelligence and Technologies

E-ISSN: 3048-3719

Research Article

AI-Powered Tutoring Systems for Personalized Learning Feedback in Developing Secondary Education Contexts

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Abstract: This study investigates how Artificial Intelligence (AI)-based Tutoring Systems can be used to provide secondary school students with personalized learning feedback and to enhance their academic performance. The two main empirical objectives were to assess individualized formative assessment in classroom settings and to examine teachers' and students' perceptions of AI adoption. A mixed-methods quasi-experimental design was employed, integrating quantitative pre-/post-tests, interviews, and focus groups across six schools (n = 600). This approach enabled triangulation between measurable learning outcomes and contextual perception data for robust validation. Quantitative data were analyzed using Python (t-tests, ANCOVA), while thematic coding in NVivo was applied to qualitative data. Expert review, pilot testing, and Cronbach's α (>0.80) were used to validate the instruments and ensure reliability, including pre-/post-tests and engagement scales. Findings revealed that students who received AI-based interventions achieved significantly higher academic performance (Cohen's d = 1.05) and engagement (d = 0.72) compared with control groups. Teachers with AI exposure reported greater preparedness (mean = 3.4) and fewer perceived barriers. The study provides empirical evidence on the pedagogical viability of AI tutoring in under-resourced contexts, contributing to self-regulated and socio-technical learning theories. It also recommends enhanced systemic teacher education, ethical leadership, and structural support to foster equitable adoption of AI in education. The findings carry strong implications for policy development and educational innovation in promoting data-driven, inclusive learning within Nigeria's secondary education system.

Keywords: AI adoption; Artificial intelligence; Educational innovation; Intelligent tutoring systems; Mixed-methods research; Personalized learning; Secondary education; Socio-technical systems.

Received: October, 26th 2025
Revised: December, 4th 2025
Accepted: December, 6th 2025
Published: December, 9th 2025
Curr. Ver.: December, 9th 2025

1. Introduction

Artificial Intelligence (AI) is a transformative technology in education, and Intelligent Tutoring Systems (ITS) represent one of its most impactful applications [1], [2]. This study aims to design and empirically evaluate an AI tutoring system that provides personalized learning feedback to secondary school students in Nigeria. The goal is to address persistent challenges such as unequal educational opportunities, insufficient formative assessment, and limited teacher feedback that characterize the Nigerian education system [3], [4]. ITS simulate human tutoring by diagnosing misconceptions and providing adaptive, real-time instructional feedback based on each learner's pace and level of understanding [2], [5], [6]. Globally, ITS have been successfully implemented in mathematics, science, and language instruction, yielding improvements in academic performance, motivation, and self-regulated learning (SRL) among students [7]–[11]. However, Nigerian classrooms continue to face systemic challenges such as overcrowding, poor infrastructure, and limited access to digital technologies, which hinder the delivery of timely and differentiated feedback by teachers [12], [13].

Previous research on the pedagogical effectiveness of ITS [9], [14] has primarily employed quantitative experimental and quasi-experimental designs using pre- and post-tests to measure learning improvement. Other studies [15]–[17] have adopted design-based approaches to iteratively enhance ITS prototypes through learner interaction, while qualitative and mixed-method studies [12], [13], [18], have explored teachers' and students' attitudes toward AI tools—highlighting trust, usability, and ethical concerns as key factors.

Although these methods each have strengths, they also present limitations. Experimental research often fails to account for socio-cultural and infrastructural realities influencing AI adoption, while design-based research offers limited generalizability [12], [13]. Similarly, qualitative studies provide valuable insights but cannot quantify learning impact. In Nigeria, most existing studies are confined to small-scale descriptive surveys without control groups, producing insufficient empirical data on the effects of AI tutoring on measurable academic outcomes or contextual factors such as teacher digital literacy and infrastructural barriers [13], [19].

The key research gap, therefore, lies in the lack of large-scale, context-sensitive empirical studies assessing both the pedagogical effectiveness and socio-technical feasibility of AI tutoring systems in Nigerian secondary schools [12]. Despite growing policy attention toward educational technology and AI integration [14], [17], [20], the connection between adaptive tutoring and tangible learning outcomes remains underexplored. Furthermore, ethical and governance issues concerning data privacy, transparency, and algorithmic accountability are still unresolved [21].

To address these challenges, this study proposes and empirically tests a localized AI-based tutoring model within Nigeria's secondary education system. The framework draws upon cognitive modeling, SRL theory, Socio-Technical Systems Theory (STST), and Technology Acceptance Models (TAM/UTAUT) [22]–[24]. Consequently, a mixed-method quasi-experimental design was selected to capture both quantitative learning outcomes and qualitative contextual variables. This design enables the integration of quantifiable performance measures with rich perceptual and contextual data, thereby enhancing both internal and external validity. As Creswell and Creswell [18] note, mixed-method research is particularly appropriate when interventions require both statistical inference and contextual interpretation. Compared to purely descriptive surveys—common in earlier Nigerian AI studies that lacked control groups and causal rigor [13], [19]—the quasi-experimental component allows the measurement of actual performance differences attributable to AI use. Likewise, while purely quantitative approaches often overlook socio-cultural dimensions, the qualitative component in this study provides insight into infrastructural, ethical, and readiness factors that influence feasibility [12], [13]. Thus, the mixed-method quasi-experimental design was strategically chosen to triangulate learning gains with lived experiences, offering a more comprehensive and contextually grounded evaluation of AI tutoring effectiveness.

Building upon prior works in socio-technical AI integration and educational technology [6], [14], [17], [20], [21], this study makes three key contributions: (1) developing and validating a context-specific AI tutoring model; (2) generating empirical evidence on its effects on student learning conditions, engagement, and teacher preparedness; and (3) establishing a socio-technical and ethical framework for AI implementation in low-resource educational systems.

The remainder of this paper is organized as follows: Section 2 presents related literature; Section 3 describes the research methodology, including design, sampling, instruments, and data analysis procedures; Section 4 discusses the results and findings; and Section 5 concludes with recommendations, limitations, and future research directions.

2. Literature Review

Tutoring systems based on AI have become among the most empirically supported innovations in personalized learning [25]. ITS are adaptive learning systems that diagnose student misconceptions and provide real-time personalized feedback based on individual performance and behavioral patterns [5], [9], [14], [15]. Such systems imitate human tutoring by dynamically adjusting instructional content to match learner progress, thereby promoting mastery learning rather than time-based instruction [7], [25]. Current ITS architectures employ technologies such as knowledge-tracing algorithms, NLP engines, feedback learning models, and student modeling modules to deliver adaptive and contextual feedback. Large-scale empirical studies in mathematics, science, and language education have consistently shown that ITS significantly improve student performance, motivation, and SRL compared with traditional instruction [8], [16], [26]. These outcomes are largely attributed to the immediacy and individualization of AI-driven feedback [4], [12], [16].

Global literature supports the view that ITS implementations tend to yield moderate-to-large learning effects, particularly when grounded in pedagogical frameworks such as SRL and feedback-based learning [9], [14], [25]. For instance, study [9] reported that interactive scaffolding combined with AI-based formative assessment can substantially enhance learner retention and engagement. Similarly, research [25] demonstrated that ITS are most effective when embedded in socio-technical classroom settings, where teachers act as facilitators rather than substitutes. These findings emphasize that AI should serve as an augmentation layer—a supplement rather than a replacement—for teacher input [4], [12]. However, most of this evidence has been drawn from technologically advanced regions such as North America, Europe, and Asia, where strong infrastructure and high levels of teacher digital competence are common [27]. This context does not accurately reflect the realities of developing regions, particularly Sub-Saharan Africa.

Historically, research on educational technology in African countries such as Nigeria [16], [19] has primarily focused on ICT integration, LMS, and digital literacy, rather than adaptive AI tutoring. The majority of Nigerian studies remain descriptive, relying on teacher surveys, needs analyses, or small pilot projects [13], [17], [19]. For example, study [17] examined teacher awareness and attitudes toward AI but did not measure student outcomes, whereas research [19] identified readiness issues related to training and infrastructure. Although these studies contribute useful contextual insights, they lack the rigor of experimental or quasi-experimental designs and fail to quantify the impact of AI tutoring on academic performance. Moreover, contextual limitations such as unreliable power supply, weak internet connectivity, high data costs, and sociocultural perceptions of AI are often overlooked in international ITS literature [2], [27]. Consequently, global discourse on AI in education risks marginalizing developing regions by proposing models that are misaligned with their infrastructural and cultural realities [12].

Advanced countries benefit from high-speed connectivity, strong teacher preparation, and robust data governance systems that enable seamless ITS implementation [25], [26]. In contrast, developing nations continue to face obstacles such as unstable infrastructure, low digital literacy, and insufficient teacher training [13], [19], [27]. While experimental studies in advanced contexts consistently report learning gains, these models are not always transferable to low-resource settings. Design-based research, though context-sensitive, lacks generalizability, whereas qualitative approaches, while rich in context, do not measure quantitative outcomes. Consequently, a methodological imbalance persists between technological validation and educational realism.

Recent empirical reviews [28]–[32], such as those examining AI-embedded technologies in education, recent developments, open issues, and the contributions of Python to AIED, have further underscored these gaps. Across multiple systematic reviews and meta-analyses, small-to-medium or short-term learning improvements have been consistently reported, though effect sizes vary depending on study domain and design [28], [29], [32]. Between 2024 and 2025, research in generative AI (GenAI) and bilingual or chatbot-based educational systems has expanded rapidly, particularly in programming instruction and secondary-level digital literacy [30], [31], [33]. Python has emerged as the lingua franca of AI literacy and AIED development, powering major libraries such as Scikit-learn, PyTorch, TensorFlow, and Hugging Face [31], [33], [34]. Empirical studies (e.g., PyChatAI) demonstrate that when culturally localized and appropriately validated, Python-based AI tools can effectively scaffold code learning [30], [31]. Collectively, these studies suggest that while AI-enhanced feedback systems successfully foster interaction and engagement, challenges remain concerning algorithmic transparency, data privacy, and contextual scalability—particularly in low-governance digital environments [8], [13], [19], [20].

To overcome such limitations, this paper adopts a mixed-method and socio-technical perspective. It bridges the gap between algorithmic efficacy and situational adaptability by integrating quantitative performance analysis with qualitative inquiry into teachers' and students' perceptions, addressing the gaps noted in previous studies [13], [19], [27]. This dual approach enables a holistic evaluation of AI tutoring not only in terms of technical accuracy but also in terms of its educational and ethical viability in resource-limited contexts.

2.1. Theoretical relevant in Developing Contexts

The theoretical model guiding this study, as presented in Figure 1, combines SRL, Cognitive Tutor Theory (CTT), STST, and TAM/UTAUT [22]–[24], [35]. This integrated framework is particularly relevant for developing countries—especially Nigeria—because it situates AI learning tools within the broader ecological context of human, technical, and institutional factors.

- SRL theory explains how learners monitor and regulate their cognitive processes, which can be enhanced by AI systems through timely feedback and goal-setting mechanisms [9], [14].
- CTT describes how adaptive systems organize the learning process by replicating expert reasoning, enabling novice learners to progress toward mastery through modeling and iterative feedback [7], [36].
- STST emphasizes that educational technologies function effectively only when they align with human actors (teachers), institutional capacities, and ethical governance structures [22]–[24].
- TAM/UTAUT provide empirically validated constructs that explain why teachers and students choose to adopt—or decline—the use of educational technologies [35], [37]–[39].

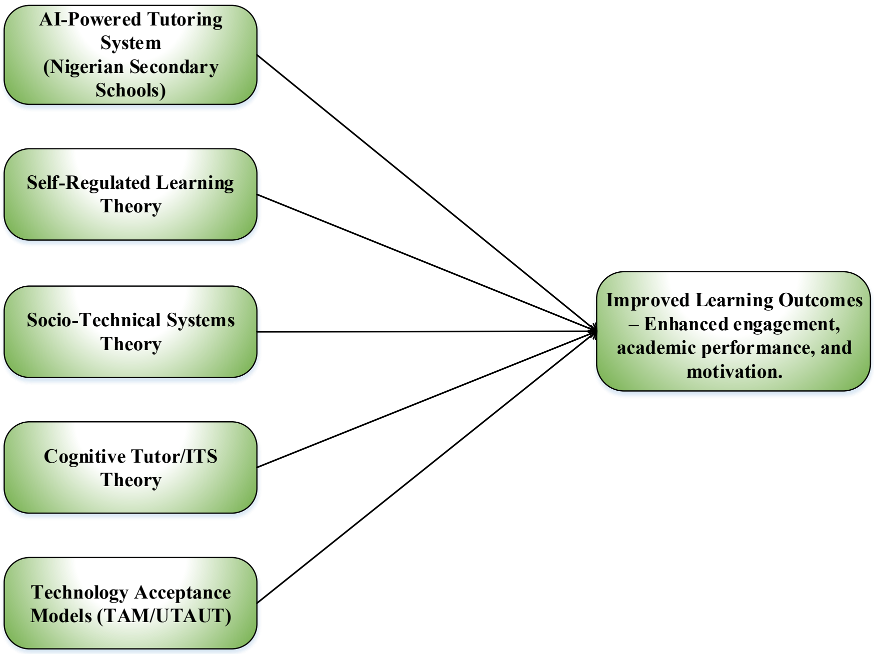

Figure 1. Theoretical framework of AI-powered tutoring system for Nigerian secondary schools [25].

This framework is particularly vital in the design of AI systems within the infrastructural and pedagogical realities of secondary schools in developing contexts. It underscores the importance of aligning AI system design with existing institutional capacities, teacher mediation, and ethical imperatives such as transparency and fairness. Ultimately, this approach ensures that AI functions not merely as a technological intervention but as a component of a comprehensive pedagogical ecosystem that is responsive to social, infrastructural, and institutional constraints [10], [20], [24], [37].

2.2. Addressing the Gaps

Although global literature highlights the transformative potential of AI tutoring systems, the African—and specifically Nigerian—context remains underrepresented in empirical, mixed-method, and ethically grounded research [1], [40]. Existing studies are often limited in scale or perception-based, lacking causal evidence and contextual depth.

The present study addresses these limitations by adopting a multi-site, mixed-method quasi-experimental design to evaluate learning performance and engagement outcomes, while simultaneously examining teacher readiness, infrastructural feasibility, and ethical considerations. By embedding AI tutoring within a socio-technical framework and adapting it to local conditions, this study contributes actionable evidence for responsible and scalable implementation of AI-assisted personalized learning feedback in developing secondary school environments [7], [16], [19], [33]. Accordingly, the study is guided by two key empirical objectives:

- To assess the effect of AI-driven tutoring systems on individualized learning feedback, academic outcomes, and student engagement in Nigerian secondary schools.
- To examine how teachers and students perceive and experience the challenges of adopting AI-based tutoring systems, and how prepared they are to integrate such systems into classroom practice.

3. Methodology

3.1. Research Design

A mixed-method research design combining quantitative and qualitative approaches was employed to analyze the impact of the AI-based tutoring system on student learning outcomes, as well as the contextual, implementation, and perception-related issues surrounding its use [18]. The quantitative component followed a quasi-experimental design involving pre-test and post-test evaluations for both control and intervention groups to determine effects on academic performance, motivation, and SRL [13], [20]. Complementing this, the qualitative component consisted of semi-structured interviews and focus group discussions with teachers and students to capture perceptions, barriers, and ethical concerns related to AI integration into classroom instruction.

3.2. Population, Sample, and Selection Criteria

The study targeted secondary school students and teachers from both public and private schools across Nigeria [17]. A total of n = 600 respondents were selected from six schools—three public and three privates, to ensure representation across different geographic and socioeconomic contexts (urban and semi-urban).

Stratified random sampling was applied to select schools based on type, location, and resource levels. For the quantitative component, simple random sampling was used to select students from each school to measure real-world effects. For the qualitative strand, purposive sampling was employed to select 30 teachers and 40 students, providing deeper insights into AI tutoring implementation and capturing socio-ethical and readiness-related factors [15].

Eligible participants included Senior Secondary Two (SS2) and Senior Secondary Three (SS3) students who had attended the school for at least one academic year. Participating teachers had a minimum of two years of teaching experience and were actively engaged in the subject areas where the AI tutoring system was implemented [36]. Schools were required to have basic infrastructure such as stable electricity and minimum internet access to ensure system functionality.

3.3. Instrumentation

The primary instrument of intervention was the AI-based tutoring system prototype, which generated real-time learner data based on individual performance patterns, response accuracy, task duration, and misconceptions. Additional instruments included standardized questionnaires and academic tests designed to measure curriculum-aligned learning outcomes. Pre- and post-tests assessed academic performance, while motivation and SRL were measured using modified versions of validated instruments. Semi-structured interviews and focus groups supported the qualitative inquiry.

Content and face validity were ensured through expert review by professionals in educational technology and psychometrics. Instrument refinement was further achieved through pilot testing with 20–30 students and teachers not included in the main study. Reliability was examined using Cronbach's α, targeting coefficients above 0.80—consistent with similar empirical studies in Nigerian education [36].

3.3.1. Instrument Development and Modification

The survey instrument was adapted from validated theoretical frameworks, including TAM, UTAUT, STST, SRL, and ITS-related constructs. Key constructs such as Perceived Use, Perceived Ease of Use, Attitude Toward Use, and Behavioral Intention were derived from [38], while UTAUT components—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intention (BI)—were adapted following [39]. Although theoretical meanings were retained, minor contextual adjustments were made to suit the educational realities of AI-based learning in secondary schools within developing countries.

3.4. Data Collection

Quantitative data were collected through pre-test and post-test assessments and structured questionnaires administered via Google Forms using a 1–5 Likert scale. Participants completed these either in person or online, depending on logistical feasibility [33]. Qualitative data were collected post-intervention through semi-structured interviews with teachers and focus group discussions with students [40]. These sessions explored participants' perceptions, implementation experiences, and ethical considerations associated with classroom AI integration [3], [13].

3.5. Data Analysis

Quantitative data were analyzed using descriptive statistics (means and standard deviations) to summarize baseline and post-intervention measures [16]. Inferential statistics were applied through paired-sample t-tests for within-group comparisons and independent-sample t-tests for between-group analyses [23]. Covariate analysis (ANCOVA) was conducted to adjust for baseline differences, while effect sizes were computed to determine the intervention's magnitude. Qualitative data were analyzed thematically following the framework of [41], which guided the identification of recurring themes related to usability, readiness, barriers, ethical concerns, and contextual factors.

3.6. Validity and Reliability

Internal validity was maintained through the use of control and intervention groups, pre/post-test design, and monitoring of AI system usage logs [24]. Construct validity was ensured by aligning instruments with theoretical constructs such as motivation and SRL. Instrument reliability was verified through expert review, pilot testing, and calculation of Cronbach's α (> 0.80), ensuring both consistency and dependability across pre/post-tests and engagement scales. Qualitative trustworthiness was established through triangulation between student and teacher data, member checking, and the maintenance of a clear audit trail during data analysis [42].

Questionnaires and engagement scales were further tested for internal consistency using SPSS reliability analysis, yielding Cronbach's α values above 0.80, indicating high reliability. Inferential analyses—including paired-sample and independent-sample t-tests—were conducted using SPSS and Python (SciPy), with $p < 0.05$ as the significance threshold.

3.7. Components of the AI Tutoring System and Its Functioning

The AI tutoring solution developed for this study, illustrated in Figure 2, comprises a series of interconnected modules designed to support adaptive, data-driven, and teacher-mediated learning. Each module performs a distinct but complementary role within the overall architecture:

- Student Modelling Module: This module employs machine learning (ML) algorithms to generate learner profiles based on performance data, engagement logs, and patterns of misconceptions [43]. It continuously tracks individual progress and behavioral patterns to provide input for subsequent modules.
- Knowledge Tracing and Diagnosis Module: This component integrates Bayesian Knowledge Tracing (BKT) and Deep Knowledge Tracing (DKT) models to detect misconceptions, estimate knowledge states in real time, and predict mastery probabilities [44]. These models enable dynamic updates to each learner's profile as new evidence is observed.

- Adaptive Feedback Engine: Using natural language processing (NLP) and reinforcement learning (RL) techniques, this engine generates personalized feedback adapted to the learner's performance over time [2], [26], [28]. The engine produces a variety of outputs—such as hints, prompts, and explanations—to guide learners toward mastery.
- Pedagogical Decision Module: This module coordinates instructional sequencing and determines the type of feedback to be delivered (e.g., hints, prompts, explanations) based on SRL principles [14], [25]. It operationalizes pedagogical rules derived from self-regulated learning theory and integrates them with system-level behavioral predictions.
- Teacher Dashboard and Analytics Interface: The dashboard visualizes learner progress, mastery estimates, and common misconceptions, providing teachers with real-time analytics and alerts when intervention is needed [27], [36]. It allows teachers to monitor AI feedback loops, assign new learning tasks, and adjust instructional strategies accordingly.

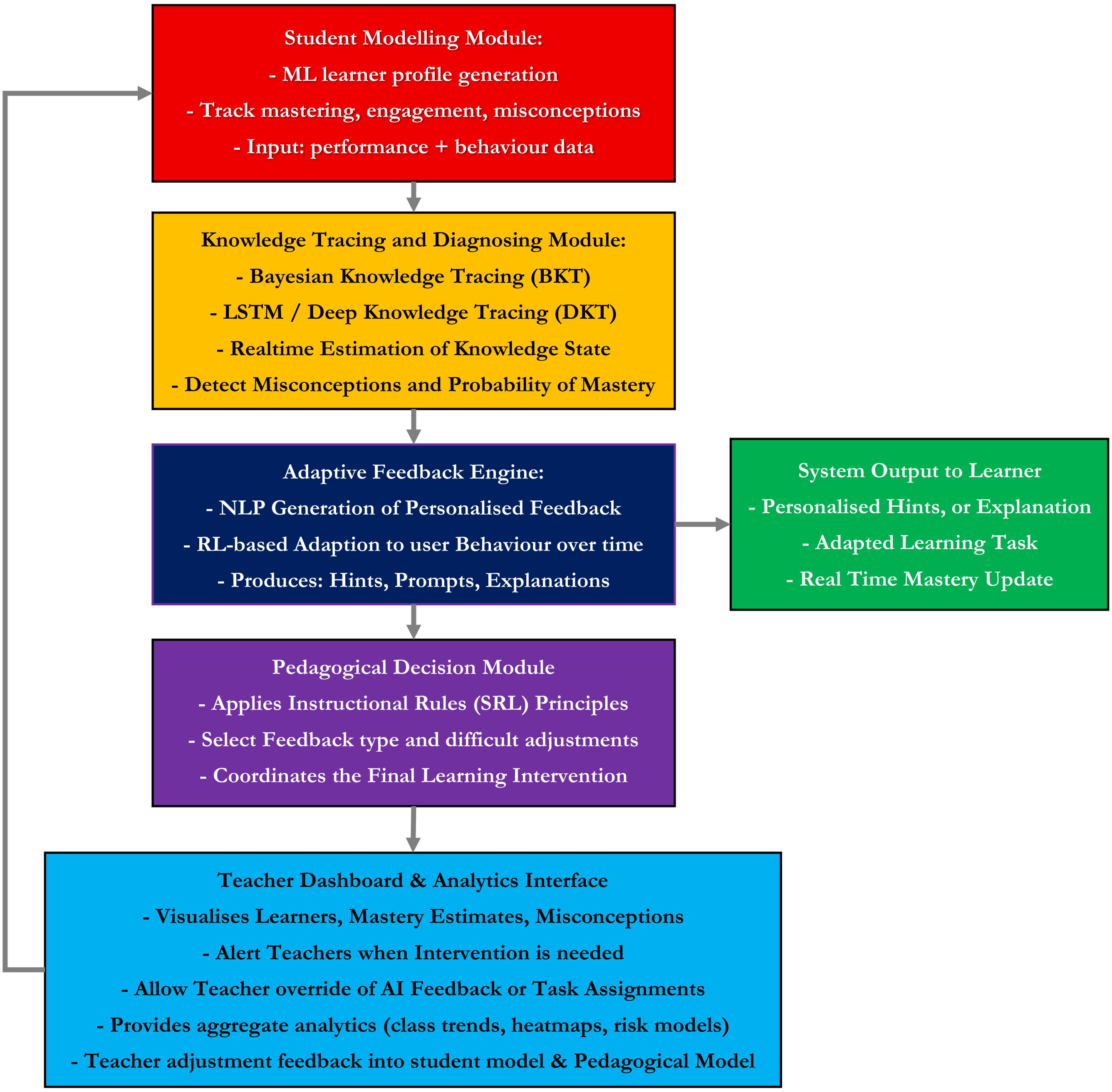

Figure 2. Proposed architecture of the AI-powered tutoring system

The AI tutoring platform implemented in this study is a hybrid adaptive feedback system, combining rule-based pedagogical logic with machine learning–driven adaptivity. The pedagogical decision module applies SRL-based rules to determine when specific feedback types—such as hints, prompts, or explanations—should be issued [9], [24], [37], [45]. These rules interact dynamically with ML components such as Bayesian and deep learning models, which continuously update learner mastery estimates in real time.

This hybrid integration results in an adaptive feedback engine capable of merging fixed pedagogical principles with data-driven behavioral insights to generate personalized recommendations. The design thus supports a semi-autonomous yet teacher-mediated tutoring process, aligning AI automation with human pedagogical oversight.

Python was selected as the development language due to its open-source nature, extensive AI libraries, and flexibility in handling educational data formats—qualities aligned with contemporary advances in Python-based artificial intelligence in education (AIED) [30]. The resulting architecture provides real-time adaptivity and includes offline and low-bandwidth operating modes, ensuring functionality in infrastructure-limited environments typical of Nigerian secondary education.

3.8. Ethical Consideration

Ethical compliance for this study followed institutional research board (IRB) protocols and national regulations. Prior approval was obtained from the relevant institutional review board, and informed consent was secured from teachers, parents, or guardians of participating students. All data collection and processing were conducted under strict conditions of confidentiality and anonymity. Both online and physical data were securely stored in password-protected and access-restricted environments to ensure data integrity.

Particular attention was given to compliance with the Nigeria Data Protection Act (NDPA) 2023 [20], which outlines ethical standards for AI applications, including data privacy, algorithmic transparency, voluntary human participation, and the principle of non-maleficence—ensuring that no participant is harmed by the implemented technology. These measures collectively ensured that the research upheld principles of fairness, accountability, and respect for human dignity throughout all stages of AI system deployment and data management.

4. Results and Discussion

The results of this study are structured around two empirical objectives (EO) that guided the investigation:

1. to assess the effect of the AI-driven tutoring system on individualized learning feedback, academic outcomes, and engagement among secondary school students in Nigeria; and
2. to examine teachers' and students' perceptions, challenges, and readiness toward adopting AI-based tutoring systems in Nigerian secondary schools.

The prototype of the AI-powered tutor was installed on medium-range laptops and school computer laboratories equipped with Intel Core i5 processors (at least 8 GB RAM), cloud-based storage, and a backup server to ensure offline continuity. The Python-based software environment integrated learning analytics models, Jupyter back-end scripts, and a student/teacher interface built into a Learning Management System (LMS) module compatible with Moodle.

Data collection utilised NVivo for qualitative coding, Google Forms for digital survey administration, and Python (SciPy and Pandas libraries) for paired and inferential statistical analysis. The data included pre-test and post-test measures of academic performance and learner engagement (1–5 scale), as well as structured interview transcripts from teachers and students across six secondary schools (n = 600). Instrument fidelity and internal validity were verified through AI system usage logs that recorded session duration, feedback response time, and error trace gradients [16].

In Table 1, the demographic characteristics show a balanced and diverse sample representing both public and private schools across urban and semi-urban regions of Nigeria, ensuring representativeness of the study population.

4.1. Quantitative Results and Statistical Analysis

This subsection presents the quantitative findings related to Empirical Objective 1 (EO1), which assessed the impact of the AI-powered tutoring system on individualized learning feedback, academic outcomes, and engagement among students.

Table 1. Demographic summary of respondents.

Attribute	Classification	Frequency	Percentage (%)
Role	Teachers	120	20
	Students	480	80
Experience (years)	0–2	30	36
	3–5	35	42
	6–10	20	24
	11+	15	18
School Type	Public	3	50
	Private	3	50
Class	SS2	200	41.6
	SS3	280	58.4
Location	Urban	3	50
	Semi-Urban	3	50
Gender	Female	290	48.4
	Male	310	51.6
Assigned Group	Experimental	300	50
	Control	300	50
Age	Teachers (21–50+)	120	20
	Students (18–20)	480	80

4.1.1. Academic Performance

The AI-tutoring intervention group demonstrated a substantial improvement in mean academic scores from pre-test to post-test compared with the control group [26]. Paired t-tests indicated that the intervention group's pre/post gain was statistically significant ($t \approx 12.20$, $p < 0.001$) with a large effect size (Cohen's $d \approx 1.05$), while the control group's improvement was smaller but still significant ($t \approx 2.73$, $p = 0.007$) with a small effect size ($d \approx 0.22$).

The post-test comparison between groups was also significant ($p < 0.001$), indicating better learning outcomes among students who used the AI system. These results are summarized in Table 2 and illustrated in Figure 3.

Table 2. Summary of the impact of AI-powered individualized feedback on academic performance (intervention vs. control)

Group	N	Pre-test Mean	Post-test Mean	Mean Gain	SD	*t*-value	*p*-value	Effect Size (Cohen's *d*)
Intervention	300	56.2	72.4	+16.2	8.2	12.0	<0.001	1.05 (large)
Control	300	59.9	60.1	+4.2	9.0	2.73	0.007	0.22 (small)

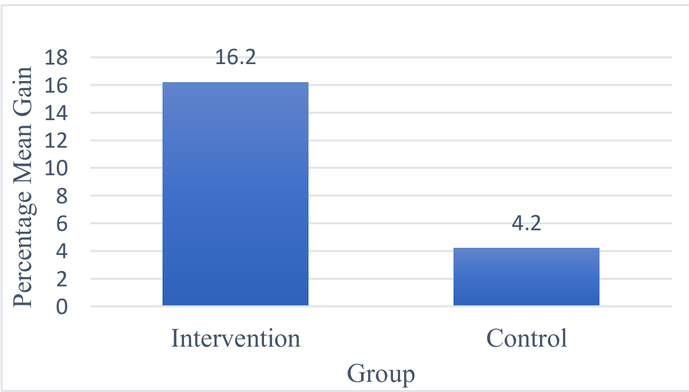

Figure 3. Percentage mean gain in academic performance between intervention and control groups

The results indicate that the AI-tutoring system produced a statistically significant and considerably larger improvement in academic achievement compared to traditional instruction.

4.1.2. Student Engagement and Motivation

Student engagement (measured on a 1–5 scale) also increased significantly in the intervention group ($t \approx 8.30$, $p < 0.001$), with a moderate effect size, compared with a small and non-substantial increase in the control group ($t \approx 2.10$, $p \approx 0.037$). Motivation and SRL scores followed a similar trend—moderate and significant gains in the intervention group ($p < 0.001$), while the control group exhibited minimal improvement [13], [20].

Table 3. Summary of the impact of AI-powered individualized feedback on student engagement (intervention vs. control)

Group	N	Pre-test Mean	Post-test Mean	Mean Gain	SD	*t*-value	*p*-value	Effect Size (Cohen's *d*)
Intervention	300	3.02	4.15	+1.13	0.85	8.30	<0.001	0.72 (moderate)
Control	300	2.98	3.11	+0.13	0.80	2.10	0.037	0.18 (small)

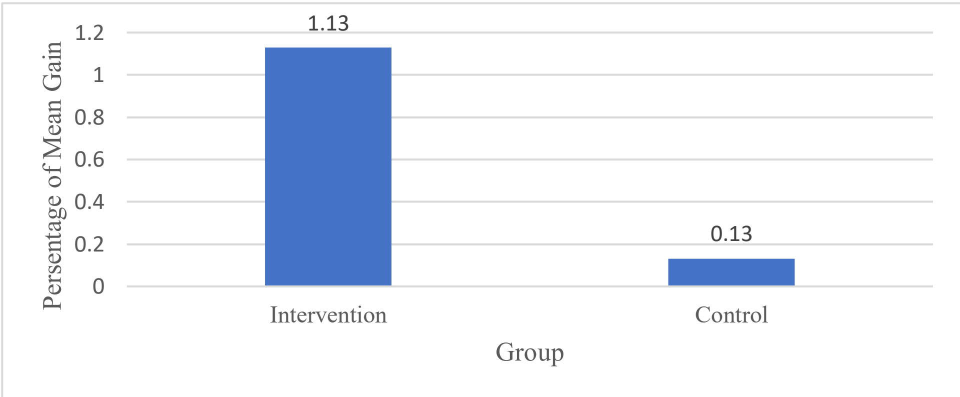

Figure 5. Percentage mean gain in student engagement between intervention and control groups.

The significant rise in engagement among students in the intervention group suggests that AI-based personalized feedback effectively enhanced classroom interaction and learner motivation. These results align with prior studies [19], [25], which emphasized that AI tutors foster metacognitive awareness and SRL by dynamically adapting to students' learning behaviors.

Reliability analysis using Cronbach's α (> 0.80) confirmed the consistency of the engagement and motivation scales, ensuring measurement validity [36]. Overall, these findings support the conclusion that integrating AI-powered individualized feedback significantly improves learning outcomes, engagement, and motivation compared to conventional teaching methods.

4.2. Qualitative Findings and Perception Analysis

The second empirical objective (EO2) explored teachers' and students' perceptions, challenges, and readiness for adopting AI-based tutoring systems in Nigerian secondary schools. The qualitative data were derived from semi-structured interviews and focus group discussions, which were analyzed thematically using NVivo software. Five dominant themes emerged, summarized in Table 4, reflecting perceptions, contextual challenges, and socio-technical readiness dimensions aligned with established theoretical frameworks.

The most dominant theme identified was perceived benefits (85%), reflecting strong positive attitudes toward AI tutoring among both teachers and students. Respondents valued the immediacy of feedback, individualized support, and enhanced engagement facilitated by the system. However, significant barriers were also reported, particularly regarding infrastructure and professional capacity. Teachers noted challenges related to unstable power supply and internet access, while both teachers and students recognized the need for continuous professional development (PD) to effectively integrate AI tools into pedagogy [27], [36].

Table 4. Summary of teachers' and students' perceptions, challenges, and readiness for AI adoption

Specific Factors	Frequency of Mentions (%)	Connotation / Interpretation	Corresponding Theoretical Construct
Perceived benefits	High (85%)	Most respondents highlighted the positive effects of AI tutoring, including prompt feedback, enhanced interaction, and individualized guidance. Teachers emphasized that the system helps to quickly identify students' weaknesses and tailor instruction accordingly.	Technology Acceptance Models (TAM/UTAUT)
Technical problems with infrastructure	High (78%)	Participants reported persistent challenges such as unreliable electricity, insufficient digital equipment, and inconsistent internet connectivity that affected AI system utilization.	Facilitating Conditions
Skill and professional development (PD) requirements	High (70%)	Several teachers and students indicated a need for additional training in AI tool usage, data interpretation, and integration into lesson plans.	SRL and Cognitive Tutor/ITS Frameworks
Issues of privacy and data protection	Moderate (62%)	Respondents raised concerns about data storage, student consent, and algorithmic transparency, emphasizing the importance of ethical AI use in compliance with the Nigeria Data Protection Act (NDPA, 2023) and international standards such as the General Data Protection Regulation (GDPR).	Trust and Ethical Readiness
Pedagogical integration	Moderate (58%)	Both groups underscored the continuing need for human facilitation to complement AI-generated recommendations and sustain learner motivation.	Human-Centered AI and Socio-Technical Systems Theory

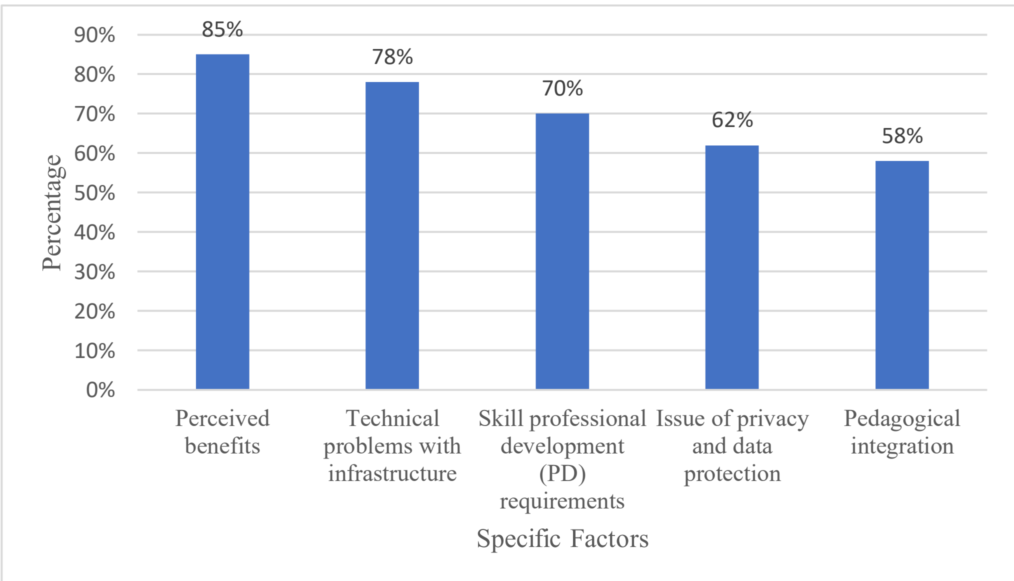

Figure 6. Distribution of thematic factors: teachers' and students' perceptions, challenges, and readiness for AI adoption

Concerns about data privacy and algorithmic transparency also emerged, emphasizing the ethical dimension of AI deployment in education. These findings align with prior socio-technical studies [3], [20] that highlight the critical role of governance, teacher mediation, and ethical compliance in successful AI adoption. Furthermore, the emphasis on pedagogical integration supports the principle of human-in-the-loop learning design, where AI complements rather than replaces teacher functions [4], [12]. Figure 6 illustrates the relative prominence of each theme, showing that perceived benefits were the most frequently mentioned, followed by infrastructural limitations and professional development needs.

Overall, the qualitative findings demonstrate that while teachers and students generally welcome AI-based tutoring systems, their effective and ethical integration depends on improved infrastructure, ongoing professional training, and robust data protection policies. These insights provide essential socio-technical context for scaling AI adoption in low-resource educational settings and underscore the need for policy frameworks that ensure responsible, human-centered implementation [3], [4], [12].

4.3. Discussion and Implications

The findings of this study demonstrate that institutionalizing Artificial Intelligence (AI)-based tutoring systems in Nigerian secondary schools can substantially enhance personalized learning feedback, academic performance, and student engagement under statistically significant conditions. As shown in Tables 1–4 and Figures 3–6, both the quantitative and qualitative analyses confirm that adaptive, data-driven feedback mechanisms improve learning outcomes by providing immediate and context-sensitive instructional responses to students' misconceptions [3], [9], [25], [36]. The results also validate the alignment of AI tutoring with the theoretical foundations of SRL, Cognitive Tutor Theory, Socio-Technical Systems Theory, and Technology Acceptance Models (TAM/UTAUT), which together explain the observed interaction between technology adoption, learner behavior, and institutional readiness [14], [20], [22]–[24].

4.3.1. Integration of Quantitative and Qualitative Insights

The quantitative results presented in Tables 2 and 3 indicate that the AI-tutored group achieved statistically significant learning gains ($t \approx 12.0$, $p < 0.001$, Cohen's $d = 1.05$), along with increased engagement levels ($t \approx 8.30$, $p < 0.001$). These outcomes confirm that adaptive AI feedback enhances learner motivation and self-regulatory capacity—outcomes also noted in previous AI tutoring studies [9], [19], [25]. Complementing these numerical findings, the qualitative results (Table 4; Figure 6) reveal strong perceived benefits among both teachers and students (85%), alongside infrastructural and professional barriers such as limited power supply, internet instability, and the need for continuous professional development (PD) [13], [27]. This triangulation reinforces that learning benefits are maximized when technological implementation is accompanied by human facilitation, ethical governance, and teacher readiness [4], [12].

4.3.2. Socio-Technical and Pedagogical Implications

From a socio-technical standpoint, these findings highlight that effective AI tutoring integration depends on systemic factors—namely infrastructure, human capacity, and institutional policy [3], [30], [46], [47]. Teachers emphasized the importance of training in AI analytics, data interpretation, and ethical use, reflecting the human-in-the-loop principle where technology augments rather than replaces educators [4], [9]. Students similarly expressed positive engagement with AI-driven feedback while stressing the need for contextualization of computer-generated recommendations within classroom instruction. These insights confirm that technological success is contingent upon alignment across human, technical, and institutional subsystems, as proposed by the STST [22]–[24].

4.3.3. Theoretical Confirmation and Policy Implications

The results substantiate the underlying theoretical framework adopted in this study.

- SRL Theory is supported by evidence of increased motivation and engagement among learners exposed to adaptive AI feedback [9], [14], [25].
- Cognitive Tutor Theory is validated by the system's ability to model expert reasoning and guide learners toward mastery through real-time correction of misconceptions [2], [7], [36].
- STST explains the dependence of AI success on infrastructural adequacy and teacher mediation [20], [23], [24].
- TAM/UTAUT models are affirmed by high perceived usefulness and behavioral intention among respondents, particularly when supported by proper training and infrastructure [35], [37]–[39].

The ethical concerns raised by participants—particularly regarding privacy, algorithmic transparency, and data security—align with emerging global debates on responsible AI in education and emphasize the relevance of the NDPA [20] and GDPR compliance [21], [44]. Policymakers and educational administrators should, therefore, prioritize developing a national framework for responsible AI integration in schools, combining technological capability with ethical safeguards and teacher capacity building.

4.3.4. Overall Evaluation

This study contributes to the growing body of empirical evidence supporting AI-assisted personalized learning in low-resource educational contexts [2], [8], [10], [11], [19], [48]. It bridges the gap between algorithmic performance and contextual adaptability by providing quantitative proof of learning improvement and qualitative insights into readiness and ethical challenges. The integrated findings demonstrate that the successful institutionalization of AI tutoring requires not only effective technological design but also sustained teacher engagement, adequate infrastructure, and robust governance frameworks [3], [42], [47].

Furthermore, the results reaffirm the theoretical foundations of the research—namely, SRL, Cognitive Tutor/Intelligent Tutoring System (ITS) Theory, Socio-Technical Systems Theory, and Technology Acceptance Models (TAM/UTAUT)—by showing that technological efficiency depends on the alignment of human, technical, and institutional subsystems [2], [5]–[8], [11]–[16], [19], [23]–[25], [27], [28], [30]–[32], [34], [35], [37]–[40], [43], [44], [49]–[51]. The willingness of teachers and the engagement of students underscore that human factors remain central to the success of AI implementation, while infrastructure and policy serve as essential enablers for sustainable adoption [3], [42].

5. Conclusions

This study provides robust empirical evidence that Artificial Intelligence (AI)-assisted tutoring systems can significantly enhance personalized feedback, student engagement, and academic performance in secondary education within developing countries such as Nigeria [2], [40], [47]. The quasi-experimental findings revealed a large effect on academic achievement (Cohen's $d = 1.05$) and a moderate-to-large effect on engagement ($d = 0.72$), confirming the effectiveness of adaptive, real-time feedback over traditional one-size-fits-all instructional models. These outcomes, supported by both quantitative and qualitative analyses, validate that AI-powered individualized tutoring fosters active learning, motivation, and mastery of concepts through continuous feedback and personalized scaffolding.

The study employed a rigorous mixed-methods design that integrated pre- and post-test data with perception-based qualitative inquiry, thereby strengthening the internal and external validity of its conclusions [28], [37], [43]. The convergence between quantitative and qualitative findings further enhances confidence in the efficacy and usability of AI tutoring systems and reveals how learners and teachers interact with AI tools in authentic classroom environments.

A key scientific contribution of this research is the empirical confirmation that the success of AI tutoring depends on socio-technical alignment. Factors such as teacher preparedness, infrastructural adequacy, and ethical governance emerged as crucial mediating conditions shaping AI effectiveness [25], [44], [46]. These findings underscore that AI integration should not be viewed solely as a technological intervention, but as part of a human-centered educational ecosystem that emphasizes teacher mediation, learner agency, and ethical responsibility [10], [20], [24]. This work represents one of the first mixed-method quasi-experimental assessments of AI tutoring in the secondary school context within Sub-Saharan Africa, addressing a notable gap in existing AI-in-education research.

From a practical standpoint, the results offer valuable guidance for policymakers, school administrators, and educational technology stakeholders seeking to implement AI tutoring in low-resource environments. Specifically, AI tutoring systems can help reduce learning gaps, enhance instructional quality, and support national digital education initiatives such as Nigeria's ongoing education digitization agenda. Nevertheless, limitations remain, including the short duration of intervention, the urban focus of the sample, and persistent infrastructural vulnerabilities that restrict scalability.

Future research should pursue longitudinal and rural-based investigations, explore AI adaptability under low-bandwidth conditions, and examine explainable AI (XAI) frameworks to improve algorithmic transparency and trust. Additionally, such studies should adhere to national and international data protection standards such as the NDPA [20] and the GDPR, ensuring that ethical safeguards evolve alongside technological innovation.

In conclusion, AI-based tutoring systems hold substantial potential to transform educational outcomes in developing contexts when implemented within supportive socio-technical and ethical frameworks. When combined with adequate teacher training, infrastructural readiness, and transparent governance, AI can contribute meaningfully to equitable, scalable, and context-sensitive educational improvement in Nigeria and beyond.

Author Contributions: Conceptualization: D.M.A.; Methodology: D.M.A.; Software: D.M.A.; Validation: I.O.O., J.N.N., and C.O.; Formal analysis: D.M.A.; Investigation: D.M.A.; Resources: D.M.A.; Data curation: D.M.A.; Writing—original draft preparation: D.M.A.; Writing—review and editing: I.O.O., J.N.N., C.O., E.M., and T.K.; Visualization: D.M.A.; Supervision: I.O.O., J.N.N., and C.O.; Project administration: D.M.A. All authors have read and agreed to the published version of the manuscript.

Funding: No funding from any organization or individual

Data Availability Statement: Data will be provided on demand and should be channelled to the corresponding author.

Acknowledgments: There was no external funding. Grammarly AI was used in spell checking errors of the original draft manuscript.

Conflicts of Interest: There is no competing conflict of interest.

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