AI-Assisted Personalized Learning versus Traditional Lecture Method: Effects on Students' Academic Achievement in Tertiary Institutions in Lagos State, Nigeria

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Abstract

This quasi-experimental study examined the effects of AI-assisted personalized learning and the traditional lecture method on students' academic achievement in tertiary institutions in Lagos State, Nigeria. The study aimed to determine the impact of AI-assisted personalized learning on students' academic performance. Using intact classes, a total of 90 three-hundred-level students from two tertiary institutions were assigned to experimental (AI-assisted personalized learning) and control (traditional lecture) groups. Three research questions were raised, and corresponding hypotheses were formulated. An Achievement Test in Administration and Management of Learning Resource Centres (ATAMLRC) was administered as both a pre-test *and post-test to measure changes in academic performance. Data were analysed using mean, standard deviation, and Analysis of Covariance (ANCOVA) at* $\alpha = 0.05$ *with the aid of SPSS version 25. Results revealed a statistically significant difference in* post-test *performance between the two groups,* $F(1, 87) = 15.528$, $p < .05$, *with the experimental group demonstrating superior achievement. The findings indicate that AI-assisted personalized learning enhances student engagement, knowledge retention, and measurable learning outcomes. The study therefore recommends the institutional adoption of adaptive AI-based instructional systems to complement conventional teaching methods and improve academic performance in Nigerian higher education.*

Keywords: *AI-Assisted personalized learning; Adaptive learning technology; Personalized learning; Academic achievement; Traditional lecture method; Gender; Knowledge retention, Tertiary education; Technology integration*

INTRODUCTION

Over the past two decades, the integration of technology into education has progressed steadily; however, the COVID-19 pandemic significantly accelerated this transition, compelling tertiary institutions worldwide to adopt digital instructional strategies. What initially emerged as an emergency response to institutional closures has evolved into sustained pedagogical reform. The disruption exposed structural limitations in conventional teaching approaches and intensified the search for more flexible, inclusive, and effective instructional models. As higher education systems adapt to an increasingly digital environment, the critical question is no longer whether technology should be integrated into teaching, but how it can be effectively leveraged to improve academic achievement.

In many Nigerian tertiary institutions, the traditional lecture method remains the dominant mode of instruction. This teacher-centered approach is largely content-driven and uniform in delivery. While it enables coverage of curricular materials within defined academic timelines, it often assumes homogeneity in learners' cognitive abilities, prior knowledge, and learning pace. Such assumptions are increasingly problematic in diverse classrooms where students vary significantly in motivation, comprehension speed, digital literacy, and academic preparedness. Consequently, reliance on a single instructional strategy may contribute to uneven learning outcomes and suboptimal academic performance.

The limitations of the lecture-based model have prompted renewed scholarly interest in learner-centered pedagogies. Advances in digital technologies, particularly Artificial Intelligence (AI), have introduced new possibilities for instructional personalization. Unlike conventional e-learning systems that present static content, AI-powered platforms utilize algorithms to analyze learner data, monitor performance trends, and dynamically adjust instructional materials. These systems generate adaptive learning pathways tailored to individual students' strengths and weaknesses, shifting the focus from standardized instruction to personalized learning experiences. AI-assisted systems support automated feedback, intelligent content recommendation, formative assessment, and real-time progress tracking.

Scholars have emphasized the transformative potential of AI in education. Ogunode, Idoko, and Peter (2021) note that AI contributes to the creation of "smart content," including interactive modules and customized instructional materials aligned with learners' needs. By reducing administrative burdens such as grading and data analysis, AI allows instructors to focus more on higher-order instructional tasks, including facilitation and mentorship. Importantly, AI is not conceptualized as a replacement for educators but as a complementary tool that enhances instructional precision and responsiveness.

The urgency of instructional innovation is particularly evident in Nigeria's higher education sector. Persistent challenges, including overcrowded classrooms, limited instructional resources, infrastructural deficits, and disparities in academic preparation continue to affect student performance. Adeyemi *et al.* (2019) highlight systemic constraints that limit equitable access to quality learning experiences. At the global level, UNESCO (2021) describes a widespread learning crisis characterized by declining achievement levels and insufficient mastery of core competencies. These concerns underscore the need to explore instructional approaches capable of improving academic outcomes in diverse contexts.

Emerging empirical evidence suggests that AI-driven instructional systems may enhance academic performance by promoting adaptive engagement and individualized support. Swargiary (2024) reported significant improvement among students exposed to AI-driven personalized tutoring compared to those relying solely on traditional study methods. Similarly, Luo (2023) found that intelligent platform-assisted instruction improved student outcomes through adaptive feedback mechanisms. By aligning instructional complexity with learner readiness, AI systems may reduce cognitive overload, enhance knowledge retention, and foster deeper conceptual understanding.

In tertiary institutions within Lagos State, the diversity of student populations further complicates instructional delivery. Differences in socioeconomic background, digital competence, prior academic exposure, and motivational orientation create variability that a standardized lecture approach may insufficiently address. AI-assisted personalized learning offers a structured mechanism for responding to learner variability through data-driven instructional adaptation, potentially narrowing achievement gaps and improving measurable academic performance.

Despite the growing discourse on AI in education and documented benefits in other contexts, empirical studies comparing AI-assisted personalized learning with the traditional lecture method in Nigerian tertiary institutions remain limited. There is a clear need for systematic research to determine whether AI-supported instruction produces significantly different academic outcomes compared to conventional pedagogical approaches. This study, therefore examines the effects of AI-assisted personalized learning versus the traditional lecture method on students' academic achievement in tertiary institutions in Lagos State, Nigeria.

Purpose of the Study

This study examined the comparative effects of AI-assisted personalized learning and the traditional lecture method on students' academic achievement in tertiary institutions in Lagos State, Nigeria. Specifically, it sought to determine whether exposure to adaptive, AI-driven instructional systems produces significantly different learning outcomes when compared with conventional teacher-centered instruction. By empirically evaluating these two pedagogical approaches, the study aims to provide evidence-based insights to inform instructional policy and practice within the Nigerian higher education context.

Research Question

Is there a significant difference in the academic achievement of students taught using AI-assisted personalized learning and those taught using the traditional lecture method in tertiary institutions in Lagos State, Nigeria?

Research Hypothesis

H_{01}: There is no significant difference in the academic achievement of students taught using AI-assisted personalized learning and those taught using the traditional lecture method. It may be noted that the null hypothesis is appropriately structured for ANCOVA testing at $\alpha = 0.05$.

LITERATURE REVIEW

Artificial Intelligence has attracted increasing scholarly attention as a transformative force in educational practice. Contemporary research suggests that AI has the capacity to redefine knowledge delivery, assessment, and instructional management. The growth of machine learning technologies, combined with the availability of large educational datasets, has accelerated the development of data-driven instructional systems.

One major contribution of AI in education is the development of intelligent tutoring systems and adaptive learning environments. These systems analyze learner performance in real time and modify instructional content accordingly (Pokrivčáková, 2019). Predictive analytics embedded within

AI platforms can identify students at risk of underperformance by examining behavioral and assessment patterns, thereby enabling timely intervention and targeted support (Harry and Sayudin, 2023).

AI also facilitates automated assessment and immediate feedback (Yufeia *et al.*, 2020). Algorithm-driven systems evaluate learner responses, provide corrective guidance, and generate individualized learning plans. This continuous feedback loop enhances students' awareness of their mastery levels and promotes self-regulated learning. Instructors benefit from real-time performance dashboards that support data-informed instructional decisions.

In distance and blended learning contexts, AI systems help bridge interaction gaps by offering responsive instructional support (Kose, 2014). As higher education increasingly incorporates hybrid models, AI-driven platforms provide scalable solutions for maintaining instructional quality across large student populations. Beyond automation, AI contributes significantly to personalized learning by adapting content, pace, and complexity to individual learner characteristics (Beese, 2019; Ayeni *et al.*, 2024).

Personalized learning enhances autonomy, motivation, and engagement. By aligning instructional materials with learner readiness and interest, AI-assisted systems reduce cognitive overload and improve retention. Empirical studies across diverse educational settings consistently report improved academic outcomes when adaptive systems are compared with rigid lecture-based formats (Swargiary, 2024). Nevertheless, empirical evidence within Nigerian tertiary institutions, particularly in Lagos State, remains scarce. This gap necessitates controlled comparative research to determine the relative effectiveness of AI-assisted personalized learning within the local higher education environment.

THEORETICAL FRAMEWORK

This study is grounded in three complementary theoretical perspectives: Self-Determination Theory, Cognitive Load Theory, and the Technology Acceptance Model. Together, these frameworks provide motivational, cognitive, and behavioral explanations for how AI-assisted personalized learning may influence academic achievement in tertiary institutions.

Self-Determination Theory

Self-Determination Theory, developed by Deci and Ryan (2000), posits that human motivation is driven by the fulfilment of three psychological needs: autonomy, competence, and relatedness. Autonomy involves a sense of control over learning activities; competence reflects perceived mastery; and relatedness concerns meaningful connection within the learning environment. AI-assisted personalized learning supports autonomy through individualized pacing and adaptive pathways, enhances competence through continuous feedback, and may foster engagement through interactive features.

Therefore, satisfaction of these needs enhances intrinsic motivation, sustained engagement, and improved performance. AI-assisted personalized learning environments are structured to support learner autonomy by allowing students to progress at individualized paces and make decisions regarding their learning paths. Continuous formative feedback strengthens perceptions of competence, while interactive learning environments can promote collaborative engagement. When these needs are met, learners are more likely to demonstrate persistence, deeper cognitive engagement, and improved academic achievement. Self-Determination Theory, therefore, provides a motivational foundation for examining the effectiveness of AI-supported instructional approaches.

Cognitive Load Theory

Cognitive Load Theory (Sweller, 1988) asserts that working memory has limited capacity, and instructional design must minimize unnecessary cognitive demands to facilitate meaningful learning. Effective instructional design must therefore minimize unnecessary cognitive demands in order to facilitate schema construction and long-term retention. CLT distinguishes between intrinsic cognitive load (inherent complexity of the material), extraneous load (inefficient instructional presentation), and germane load (mental effort directed toward meaningful learning).

AI-assisted personalized learning aligns with the principles of Cognitive Load Theory by structuring content in manageable segments and adjusting instructional difficulty according to learner performance. By tailoring content sequencing and pacing, such systems may reduce extraneous cognitive load while enhancing germane processing. This optimization supports deeper understanding and improved retention. Within this study, CLT provides a cognitive explanation for potential differences in academic achievement between students exposed to adaptive learning environments and those taught through uniform lecture-based instruction.

Technology Acceptance Model

The Technology Acceptance Model (TAM) (Davis,1989) explains individuals' adoption of technological systems based on two principal constructs: perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which users believe that a technology enhances performance, while perceived ease of use reflects the degree to which the system is considered manageable and accessible.

In the context of AI-assisted personalized learning, students' academic outcomes may be influenced by their acceptance of the instructional technology. When learners perceive the platform as beneficial and straightforward to use, their willingness to engage increases. This behavioral intention contributes to sustained participation and meaningful interaction with instructional materials. TAM therefore provides a behavioral framework for understanding the relationship between technology adoption and academic achievement in tertiary education.

Collectively, these theoretical perspectives offer an integrated framework for examining the motivational, cognitive, and behavioral mechanisms through which AI-assisted personalized learning may affect students' academic performance in tertiary institutions in Lagos State, Nigeria.

METHODOLOGY

This section presents the systematic procedures adopted to investigate the effects of AI-assisted personalized learning versus the traditional lecture method on students' academic achievement. It details the research design, participants, instrument, validity and reliability measures, ethical considerations, data collection and treatment procedures, as well as the statistical techniques employed for data analysis. The methodological choices were guided by the need to ensure internal validity while accommodating the practical constraints of conducting research within active tertiary institutions in Lagos State, Nigeria.

Research Design

The study employed a quasi-experimental pre-test–post-test control group design. This design was deemed appropriate because intact classes were used, making random assignment of individual students impractical within the institutional setting. In Nigerian tertiary institutions, students are typically organized into predetermined class groups based on departmental registration and course allocation. Disrupting these groups for randomization could have caused administrative challenges and affected the normal academic schedule.

The quasi-experimental design facilitated a comparison of academic achievement between students exposed to AI-assisted personalized learning (experimental group) and those taught via the traditional lecture method (control group), while statistically controlling for baseline differences. Pre-test administration ensured initial equivalence between groups, allowing any post-test differences to be attributed to the instructional intervention.

Participants

The study population comprised of 300-level students enrolled in the Educational Technology unit across two selected tertiary institutions in Lagos State, Nigeria. This level was chosen because students possess sufficient foundational knowledge and digital literacy to engage effectively with AI-driven learning platforms.

A purposive sampling technique was used to select a total of 90 participants. Two intact classes from each institution were assigned to either the experimental group (45 students) or the control group (45 students). These institutions were chosen based on the availability of basic digital infrastructure and their willingness to participate in the study.

Instrument for Data Collection

Data were collected using the Achievement Test in Administration and Management of Learning Resource Centres (ATAMLRC). The instrument consisted of 40 multiple-choice items, each with four options (A–D), designed to measure students' understanding of core course content. The ATAMLRC was administered as both a pre-test and post-test, enabling a direct assessment of learning gains attributable to the intervention. Each correct response earned one mark, giving a maximum possible score of 40.

Validity and Reliability

To ensure content validity, the ATAMLRC was reviewed by three experts in Educational Technology and Measurement and Evaluation from Lagos State universities. They evaluated the items for clarity, relevance, and appropriateness of difficulty. Feedback from these experts was used to refine ambiguous items and ensure comprehensive content coverage.

Although a formal reliability coefficient was not computed due to logistical constraints, internal consistency was maintained through the use of clear multiple-choice items, standardized administration conditions, and uniform scoring procedures. These measures minimized subjectivity and ensured reliable data collection.

Ethical Considerations

Ethical approval was obtained from relevant institutional authorities prior to data collection. Participants were fully informed of the study's purpose, procedures, and their right to withdraw at any stage without academic penalty. Informed consent was obtained from all participants, and anonymity was preserved by coding test scripts instead of using names.

To ensure equity, the AI-assisted learning materials were made available to the control group after the study, preventing deprivation of potential learning benefits. These measures reflect adherence to standard ethical practices in educational research.

Data Collection Procedure

Data collection occurred in three phases: pre-intervention, intervention, and post-intervention.

Pre-intervention Phase

Approval was secured from institutional authorities, and participants were briefed on the study's objectives and confidentiality procedures. The ATAMLRC pre-test was administered under supervised conditions to establish baseline academic performance.

Intervention Phase

Over four weeks, the experimental group engaged with the AI-assisted personalized learning platform, which provided sequenced lessons, adaptive quizzes, and immediate feedback tailored to individual performance. The control group received instruction through the conventional lecture method, involving instructor-led explanations, chalkboard notes, and periodic assessments. Both groups covered identical course content and learning objectives.

Post-intervention Phase

The ATAMLRC post-test was administered under conditions similar to the pre-test. All test scripts were collected, screened for completeness, and prepared for statistical analysis.

Treatment Procedure

Students in the experimental group interacted with an AI-driven platform that adapted instructional content based on individual responses. If a student struggled with a concept, additional resources and practice exercises were provided before progression, ensuring personalized learning.

The control group received conventional lecture-based instruction, characterized by instructor-led content delivery and structured class interactions without individualized adaptive feedback. Instructional duration and course coverage were identical for both groups to isolate the effect of the teaching method.

Data Analysis

Descriptive statistics (mean and standard deviation) were computed to summarize students' performance and examine group characteristics. Inferential analysis was conducted using Analysis of Covariance (ANCOVA) via SPSS version 25, with pre-test scores serving as covariates to adjust post-test scores for baseline differences. The significance level was set at 0.05.

ANCOVA was selected because it provides a precise estimate of treatment effects by controlling for initial performance differences, thereby ensuring that observed outcomes accurately reflect the impact of the instructional method.

RESULTS

This section presents the findings of the study on the effect of AI-assisted personalized learning versus the traditional lecture method on students' academic achievement. The analysis was conducted in two stages: descriptive statistics to summarize group performance and inferential statistics using Analysis of Covariance (ANCOVA) to test the research hypothesis while controlling for baseline differences.

Respondent Response Rate

All 90 distributed Achievement Tests in Administration and Management of Learning Resource Centres (ATAMLRC) were properly completed and returned, yielding a response rate of 100%, which indicates full participation and minimizes potential non-response bias.

Descriptive Statistics

Table 1 shows the pre-test and post-test mean scores and standard deviations for the experimental (AI-assisted) and control (lecture method) groups. Both groups demonstrated comparable baseline performance on the pre-test, supporting initial equivalence.

Table 1: Descriptive statistics for pre-test and post-test scores by instructional group.

Group	n	Pre-test M (SD)	Post-test M (SD)	Mean Gain
Experimental (AI-assisted)	45	12.33 (3.84)	21.07 (6.07)	+8.74
Control (Lecture)	45	12.18 (3.62)	20.51 (5.09)	+8.33
Total	90	12.26 (3.72)	20.79 (5.58)	+8.53

The pre-test results indicate that the experimental and control groups were statistically similar before the intervention. Post-intervention, both groups improved; however, the experimental group achieved a slightly higher mean score ($M = 21.07$, $SD = 6.07$) than the control group ($M = 20.51$, $SD = 5.09$). Although the descriptive difference appears modest, inferential analysis was conducted to determine statistical significance after adjusting for pre-test scores.

Inferential Statistics

ANCOVA was conducted to test the effect of instructional method on post-test scores while controlling for baseline differences. The pre-test scores were included as a covariate to ensure that initial performance differences did not bias the results.

The ANCOVA results (Table 2) reveal a statistically significant effect of instructional method on post-test performance, $F(1, 87) = 15.53$, $p < .001$, with a medium-to-large effect size (partial $\eta^2 = .151$). Approximately 51.6% of the variance in post-test scores was explained by the model ($R^2 = .516$; Adjusted $R^2 = .505$). The pre-test covariate was also significant, $F(1, 87) = 92.31$, $p < .001$, confirming that baseline academic performance influenced post-intervention outcomes.

Since the p-value for the instructional method was well below the 0.05 threshold, the null hypothesis (H_0) was rejected. This finding indicates that AI-assisted personalized learning produced significantly higher academic achievement compared to the traditional lecture method after adjusting for initial ability differences.

Summary of Key Findings

Baseline Equivalence

Pre-test scores confirmed that both groups were statistically comparable prior to the intervention.

Post-test *Performance*

Both groups improved, but the AI-assisted personalized learning group achieved higher adjusted post-test means.

Table 2: ANCOVA results for effect of instructional method on post-test scores (controlling for pre-test).

Source	Type III Sum of Squares	df	Mean Square	F	p	Partial η^2
Corrected Model	1428.83	2	714.42	46.38	<.001	.516
Intercept	5.29	1	5.29	0.34	.560	—
Pretest (Covariate)	1421.89	1	1,421.89	92.31	<.001	.515
Group (Instructional Method)	239.20	1	239.20	15.53	<.001	.151
Error	1340.16	87	15.40	—	—	—
Corrected Total	2768.99	89	—	—	—	—

Statistical Significance

ANCOVA demonstrated a significant treatment effect, $F(1, 87) = 15.53$, $p < .001$, with a medium-to-large effect size (partial $\eta^2 = .151$).

Practical Implication

The results suggest that adaptive, AI-driven instructional systems may enhance academic achievement beyond what is attainable through conventional lecture-based methods.

DISCUSSION

This study examined the effect of AI-assisted personalized learning on students' academic achievement in tertiary institutions in Lagos State, Nigeria. Findings revealed a statistically significant difference in post-test performance between instructional groups, $F(1, 87) = 15.53$, $p < .001$, with the experimental group outperforming the control group.

The advantage of AI-assisted learning can be explained through Self-Determination Theory (Deci and Ryan, 2000), which emphasizes autonomy, competence, and relatedness. The adaptive platform allowed students to progress at their own pace, provided immediate feedback, and included interactive features, enhancing motivation and engagement. Cognitive Load Theory (Sweller, 1988) further suggests that adaptive sequencing and targeted scaffolding reduce extraneous cognitive load, enabling deeper understanding. Additionally, the Technology Acceptance Model (Davis, 1989) indicates that students' perceptions of usefulness and ease of use promoted consistent engagement with the platform.

These results align with prior studies demonstrating the effectiveness of AI-driven learning (Anuradha *et al.*, 2023; Fassi and Sabti, 2024). Swargiary (2024) and Luo (2023) reported improved academic outcomes with adaptive platforms, while Ayeni *et al.* (2024) highlighted enhanced engagement and achievement through individualized pacing. In Nigeria, Ngonso *et al.* (2025) confirmed that AI utilization positively influences academic performance. This study extends the evidence by providing controlled experimental data from Lagos State institutions.

Although statistically significant, the mean difference between groups was modest, suggesting AI-assisted learning complements rather than replaces traditional lectures. Implementation should consider infrastructural limitations, digital literacy, and cultural expectations in Nigerian higher education.

Overall, the findings support the integration of AI-assisted personalized learning as a supplementary pedagogical tool that enhances engagement, optimizes cognitive resources, and improves academic achievement when aligned with existing instructional practices.

CONCLUSION

This study provides compelling evidence that AI-assisted personalized learning enhances academic achievement among tertiary students in Lagos State, Nigeria. Students who engaged with adaptive, data-driven instructional platforms outperformed those taught through traditional lectures. By offering individualized pacing, targeted feedback, and interactive learning pathways, AI-supported instruction promotes deeper engagement, optimizes cognitive processing, and strengthens knowledge retention. While not intended to replace conventional teaching, AI-assisted learning serves as a strategic complement that addresses learner diversity and improves instructional effectiveness.

Limitations

The study's findings should be interpreted in light of the following limitations:

- *Sample and context*: The study involved 90 students from two tertiary institutions within a single academic discipline, limiting generalizability to other programs, institutions, or regions.
- *Short intervention period*: The four-week study captured immediate learning gains but does not provide insight into long-term retention or sustained learning behaviors.
- *Contextual constraints*: Factors such as internet reliability, device availability, and varying digital literacy levels may affect the practical implementation of AI-assisted platforms in real-world settings.

Recommendations

In light of the findings of this study, several recommendations are proposed to enhance instructional effectiveness in tertiary institutions:

- *Integrate AI-assisted learning into formal instruction*: AI platforms should complement lecturer-led teaching by providing real-time feedback, monitoring learner progress, and supporting individualized learning pathways.
- *Adopt blended pedagogical models*: Combining AI-driven learning with traditional lectures enhances engagement and academic outcomes while preserving the educator's central role.
- *Curriculum redesign*: Include adaptive assessments, self-paced modules, and continuous feedback mechanisms in course structures to ensure sustainable and consistent application of AI technologies.
- *Invest in infrastructure and capacity-building*: Reliable internet, digital learning facilities, and professional development programs are essential to maximize the benefits of AI-assisted learning.
- *Establish supportive policy frameworks*: Institutional and governmental policies should ensure ethical, equitable, and pedagogically sound deployment of AI tools, addressing accessibility, privacy, and inclusivity.

In summary, strategic integration of AI-assisted personalized learning offers a practical pathway for enhancing student performance, optimizing instructional effectiveness, and advancing the quality of higher education delivery in Lagos State and beyond.

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The present research did not receive any financial support to conduct the research.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

Life Science Reporting

No life science threat was practised in this research.

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