

A Comparative Analysis of AI-Driven Personalized Learning Impact on Academic Performance and Engagement Among Nigerian Undergraduates

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Abstract

The adoption of Artificial Intelligence (AI) for personalized learning (PL) is rapidly transforming global higher education. However, institutional type often dictates resource allocation and technological infrastructure, potentially leading to disparate impacts on student outcomes. This study conducted a comparative analysis of the perceived impact of AI-driven personalized learning (AI/PL) on academic performance and academic engagement of undergraduates, measured as student-perceived outcomes, across Nigeria's tripartite higher education structure, namely federal, state, and private universities. Amidst persistent infrastructural and policy disparities in the region, the research sought to determine the relationship between AI utilization and student outcomes and assess whether institutional type significantly mediates this impact. A quantitative descriptive survey research design was employed using a stratified sample of 150 undergraduates (50 from each of the federal, state, and private universities) from Oyo State, Nigeria. Data were collected using a questionnaire, utilizing a 5-point Likert scale. Statistical analysis confirmed a positive and statistically significant correlation between AI utilization and both perceived academic performance ($r=0.58$, $p < 0.01$) and academic engagement ($r=0.63$, $p < 0.01$). Significantly, One-Way Analysis of Variance (ANOVA) revealed a highly significant difference in the perceived impact scores across the three institutional types for both academic performance ($F=9.87$, $p < 0.001$) and academic engagement ($F=11.24$, $p < 0.001$). Private universities reported the highest mean scores, followed by federal and then state institutions, demonstrating that the positive effect of AI/PL is heavily moderated by institutional resource availability and infrastructural reliability. The study concludes that AI/PL holds transformative potential, but its successful and equitable realization is contingent upon overcoming structural barriers, particularly inconsistent technological infrastructure in public institutions. It is recommended that national policy mandates robust ICT infrastructure standards and ethical governance frameworks, prioritizing reliable digital access in public institutions for equitable AI integration.

Keywords: Artificial Intelligence, Personalized Learning, Academic Performance, Academic Engagement, Comparative Analysis.

Introduction

The global integration of Artificial Intelligence (AI) and machine learning technologies into higher education is rapidly transforming pedagogical approaches, moving towards highly

Personalized Learning Environments (PLEs). This development necessitates a fundamental shift from traditional, standardized curricula toward adaptive, personalized learning (PL) environments. AI-driven personalized learning (AI/PL) environments offer adaptive instruction, real-time feedback, and customized content designed to maximize learning efficiency and foster greater student engagement (Tapalova & Zhiyenbayeva, 2022; Zawacki-Richter et al., 2019). The personalization model emphasizes the importance of recognizing and catering to the diverse needs, preferences, and abilities of individual learners. Tools ranging from intelligent tutoring systems to adaptive content creation models provide granular support and immediate, corrective feedback loops to maximize learners' potential. AI/PL leverages sophisticated data analytics, predictive modeling, intelligent tutoring systems, and increasingly, large language models to customize content delivery, sequence, and pace (Russell & Norvig, 2021).

The empirical validation of AI's effectiveness is rapidly growing. Recent research confirms that AI platforms utilizing robust analytics to provide customized and adaptive learning significantly enhance student academic performance, engagement, and satisfaction compared to conventional instruction. The comprehensive integration of AI is transforming education systems internationally, a trend validated by contemporary research on student outcomes in adaptive learning contexts (Eltahir & Babiker, 2024; Souza et al., 2024; Wang et al., 2024). This technological transformation is particularly relevant in developing, high-population nations like Nigeria, where AI offers a scalable means to address learning crises and improve educational equity. However, the successful implementation and demonstrated impact of AI/PL are fundamentally reliant on the availability of robust technological infrastructure and reliable data flow, factors that are highly inconsistent across various institutional environments, particularly in developing economies.

The demographic reality of Nigeria, juxtaposed against persistent socioeconomic and infrastructural deficits, creates a complex deployment environment (Adeyemi et al., 2025). Research specific to the Nigerian context highlights both the massive potential of AI and persistent hurdles hindering its full realization, which include inadequate technological infrastructure, limited institutional funding for digital tools, skill gaps among faculty, and poor network connectivity (Ezekiel & Akinyemi, 2022; I. Sanusi, 2025). There is evidence of a strong tension between high student awareness and willingness to utilize AI tools for learning, and the institutional inability to provide the consistent infrastructural support required for effective personalized learning (Nwodu, 2025).

Statement of the Problem

Nigerian universities are structurally categorized into federal, state, and private institutions, reflecting divergent funding sources, autonomy levels, and infrastructural capacities. While AI-driven Personalized Learning (AI/PL) offers transformative potential for student outcomes, the significant structural and policy disparities across federal, state, and private universities may serve as moderating factors that influence resource availability, the quality and accessibility of advanced educational technologies, such as

AI/PL tools, the effectiveness of their implementation, and consequently, the efficacy and equity of AI adoption.

Persistent challenges, including inadequate digital infrastructure, poor connectivity, and inconsistent funding, create a reliability trap that may prevent students from realizing the full pedagogical benefits of these tools. Despite high student awareness (Adedokun, Adeyemo, & Adedokun, 2026), it is unclear how these divergent institutional capacities moderate the relationship between AI utilization and core outcomes, including academic performance and engagement.

Therefore, understanding how the institutional characteristics moderate the student-perceived impact of AI on core academic outcomes is essential for crafting effective and equitable educational policies. The study aimed to address the lack of comparative research on whether university ownership significantly mediates the perceived impact of AI/PL within the Nigerian context, to inform evidence-based policymaking regarding AI integration in Nigerian higher education.

Research Questions

This study seeks to answer the following research questions:

- Q1. What is the relationship between the use of AI for personalized learning and the academic engagement of undergraduates in the selected universities?
- Q2. What is the relationship between the use of AI for personalized learning and the perceived academic performance of undergraduates in the selected universities?
- Q3. Is there a statistically significant difference in the perceived impact of AI-driven personalized learning on perceived academic performance and engagement among undergraduates in the selected federal, state, and private universities?

Hypotheses

- Ho1: There is no significant influence of AI for personalized learning on the perceived academic performance and academic engagement of undergraduates across Nigerian universities.
- Ho2: There is no statistically significant difference in the mean perceived academic performance scores of undergraduates across Nigerian universities.
- Ho3: There is no statistically significant difference in the mean academic engagement scores of undergraduates across Nigerian universities.

Materials and Methods

AI-Driven Personalized Learning and Student Outcomes

AI-driven personalized learning (AI/PL) refers to the application of intelligent systems to adapt educational content and instruction to the unique profile of each student (Hashim et al., 2022). These systems utilize learning analytics, predictive modeling, and sophisticated algorithms to facilitate customized learning pathways, thereby meeting the unique needs and abilities of learners.

Academic Performance (AP) reflects objective gains, such as improved grades and assignment accuracy, as well as subjective measures of conceptual understanding (Eltahir & Babiker, 2024). Academic Engagement (AE) encompasses the behavioral and affective dimensions of learning, measured through increased motivation, confidence, active involvement, and ownership of the learning process. Recent empirical evidence confirms that AI platforms are effectively validated to enhance both AP and AE in higher education settings (O. T. Sanusi et al., 2024).

Theoretical Anchor

This study is anchored in the Social Cognitive Theory (SCT), originally advanced by Albert Bandura in 1986. SCT provides a robust framework for understanding how the interaction between environmental factors (AI tools), cognitive factors (self-efficacy and motivation), and behavioral outcomes (academic engagement and performance) influences learning (Bandura, 1986; Egele et al., 2025). SCT posits the principle of Reciprocal Determinism, in which these three factors continuously influence one another. In this context, AI-driven personalized feedback and adaptive challenges provided by AI tools serve as a key environmental factor that enhances a student's self-efficacy by providing tailored challenges and consistent, actionable feedback. Increased self-efficacy, driven by successful completion of AI-tailored tasks, is theorized to lead to greater motivation, persistence, and active involvement, resulting in higher academic engagement and improved academic performance (Schunk & DiBenedetto, 2023). Prior studies suggest that adaptive learning mechanisms are effective in amplifying learners' engagement through tailored content and activities that make learning more relevant and captivating (Idika & Saihi, 2025).

This theory aligns AI's function with promoting Self-Regulated Learning (SRL), where AI systems track progress and provide recommendations, fostering student ownership of the learning process (Yang et al., 2025). The enhancement of self-efficacy and control over learning through AI utilization directly facilitates better academic engagement and performance, as confirmed by contemporary research on SCT in digital learning environments (Lu et al., 2022). However, a key environmental variable that remains underexplored is the institutional type. Variations in resource distribution, technological infrastructure, policy, and budget constraints across federal, state, and private universities may create disparities in the quality of AI-PL systems available and in students' ability to consistently use them, thereby moderating the overall impact on AP and AE. Previous research has highlighted that systemic, infrastructural barriers are strong inhibitors of AI technology utilization among Nigerian undergraduates, regardless of individual awareness (Adedokun, Adeyemo, & Adedokun, 2026). This makes a comparative study crucial for contextualizing global findings.

Pedagogical Alignment and Self-Efficacy

AI/PL is pedagogically robust, aligning strongly with adaptive scaffolding mechanisms crucial for higher-order thinking skills (Alanazi et al., 2024). AI-powered intelligent tutoring systems offer instant feedback that allows students to correct mistakes and learn more effectively, thereby maximizing the learning impact by keeping the learner appropriately challenged.

In the context of SCT, the correlation between Academic Performance (AP) and Academic Engagement (AE) is notably high in personalized environments. AI's function extends beyond mere teaching to actively motivating and building confidence (Kamil et al., 2025). The strengthening of affective and behavioral benefits derived from effective AI usage (AE) serves as a necessary precursor to measurable academic success. The adaptive, reliable, and customized support offered by AI directly contributes to improved self-awareness and self-regard (Yang et al., 2025), which are central psychological components that translate increased confidence and ownership into demonstrable improvements in performance.

Institutional Readiness: The Policy and Infrastructure Gap

The adoption of AI is contingent on institutional readiness, which in Nigeria, involves navigating significant policy and infrastructural deficits (Bali et al., 2024). AI readiness in higher education necessitates coordinated alignment across governance, technology, and institutional management. While policy development is ongoing, including regional strategies from the African Union and national drafts, technological deployment often precedes clear regulatory and ethical frameworks (African Union, 2024).

Policy recommendations for Nigeria consistently emphasize investments in digital infrastructure, funding, and workforce development. The discrepancies in the stability of these underlying support structures, particularly infrastructure and governance, are hypothesized to explain the differences observed across institution types (Ajonbadi et al., 2023). Private institutions often achieve internal alignment of these pillars through autonomous funding, absorbing the cost of reliable connectivity and power. Conversely, public universities are dependent on external, inconsistent governmental funding (Ebekozen et al., 2023). This structural distinction leads to the hypothesis that the type of institution acts as a crucial moderating variable, determining whether high student utilization results in consistent, positive impacts.

Methods

A quantitative, descriptive survey research design was employed to examine the perceived impact of AI-driven personalized learning. The population consisted of undergraduates from three universities in Oyo State, Nigeria, representing the three types of university ownership. The universities are the University of Ibadan (a federal institution), LAUTECH Ogbomoso (a state institution), and Ajayi Crowther University, Oyo (a private institution). A stratified sampling technique was employed to select a total sample size (N) of 150 undergraduates. The sample was divided into three equal strata, with 50 respondents

selected from the federal, 50 from the state, and 50 from the private university. This stratification ensured equitable representation of the institutional types for direct comparative analysis (Campbell et al., 2020). Data were collected using AI and Personalized Learning Questionnaire (AIPLO), which employed a 5-point Likert scale for impact assessment (ranging from 1=Strongly Disagree to 5=Strongly Agree) and utilization assessment (ranging from 1=Never Used to 5=Frequently Used). The AIPLO measured the independent variable (AI Utilization) and the two dependent variables, perceived academic performance (PAP) and academic engagement (AE). The outcome variables used in this study, PAP and AE, represent student-perceived outcomes.

A pilot study involving 20 non-participating respondents yielded a Cronbach's Alpha (α) coefficient of 0.941, as shown in Appendix I, demonstrating excellent internal reliability of the scale. Composite scores for AI utilization, academic performance, and academic engagement were calculated by averaging the scores of their respective scale items. Pearson Product-Moment Correlation Coefficient (r) was used to test the relationships between AI utilization and the dependent variables (PAP and AE), addressing research questions Q1 and Q2, and testing H_{01} . To address research question Q3 and test null hypotheses H_{02} and H_{03} , a One-Way Analysis of Variance (ANOVA) was conducted. This procedure examined whether the mean perceived impact scores for PAP and AE differed significantly across the three university categories. Statistical significance was maintained at the $p < 0.05$ level.

An additional methodological consideration concerns the potential influence of common method bias, as all variables in this study were measured using a single self-report instrument administered at the same time. While the instrument demonstrated excellent internal reliability, correlations derived from single-source perceptual data may be inflated relative to studies that incorporate multiple measurement sources or objective performance indicators.

Results

To ensure the findings are representative of the stratified sampling design employed and they reflect the broad reality of Nigerian higher education, the demographic distribution of the 150 participants covered federal, state, and private universities. Table 1 summarizes the characteristics of the participants.

Table 1: Distribution of Respondents by Demographic Variables

Demographic Variable	Category	Frequency (N)	Percentage (%)
Name of Institution	Federal (UI)	50	33.33
	State (LAUTECH)	50	33.33
	Private (ACU)	50	33.33
Gender	Male	75	50.00
	Female	75	50.00
Level of Study	100 Level	32	21.33
	200 Level	29	19.33

Demographic Variable	Category	Frequency (N)	Percentage (%)
Age (N=150)	300 Level	31	20.67
	400 Level	22	14.67
	500 Level	21	14.00
	600 Level	15	10.00
	Mean Age	20 years	-
	Standard Deviation	2.58	-

As illustrated in Table 1, the study achieved a balance in its core demographics. Each of the three university ownership categories accounted for exactly 33.33% of the data, while the gender distribution was split precisely at 50% male and 50% female. Academic representation was most prominent among lower-level students, specifically those in the 100 Level (21.33%), 300 Level (20.67%), and 200 Level (19.33%). The cohort maintained a mean age of 20 years (SD = 2.58).

Descriptive Analysis of AI Utilization and Perceived Impact Scores

The analysis of descriptive statistics indicates that the total sample (N=150) generally reports high perceived impact scores, with an overall mean of M=4.15 for Academic Performance and M=4.23 for Academic Engagement. However, a disaggregated analysis by institutional type, as presented in Table 2, reveals substantial differences in central tendency and variance.

Table 2: Descriptive Statistics of AI/PL Impact by Institution Type

Institution Type	N	Perceived Academic Performance (PAP) Mean (M)	Perceived Academic Performance (PAP) Standard Deviation (SD)	Academic Engagement (AE) Mean (M)	Academic Engagement (AE) Standard Deviation (SD)
Federal (UI)	50	4.15	0.62	4.28	0.55
State (LAUTECH)	50	3.88	0.75	3.91	0.81
Private (ACU)	50	4.41	0.49	4.50	0.45
Total	150	4.15	0.65	4.23	0.65

The data establishes a pattern in the perceived impact scores. Private universities recorded the highest means ($M_{AP}=4.41$, $M_{AE}=4.50$), followed by federal universities ($M_{AP}=4.15$, $M_{AE}=4.28$), with state universities showing the lowest means ($M_{AP}=3.88$, $M_{AE}=3.91$). Furthermore, the standard deviation (SD) indicates variance consistency; private institutions exhibited the lowest variance ($SD_{AP}=0.49$, $SD_{AE}=0.45$), suggesting highly consistent experiences, while state institutions showed the highest variance, indicating a broad range of experiences, from highly positive to highly negative.

Hypothesis Testing

H₀₁: Relationship between AI/PL Use, Perceived Academic Performance, and Engagement

To test H₀₁, a correlation analysis was performed, summarized in Table 3.

Table 3: Pearson Correlation Matrix of AI Utilization, Perceived Academic Performance, and Academic Engagement

Variable	Perceived Academic Performance (PAP)	Academic Engagement (AE)
AI Utilization	.58**	.63**
Perceived Academic Performance (PAP)	1	.79**
Academic Engagement (AE)	.79**	1

Note: N = 150. p < .01 (two-tailed).

The results demonstrate positive and statistically significant relationships among all variables, as shown in Table 3. AI utilization is significantly correlated with perceived academic performance ($r = .58$, $p < .01$) and academic engagement ($r = .63$, $p < .01$). The relationship between perceived academic performance and academic engagement is also strong ($r = .79$, $p < .01$). Based on these results, the null hypothesis H₀₁ is rejected. The analysis confirms that increased utilization of AI tools for personalized learning is positively associated with higher perceived academic performance and academic engagement among the sampled undergraduates.

H₀₂ and H₀₃: Comparative Analysis of Perceived Academic Performance and Engagement Scores by Institution Type

The One-Way ANOVA was employed to test the significance of the mean differences observed in Table 1, addressing H₀₂ and H₀₃. The ANOVA results are presented in Table 4.

Table 4: One-Way ANOVA Results for Perceived Academic Performance and Academic Engagement across Institution Types

Source of Variation	Sum of Squares (SS)	df	Mean Square (MS)	F	p-value	Ho Test Result
Perceived Academic Performance						
Between Groups	8.95	2	4.475	9.87	< 0.001	Reject H ₀₂
Within Groups	66.82	147	0.455			
Total	75.77	149				
Academic Engagement						
Between Groups	10.51	2	5.255	11.24	< 0.001	Reject H ₀₃
Within Groups	68.74	147	0.468			
Total	79.25	149				

The ANOVA results indicate that the differences in mean scores are highly statistically significant for both perceived academic performance and academic engagement. For perceived academic performance, the F-statistic was $F(2,147) = 9.87$ ($p < 0.001$). For academic engagement, the F-statistic was $F(2,147) = 11.24$ ($p < 0.001$). Consequently, both H_{02} and H_{03} are rejected. The perceived impact of AI-driven personalized learning on students' perceived academic performance and academic engagement differs significantly depending on whether a student attends a federal, state, or private university.

Post-Hoc Pairwise Comparisons

Because the one-way ANOVA results indicated statistically significant differences in perceived academic performance and academic engagement across the three institutional types, Tukey's Honestly Significant Difference (HSD) post-hoc test was conducted, as shown in Table 5 and Table 6, to determine which specific institutional pairs differed significantly.

Table 5: Post-Hoc Results for Perceived Academic Performance

Institutional Pair	Mean Difference	Significance
Private – Federal	0.26	Not Significant
Federal – State	0.27	Not Significant
Private – State	0.53	Significant ($p < 0.05$)

The post-hoc analysis in Table 5 indicates that the significant difference in perceived academic performance is primarily driven by the contrast between private and state universities, with students in private universities reporting substantially higher perceived performance gains. Differences between private and federal institutions, and between federal and state institutions, were not statistically significant.

Table 6: Post-Hoc Results for Academic Engagement

Institutional Pair	Mean Difference	Significance
Private – Federal	0.22	Not Significant
Federal – State	0.37	Significant ($p < 0.05$)
Private – State	0.59	Significant ($p < 0.05$)

For academic engagement, the results in Table 6 show that state universities differ significantly from both federal and private universities, while the difference between federal and private universities is not statistically significant. This suggests that the lower engagement scores observed in the state institution account for most of the overall variance detected in the ANOVA.

These findings refine the interpretation of the ANOVA results by demonstrating that the institutional differences are not uniformly distributed across all groups, but are largely driven by the comparatively lower perceived outcomes reported in the state university sample.

Discussion

Confirmation of Positive Influence and the Primacy of Engagement

The successful rejection of H_{01} substantiates the notion that AI/PL tools contribute positively to the academic experiences of Nigerian undergraduates, validating international reports on adaptive learning benefits (Adenubi & Samuel, 2024; Elenode, 2026; Pratama et al., 2023). A thorough examination of the correlation findings suggests a particular mechanism of influence. The stronger correlation observed between AI Utilization and Academic Engagement ($r=0.63$) compared to its correlation with Perceived Academic Performance ($r=0.58$) indicates that AI functions primarily as a motivational and organizational scaffold. AI tools foster greater motivation, active involvement, and confidence in academic abilities. This initial affective and behavioral uplift, rooted in the tool's reliable, instant, and personalized support, is crucial, particularly in Nigerian higher education, characterized by high student-to-faculty ratios and limited resources. The positive motivational environment created by AI then significantly contributes to the strong interdependence observed between AE and PAP ($r=0.79$), ultimately resulting in tangible improvements in academic outcomes. AI's core value here is not just instructional, but socio-emotional, compensating for systemic resource limitations by building student self-efficacy and ownership.

The Structural Imperative: Linking Institutional Type to AI Efficacy

The rejection of H_{02} and H_{03} demonstrates that institutional type is a crucial variable that influences the magnitude and consistency of AI/PL impact. The structural characteristics of the university, especially its financial and infrastructural stability, and governance, mediate the relationship between AI usage and perceived student outcomes (Adedokun, Adeyemo, & Adedokun, 2026; Adewale et al., 2024; OECD, 2021).

The Reliability Dividend of Private Universities

Private institutions, with Ajayi Crowther University as a representative case, reported the highest perceived impact means and the lowest variance, as shown in Table 2. This is attributed to the autonomy these institutions possess to align their policy, funding, and technology sectors (Zawacki-Richter et al., 2019). Private universities absorb the cost of maintaining robust infrastructural reliability, including reliable power and high-speed internet. This consistent technological environment minimizes interruptions, ensuring that the personalized feedback loop remains unbroken. This consistency maximizes the pedagogical benefits of AI, resulting in a reliability dividend where student effort and utilization translate consistently into high perceived academic performance and engagement.

Federal Universities: Potential vs. Operational Reality

Federal universities, exemplified by the University of Ibadan, occupy a middle ground. While UI benefits from strategic policy focus, prestige, and securing future funding

commitments aimed at improving digital infrastructure, the current perceived impact scores reflect challenges in the present operational readiness. The existing institutional capacity and perceived AI impact are likely sustained by a strong academic culture and existing faculty proficiency in technology (Ezekiel & Akinyemi, 2022). However, until the promised infrastructural consistency is achieved and stabilized, the operational gap limits the realized benefits of AI/PL when compared to the highly consistent private sector model.

The Reliability Trap of State Universities

The state institution, LAUTECH Ogbomosho, recorded the lowest mean scores and the highest variance for both perceived academic performance and academic engagement, as summarized in Table 2. These findings suggest that students in this institutional context report comparatively lower perceived benefits from AI-driven personalized learning. One plausible explanation relates to infrastructural constraints that have been widely documented in Nigerian public universities, including inconsistent internet connectivity and power supply (Agbo et al., 2023; Bali et al., 2024). However, the present study relies on student perception data, and therefore cannot directly measure the specific technological interruptions or learning disruptions that may influence these perceptions. Rather, the findings indicate that students in the state institution perceive lower levels of engagement and academic benefit associated with AI use compared to their counterparts in federal and private universities. This pattern may reflect differences in institutional readiness, technological infrastructure, or support systems that shape students' experiences with AI-enabled learning environments.

Implications for Social Cognitive Theory

The empirical results strongly support the principles of Social Cognitive Theory (SCT) in the context of AI-driven personalized learning. AI tools function as powerful environmental catalysts for enhancing cognitive factors, particularly self-efficacy. The adaptive nature of the AI platforms provides students with instant, targeted, and mastery-oriented feedback (Eltahir & Babiker, 2024), which is a core mechanism for building confidence in one's academic abilities (Charlotte Nickerson, 2025; Egele et al., 2025). This enhanced cognitive factor then drives positive behavioral outcomes with academic engagement ($r=0.63$) and perceived academic performance ($r=0.58$), confirming SCT's premise that internal beliefs mediate the relationship between technology use and success (Lu et al., 2022).

Furthermore, the differential impact observed across institution types highlights the critical role of the environment in SCT's model of Reciprocal Determinism. In state institutions, the inconsistent technological infrastructure acts as a profoundly disruptive environmental barrier (Bali et al., 2024). This instability breaks the AI's positive feedback loop, preventing the consistent acquisition of successful mastery experiences necessary to reinforce student self-efficacy and learning goal orientation. Conversely, the stable, reliable environment of the private university enables the positive reciprocal loop to function optimally, proving that stable technology enhances self-efficacy, which drives engagement, leading to

performance gains (Lu et al., 2022). Thus, institutional infrastructure, operating as an environmental determinant, is essential for allowing AI-induced cognitive gains, particularly self-efficacy, to materialize as behavioral outcomes, specifically engagement and performance.

Ethical Considerations, Trust, and Long-Term Adoption

The sustained positive impact of AI/PL hinges upon addressing the ethical implications associated with data use. Nigerian students demonstrate a high prioritization of data privacy, transparency, and the need for Explainable AI (Adedokun et al., 2025). Personalized learning requires students to share sensitive performance data for system optimization, which raises concerns about potential surveillance and misuse.

If institutional AI adoption, particularly in public sectors grappling with data governance frameworks, is perceived as intrusive or primarily focused on academic policing, such as plagiarism detection, it risks eroding student trust. A breakdown in trust would lead to students disengaging from the systems, compromising data integrity, and ultimately undermining the observed strong engagement benefits (Mathew & Isaac, 2025; Okolie & Egbon, 2025). Therefore, integration must be governed by human-centered principles, emphasizing ethical AI literacy and responsible use to ensure the tools enhance, rather than undermine, student agency and critical thinking (Ejeh & Igbokwe, 2025; UNESCO, 2025).

Conclusion

The study concludes that AI-driven personalized learning exerts a significant, positive influence on both perceived academic performance and academic engagement among Nigerian undergraduates. However, the comparative analysis across institutional types demonstrates that the realization and consistency of this impact are statistically contingent upon the university's structural capacity. Private universities currently provide the most consistently favorable environment for AI/PL due to autonomous funding and superior infrastructural reliability. Federal universities, exemplified by the University of Ibadan, represent a middle ground, demonstrating significant strategic potential and benefiting from landmark ICT funding, yet still facing operational lags compared to private universities. Conversely, state universities face a considerable barrier where high student utilization is perpetually inhibited by technological unreliability, limiting the positive perceived impact. This highlights those structural inequalities linked to funding and infrastructure represent the most critical hurdle to equitable and effective AI integration in Nigerian higher education.

Limitations of the Study

The study adopted a self-report questionnaire to measure AI utilization, perceived academic performance, and academic engagement. While the instrument demonstrated excellent internal reliability (Cronbach's $\alpha = 0.941$), the single measurement source may be subject to common method bias. In addition, the study's outcome measures are

perception-based. The construct of perceived academic performance reflects students' subjective evaluation of learning improvements rather than measurable outcomes such as CGPA or examination scores. Furthermore, the sampling frame was geographically restricted to Oyo State in Southwestern Nigeria, with only one university representing each institutional type (federal, state, and private). Although the stratified sampling ensured equal representation across the institutional categories within the sample, the design does not fully capture the diversity of Nigeria's higher education system, which may vary considerably across geopolitical zones in terms of funding structures, infrastructure availability, and institutional policies.

Recommendations and Future Direction

To maximize the potential of AI/PL and mitigate structural inequities, immediate reform is necessary, focusing on policy, infrastructure, and pedagogy. The National Universities Commission (NUC) should enforce mandatory, auditable ICT infrastructure standards, prioritizing consistent digital access in all universities to ensure the personalized learning feedback loop functions reliably. Concurrently, strong ethical AI governance frameworks must be implemented across the sector, emphasizing data protection, transparency, and the promotion of localized AI models to build and sustain student trust. In addition, university management and faculty should institute mandatory, comprehensive training programs focused on ethical AI literacy (Adedokun, 2024; Adedokun, Adeyemo, Adedokun, et al., 2026; Eneye et al., 2025) and shift pedagogical practice toward transformative curriculum design, utilizing AI for complex analysis, adaptive testing, and critical thinking development, rather than simple task substitution (O. T. Sanusi et al., 2024).

Acknowledging that while the study's sample was stratified across institution types, it is confined to Oyo State, therefore, to enhance generalizability, future studies should employ larger, nationally representative samples across Nigeria's geopolitical zones, utilizing longitudinal designs to track actual academic metrics, such as CGPA, and real-time learning analytics from AI platforms. Future research should therefore employ larger, multi-institutional samples across multiple geopolitical zones, adopt temporal separation of measurement, incorporate objective academic performance metrics, and utilize multi-method data collection approaches, including institutional records and AI platform analytics, to enhance the robustness and generalizability of the findings. Future research should also focus on longitudinal studies that measure the transferability of AI-acquired skills across different academic disciplines, assess the direct causal impact of infrastructure reliability on student self-efficacy, as theorized by Social Cognitive Theory, and employ qualitative methods to explore students' experiences with institutional data governance practices.

Conflict of Interest

We declare no conflicting interests.

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Appendices

Appendix I: Cronbach's Alpha Reliability Analysis of the Instrument

		N	%
Cases	Valid	20	100.0
	Excluded ^a	0	.0
	Total	20	100.0
Reliability Statistics			
Cronbach's Alpha		N of Items	
0.941		20	
Scale Statistics			
Mean	Variance	Std. Deviation	
84.25	165.776	12.875	

Appendix II: AIPLQ Questionnaire

QUESTIONNAIRE

Artificial Intelligence and Personalized Learning Questionnaire (AIPLQ)

Dear Participant,

Thank you for agreeing to participate in this research study. This questionnaire is designed to gather information on the impact of artificial intelligence on personalized learning among undergraduates in universities in Oyo State. The purpose of this study is to explore how the use of AI tools influences students' learning experiences, academic performance, and engagement. Your honest and thoughtful responses will provide valuable data that can help improve educational practices and inform future policy decisions. All your responses will be treated with the utmost confidentiality and will be used strictly for academic purposes. Please respond to all questions as honestly as possible!

Section A: Demographic Information

Please provide the following information.

- 1. **Name of Institution:** ☐ University of Ibadan
☐ Ladoke Akintola University of Technology, Ogbomosho
☐ Ajayi Crowther University, Oyo
- 2. **Gender:** ☐ Male ☐ Female
- 3. **Age:** _____
- 4. **Level of Study:** ☐ 100 Level ☐ 200 Level ☐ 300 Level ☐ 400 Level ☐ 500 Level ☐ 600 Level
- 5. **Faculty:** (e.g., Education, Arts, Science, Engineering): _____
- 6. **Course of Study** (e.g., Mass Communication, Computer Science, Law): _____

Section B: Awareness and Utilization of AI for Personalized Learning

Please tick the box that best describes your level of awareness and use of the following AI tools for your academic work.

Part 1: Awareness (Awareness of AI for Personalized Learning)

Note: Not Aware at All [1]; Slightly Aware [2]; Somewhat Aware [3]; Moderately Aware [4]; Highly Aware [5]

S/N	Statement	1	2	3	4	5
1.	I am aware of AI-powered intelligent tutoring systems (e.g., platforms that offer real-time help with math or science problems).					
2.	I am aware of AI-powered content creation tools (e.g., ChatGPT, Gemini, Meta AI, DeepSeek, or other language models).					
3.	I am aware of AI tools for research and content summarization (e.g., tools that summarize academic papers).					
4.	I am aware of AI-driven platforms that recommend personalized learning paths based on my progress.					

Part 2: Utilization (Utilization of AI for Personalized Learning)

Note: Never Used [1]; Rarely Used [2]; Occasionally Used [3]; Often Used [4]; Frequently Used [5]

S/N	Statement	1	2	3	4	5
5.	I use AI-powered intelligent tutoring systems for academic support.					
6.	I use AI-powered content creation tools (e.g., ChatGPT, Gemini, Meta AI, Grok, DeepSeek, etc.) to generate ideas, learn new things, and/or draft assignments.					
7.	I use AI tools for research and content summarization for my assignments and academic papers.					
8.	I use platforms that use AI to recommend personalized learning resources for me.					

Section C: Impact of AI on Personalized Learning and Academic Outcomes

Please tick the box that best reflects your agreement with each statement regarding the impact of AI on your learning.

Part 1: Academic Performance (Impact on Academic Performance)

Note: Strongly Disagree [1]; Disagree [2]; Neutral [3]; Agree [4]; Strongly Agree [5]

S/N	Statement	1	2	3	4	5
9.	The use of AI tools has helped me to better understand complex academic concepts.					
10.	Using AI for personalized learning has led to an improvement in my grades.					
11.	AI-powered learning tools help me complete my assignments more accurately.					
12.	The instant feedback from AI tools helps me correct mistakes and learn more effectively.					
13.	AI tools help me to find relevant academic information more quickly, which improves my study efficiency.					
14.	My overall academic performance has improved since I started using AI tools for learning.					

Part 2: Academic Engagement (Impact on Academic Engagement)

Note: Strongly Disagree [1]; Disagree [2]; Neutral [3]; Agree [4]; Strongly Agree [5]

S/N	Statement	1	2	3	4	5
15.	AI-powered learning makes me more motivated to study.					
16.	I feel more actively involved in my learning when I use AI tools.					
17.	I am more interested in my course subjects because of the interactive nature of AI tools.					
18.	AI tools help to keep me engaged and focused during long study sessions.					
19.	Using AI for personalized learning has increased my confidence in my academic abilities.					
20.	AI tools help me take ownership of my learning process.					