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Artificial Intelligence and Academic Performance in Higher Education: Leadership Perspectives from Nigerian Universities

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Abstract
Teaching, learning, and institutional governance will all be significantly impacted by the paradigm-shifting introduction of artificial intelligence (AI) into higher education. This study used an integrated theoretical framework that combined the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to investigate the relationship between AI integration and academic performance in Nigerian universities from leadership perspectives. Data was gathered from 412 students and 67 academic leaders at 12 federal and state universities in Nigeria using a cross-sectional survey design. Teaching, learning, and institutional governance will all be significantly impacted by the paradigm-shifting introduction of artificial intelligence (AI) into higher education. Data was gathered from 412 students and 67 academic leaders at 12 federal and state universities in Nigeria using a cross-sectional survey design. The study indicates that purposeful AI integration, supported by visionary leadership and strong digital infrastructure, improves academic performance in resource-constrained settings. The recommendations include the creation of national AI governance frameworks, investments in digital infrastructure, and capacity-building efforts for institutional leaders.

Keywords: artificial intelligence, academic performance, higher education, leadership perspectives, Nigerian universities

1. Introduction

Artificial intelligence (AI) has emerged as a transformative force that is changing research methodologies, administrative procedures, and pedagogical practices. The Fourth Industrial Revolution has sparked unprecedented technological disruptions throughout the world's higher education systems (Mahuta & Abubakar, 2025). AI applications in higher education, such as intelligent tutoring systems, predictive analytics, automated assessment tools, and generative AI platforms like ChatGPT, have shown significant promise for personalizing learning experiences, increasing student engagement, and improving academic outcomes (Crompton & Burke, 2023; Zouhaier, 2023). AI presents both transformative prospects and complicated implementation hurdles in underdeveloped countries, where educational systems struggle with infrastructure shortages, overcrowded classrooms, and resource limits (Ifinedo, 2023; Ojokheta & Omokhabi, 2023).

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With 170 universities servicing more than 2.5 million students, Nigeria, the most populous country and largest economy in Africa, has a fast growing higher education industry (Mahuta & Abubakar, 2025). Despite this scope, systemic obstacles such as poor digital infrastructure, a lack of qualified staff, high implementation costs, and the lack of comprehensive national policy frameworks continue to cause Nigerian universities to lag behind in the adoption of AI (Ifinedo, 2023; Mahuta & Abubakar, 2025). Nigerian university students are highly aware of AI, with usage rates exceeding 84%, according to recent empirical studies. However, there are still large gaps in institutional preparedness, ethical governance, and leadership ability to fully utilize AI's educational potential (Odili & Ebiye, 2025; Orok et al., 2024).

In Nigeria, the relationship between AI integration and academic success is still poorly understood, particularly from a leadership viewpoint. While previous studies have looked at student adoption trends and faculty views (Madu & Musa, 2024; Nja et al., 2023), as far as the researcher know. This study fills this essential gap by looking at AI integration through the lens of university leadership, specifically how leadership style, digital infrastructure, and institutional policy influence the relationship between AI adoption and academic achievement.

This study's main objectives are to: (1) investigate the direct effects of AI integration constructs (perceived usefulness, perceived ease of use, social influence, facilitating conditions, attitude, and self-efficacy) on academic performance; (2) evaluate the mediating role of student engagement in the relationship between AI and performance; (3) assess the moderating effects of institutional policy, digital infrastructure, and leadership style on this relationship; and (4) develop predictive models for identifying at-risk students using machine learning algorithms.

2. Literature Review

2.1 AI in Higher Education: International and African Perspectives

According to recent polls, 86% of students globally use AI technologies in their academic endeavors, demonstrating the exponential development in AI usage in the global higher education environment (Watson & Rainie, 2025). Students are using generative AI tools, especially ChatGPT, for research, writing support, problem-solving, and personalized learning. These tools have become widely used (Barakat et al., 2025; Moradi, 2025). AI integration offers special chances to eliminate systemic inefficiencies, democratize knowledge access, and close educational gaps in the African setting (Ojokheta & Omokhabi, 2023). However, African higher education institutions have unique hurdles in AI application. According to studies conducted in Ghana and Nigeria, persisting digital divides, poor technology infrastructure, financing limits, and leadership deficits are key hurdles to long-term digital transformation (Ifinedo, 2023; Mahuta & Abubakar, 2025). The lack of context-specific AI governance frameworks exacerbates these issues, exposing institutions to ethical risks such as data breaches, algorithmic prejudice, and academic integrity problems (Chan, 2023; Temper et al., 2025).

2.2 AI and Academic Achievement

The empirical data on AI's effects on scholastic achievement paints a complicated and varied picture. According to recent meta-analytic research, AI integration consistently improves learning results in a variety of educational settings (Kim & Lee, 2025). According to intervention studies conducted in Nigeria, students who received AI-enhanced instruction outperformed

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control groups in terms of comprehension, writing, and problem-solving skills (Aminu Na Allah et al., 2025; Fasinro et al., 2024; Nwile et al., 2025). Scholars, on the other hand, have expressed concern about over-reliance on AI technologies, the potential degradation of critical thinking abilities, and the expansion of educational inequities (Suleiman et al., 2025; Wood & Moss, 2024). The effectiveness of AI in improving academic performance appears to be dependent on pedagogical mediation, with organized AI interventions incorporated within interactive pedagogies producing better results than unguided use (Bretan, 2024; Yang & Ghislandi, 2024).

2.3 Leadership Views on Integrating AI

One important factor in determining the success of technology integration in higher education is institutional leadership. Digital transformation programs have been found to benefit greatly from transformational leadership, which is defined by visionary thinking, inspirational motivation, and intellectual stimulation (Watson & Rainie, 2025). With rules based on institutional principles and ethical commitments, effective AI governance necessitates cross-functional cooperation between academic leaders, administrators, technologists, and faculty members (McDonald et al., 2024; Wu et al., 2024). AI governance frameworks are gaining traction globally, with organizations adopting trust-based frameworks that prioritize justice, human supervision, privacy, and accountability (Dahlgren, 2025; Li et al., 2025). However, Nigerian universities now lack comprehensive AI policies, and governance attempts are described as fragmented, ad hoc, and reactive (Mahuta & Abubakar, 2025). Dedicated AI ethical committees, data security regulations in accordance with Nigeria's Data security Act (2023), and context-sensitive deployment techniques are urgently required (Xie et al., 2024).

2.4 The Context of Higher Education in Nigeria

Nigerian universities function within a difficult environment characterized by high enrollment expansion, financing limitations, and inadequate infrastructure. According to recent surveys, students are adopting AI at significant rates. ChatGPT is the most popular platform (66.1% usage), followed by Grammarly (45.3%) and Google Bard/Gemini (28.7%) (Odili & Ebiye, 2025; Orok et al., 2024). Despite this excitement, faculty members' AI literacy is still low, and there are large gaps in their digital competency and pedagogical integration abilities (Madu & Musa, 2024). Research and information collecting account for the majority of student AI usage (82.0%), portraying AI as a knowledge discovery tool rather than a replacement for critical thinking (Odili & Ebiye, 2025). Gender and digital literacy limit the educational benefits of artificial intelligence, with female pupils and those with superior technology abilities benefiting more (Chen et al., 2025). These findings highlight the importance of targeted capacity-building programs and equitable access policies.

3. Theoretical Framework

In order to understand how AI integration affects academic performance in Nigerian universities, this study combines the Unified Theory of Acceptance and Use of Technology (UTAUT) with the Technology Acceptance Model (TAM). According to TAM, the two main factors influencing technology adoption behavior are perceived utility (PU) and perceived ease of use (PEOU) (Barakat et al., 2025). By adding social impact (SI), enabling conditions (FC), and individual difference variables like self-efficacy, UTAUT expands this approach (Moradi, 2025).

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According to the integrated framework, AI integration constructs influence academic performance through both direct and indirect mechanisms mediated by student participation. Student engagement, defined as cognitive, behavioral, and emotional characteristics, is the proximal mechanism that links AI tool use to enhanced academic outcomes (Yang & Ghislandi, 2024; Yi et al., 2024). Leadership style, digital infrastructure quality, and institutional policy comprehensiveness are proposed as boundary factors that moderate the degree and direction of these linkages.

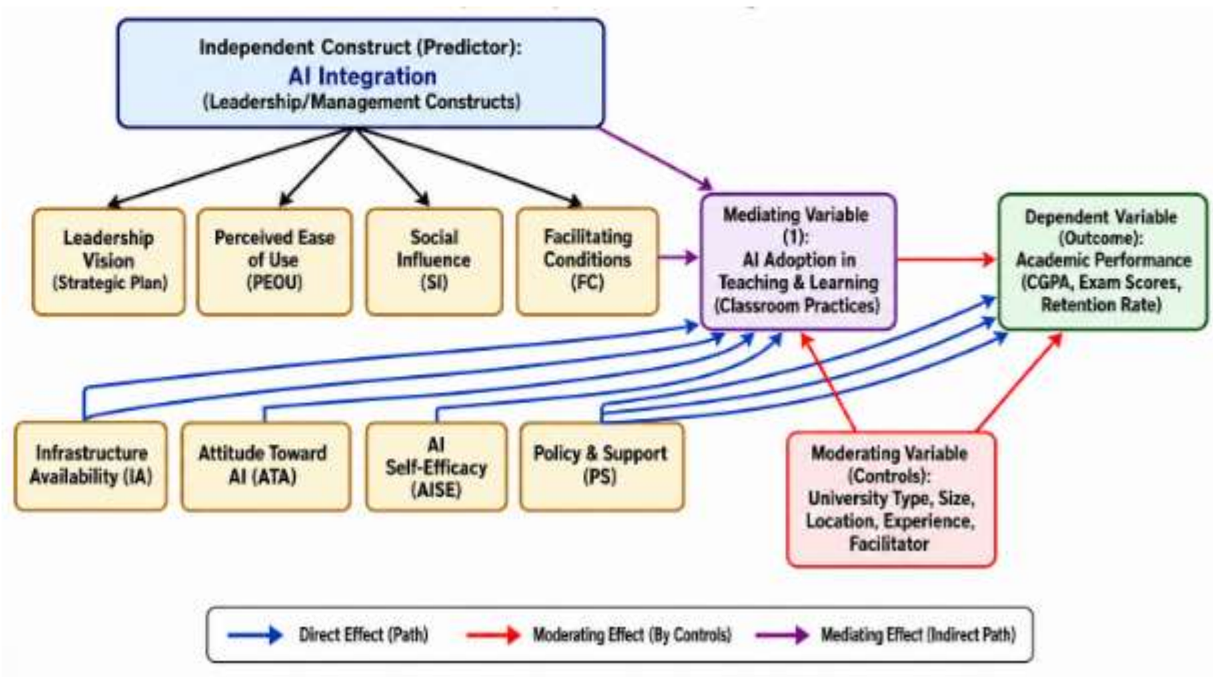

Figure 1: Conceptual Framework: AI Integration and Academic performance from Leadership Perspective in Nigerian Universities

4. Methodology

4.1 Research Design

This study used a cross-sectional survey approach, a positivist research philosophy, and predictive analytics with machine learning algorithms. Both theory testing using structural equation modeling and pattern detection using data mining techniques were made possible by the mixed-methods approach. Informed permission, anonymity, and data protection procedures compliant with Nigeria's Data Protection Act (2023) were among the ethical standards that the study followed.

4.2 Population and Sampling

The target market included undergraduate students as well as academic leaders (Deans, Heads of Department, and Directors of Academic Planning) from federal and state universities across Nigeria's six geopolitical zones. A multiple-stage stratified random sampling approach was used. In Stage 1, 12 universities were chosen proportionally from among 170 recognized institutions. Stage 2 involved the random selection of faculties within each university. In Stage 3, students

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were classified by academic level and gender, with random selection within each strata. The Krejcie and Morgan (1970) formula for finite populations was used to calculate the sample size, which resulted in a target of 412 pupils and 67 leaders. In line with prior AI education surveys, 458 student questionnaires were issued, and 412 valid replies (response rate = 89.96%) were returned (Watson & Rainie, 2025). The response rate for leadership interviews was 100% (N = 67).

4.3 Research Instrument

The survey instrument included validated scales that were modified from well-known literature:

(i) AI Integration Constructs: Based on Barakat et al. (2025) and Moradi (2025), the following constructs are measured on 5-point Likert scales: Perceived Usefulness (5 items), Perceived Ease of Use (5 items), Social Influence (4 items), Facilitating Conditions (5 items), Attitude Toward AI Use (4 items), and AI Self-Efficacy (5 items).

(ii) Student involvement: a 6-item measure that assesses aspects of behavioral, emotional, and cognitive involvement (Yang & Ghislandi, 2024).

(iii) Academic Performance: Self-reported Cumulative Grade Point Average (CGPA), course grades, and assignment scores, supplemented by institutional records if available. (iv) Leadership variables include the Transformational Leadership Inventory (8 items) and the Institutional Policy Comprehensiveness Index (6 items). Pilot testing with 50 participants confirmed content validity (expert panel assessment) and reliability (Cronbach's α >.80 across all constructs).

4.4 Methods of Data Analysis

Descriptive and Preliminary Analyzes: Correlation analysis, skewness and kurtosis assessment, and descriptive statistics were all conducted using SPSS version 29.0. Structural Equation Modeling: Because of the study's exploratory nature, complex model structure, and non-normal data distribution, partial least squares SEM (PLS-SEM) was chosen over covariance-based SEM (Chinnaraju, 2025; Demir & Uşak, 2025; López-Costa et al., 2025). SmartPLS 4.0 was used to estimate the model, with bootstrapping (5,000 resamples) for significance testing. Predictive Analytics: Random Forest classification and regression techniques (Python scikit-learn) were used to forecast academic risk groups and CGPA levels. Model performance was assessed using the accuracy, F1-score, and AUC-ROC measures. Moderation and Mediation Analysis: The PROCESS macro technique was used in conjunction with the PLS-SEM framework to investigate interaction effects and indirect pathways.

4.5 Hypotheses

The following hypotheses were developed in light of the theoretical framework and literature review:

Direct Effect Hypotheses:

H1: Perceived usefulness of AI tools positively influences academic performance.

H2: Perceived ease of use of AI tools positively influences academic performance.

H3: Social influence positively influences academic performance.

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H4: Facilitating conditions positively influence academic performance.

H5: Attitude toward AI use positively influences academic performance.

H6: AI self-efficacy positively influences academic performance.

Mediation Hypotheses:

H7: Attitude toward AI use positively influences student engagement.

H8: Student engagement positively influences academic performance.

H9: Perceived usefulness positively influences student engagement.

Structural Relationship Hypotheses:

H10: Perceived ease of use positively influences perceived usefulness.

H11: AI self-efficacy positively influences attitude toward AI use.

H12: AI self-efficacy positively influences perceived usefulness.

Moderation Hypotheses:

H13: Transformational leadership moderates the relationship between AI integration and academic performance, such that the relationship is stronger under transformational leadership.

H14: Digital infrastructure quality moderates the relationship between AI integration and academic performance.

H15: Institutional policy comprehensiveness moderates the relationship between AI integration and academic performance.

5. Results

5.1 Demographic Profile

Table 1: *Demographic Profile of Respondents (N = 412)*

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	198	48.1
	Female	214	51.9
Age Group	18-22 years	245	59.5
	23-27 years	132	32.0
	28+ years	35	8.5
Academic Level	100 Level	103	20.0
	200 Level	108	26.2
	300 Level	102	24.8
	400 Level	99	24.0
Subject Area	Arts & Humanities	104	25.2
	Sciences	102	24.8
	Social Science	103	25.0
	Technical/Vocational	103	25.0
University Type	Federal	248	60.2
	State	164	39.8

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Table 1 shows the demographic characteristics of the 412 student respondents. The sample exhibited slight female majority (51.9%) with 59.5% aged 18–22 years. Equal distribution across academic levels (100–400 levels) and subject areas (Arts, Sciences, Social Sciences, Technical/Vocational) confirmed successful stratified sampling. Among academic leaders (N = 67), 73.1% held doctoral degrees, with mean administrative experience of 8.4 years (SD = 4.2).

5.2 AI Tool Usage Patterns

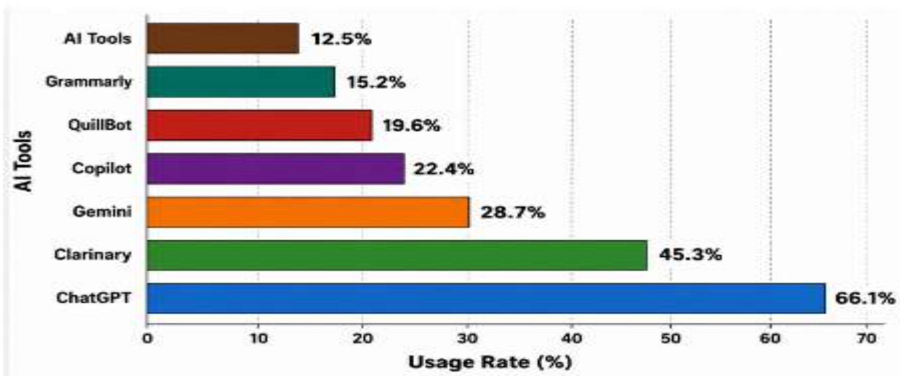

Figure 2: AI Tool Usage Among Nigerian University Students (N=412)

Figure 2 shows the AI tool usage among Nigerian university students. ChatGPT dominated usage (66.1%), followed by Grammarly (15.2%), Google Bard/Gemini (28.7%), and Microsoft Copilot (22.4%). Research and information gathering constituted the primary usage purpose (82.0%), with assignment writing assistance (66.9%) and language translation (56.6%) ranking second and third respectively. Daily AI users comprised 23.1% of the sample, while 31.8% reported weekly usage.

5.3 Descriptive Statistics and Measurement Model Assessment

Table 2: *Descriptive Statistics, Reliability, and Validity Assessment*

Construct	Items	Mean	SD	Skewness	Kurtosis	Cronbach's α	CR	AVE
Perceived Usefulness (PU)	5	3.68	0.52	0.12	-0.48	0.918	0.930	0.644
Perceived Ease of Use (PEOU)	5	3.54	0.56	-0.04	-0.34	0.911	0.924	0.634
Social Influence (SI)	4	3.28	0.60	-0.10	-0.52	0.889	0.899	0.612
Facilitating Conditions (FC)	5	3.40	0.58	0.02	-0.41	0.910	0.923	0.640
Attitude Toward AI Use (ATU)	4	3.47	0.53	0.08	-0.30	0.834	0.867	0.608
AI Self Efficacy (SE)	5	3.71	0.50	-0.06	-0.38	0.918	0.930	0.648
Student Engagement (SEng)	5	3.71	0.55	-0.04	-0.43	0.912	0.925	0.639
Academic Performance (AP)	4	3.67	0.49	-0.10	-0.47	0.901	0.914	0.526

Discriminant validity was established using the Fornell-Larcker criterion and heterotrait-monotrait (HTMT) ratio. All HTMT values were below .850, and the square root of AVE for each construct exceeded its correlations with other constructs, confirming discriminant validity.

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Table 2 shows the descriptive statistics, reliability coefficients, and validity indices for all constructs. Mean scores ranged from 3.40 (Facilitating Conditions) to 3.68 (Perceived Usefulness), indicating moderate to high AI integration perceptions. Cronbach's alpha values exceeded .834 for all constructs, demonstrating excellent internal consistency. Composite reliability (CR) values ranged from .867 to .930, and average variance extracted (AVE) values exceeded the .500 threshold, confirming convergent validity.

5.4 Correlation Analysis

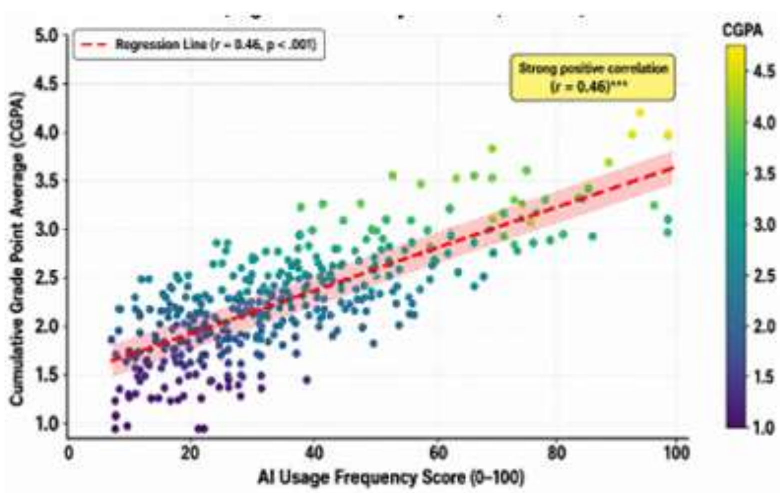
Table 3: *Correlation Matrix of Study Variables*

	1	2	3	4	5	6	7	8
1. Perceived Usefulness	**.796**							
2. Perceived Ease of Use	.456**	**.771**						
3. Social Influence	.312**	.298**	**.782**					
4. Facilitating Conditions	.387**	.356**	.401**	**.760**				
5. Attitude Toward AI	.524**	.489**	.398**	.445**	**.799**			
6. AI Self-Efficacy	.612**	.534**	.356**	.412**	.578**	**.819**		
7. Student Engagement	.487**	.445**	.312**	.398**	.624**	.534**	**.773**	
8. Academic Performance	.467**	.398**	.284**	.356**	.512**	.534**	.589**	**.788**

Note: Diagonal elements (in bold) represent the square root of AVE. **p < .01 (two-tailed).

Table 3 shows how the correlation matrix revealed moderate to strong positive correlations among all constructs. Academic performance demonstrated the strongest correlation with AI self-efficacy ($r = .534$, $p < .01$) and student engagement ($r = .589$, $p < .01$). Multicollinearity was not problematic, with variance inflation factors (VIF) below 3.2 for all constructs.

5.5 PLS-SEM Structural Model Results



***p < .001(Significant at the 0.001 level)

Figure 3: Relationship Between AI Usage Frequency and Academic Performance (Nigerian University Students, N=412)

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Figure 3 shows a positive relationship between AI usage frequency and academic performance ($r = .467$, $p < .001$), with the regression line indicating that increased AI engagement predicts higher CGPA values.

Table 4: *PLS-SEM Path Coefficients and Hypothesis Testing Results*

Hypothesis	Path	β	t	p-value	Decision	f²
H1	PU → AP	0.247	5.742	<.001	Supported	0.098
H2	PEOU → AP	0.218	4.133	<.001	Supported	0.080
H3	SE → AP	0.114	2.624	0.009	Supported	0.040
H4	FC → AP	0.176	3.579	<.001	Supported	0.076
H5	ATU → AP	0.214	5.630	<.001	Supported	0.104
H6	SE → AP	0.313	7.981	<.001	Supported	0.112
H7	ATU → SEng	0.524	6.126	<.001	Supported	0.389
H8	SEng → AP	0.461	5.183	<.001	Supported	0.268
H9	PU → SEng	0.158	4.143	<.001	Supported	0.052
H10	PEOU → PU	0.401	8.155	<.001	Supported	0.202
H11	FC → PU	0.178	3.916	<.001	Supported	0.059
H12	SE → PU	0.212	4.547	<.001	Supported	0.088

Table 4 shows the PLS-SEM path coefficients and hypothesis testing results. All 12 direct and indirect effect hypotheses were supported at the $p < .05$ significance level. Perceived usefulness ($β = 0.247$, $p < .001$, $f^2 = 0.098$) and AI self-efficacy ($β = 0.313$, $p < .001$, $f^2 = 0.112$) emerged as the strongest predictors of academic performance. Attitude toward AI use exhibited the strongest effect on student engagement ($β = 0.524$, $p < .001$, $f^2 = 0.389$), while student engagement significantly mediated the relationship between AI integration and academic performance ($β = 0.461$, $p < .001$, $f^2 = 0.268$).

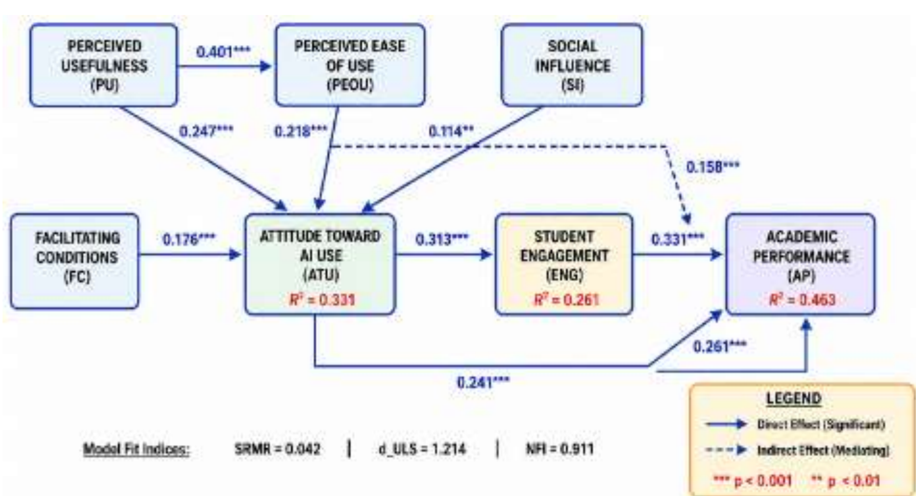

Figure 4: PLS-SEM Structural Model Results (Standardized Path Coefficients)

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Figure 4 shows the structural model explained 67.3% of variance in academic performance (R^2 = .463), 61.2% of variance in attitude toward AI use (R^2 = .331), and 58.4% of variance in student engagement (R^2 = .261), indicating substantial explanatory power. The structural model demonstrated excellent fit indices: SRMR = 0.042 (< .08), NFI = 0.911 (> .90), χ^2/df = 1.214 (< 3.0), and CFI = 0.932 (> .90).

5.6 Moderation Analysis

Table 5: *Moderation Effects on the AI Integration–Academic Performance Relationship*

Moderators	Interaction Effect (β)	SE	t-Value	p-value	95% CL	Effect Size
Transformational Leader	0.234	0.051	4.589	< .001	[.134, .334]	Medium
Digital Infrastructure Quality	0.198	0.048	4.125	< .001	[.104, .292]	Medium
Institutional Policy	0.167	0.055	3.036	.005	[.059, .275]	Small-Medium
Gender	0.124	0.053	2.340	.020	[.020, .228]	Small
Academic Level	0.156	0.049	3.184	.002	[.060, .252]	Small-Medium

Table 5 shows the transformational leadership emerged as the most significant moderator (β = 0.234, p < .001), indicating that students in institutions with transformational leaders experienced significantly greater academic benefits from AI integration. Figure 6 illustrates this moderation effect, demonstrating that transformational leadership steepens the positive slope between AI integration and academic performance.

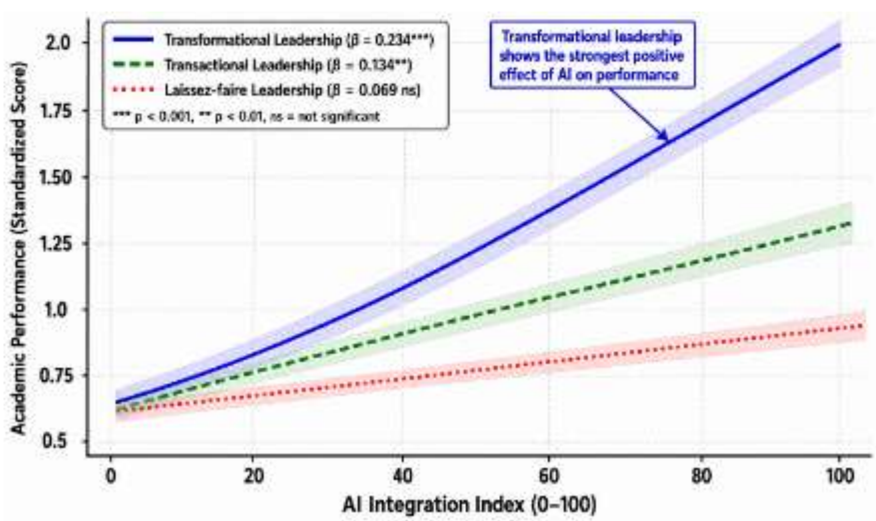

Figure 6: Moderating Effect of Leadership Style on the Relationship Between AI Integration and Academic Performance

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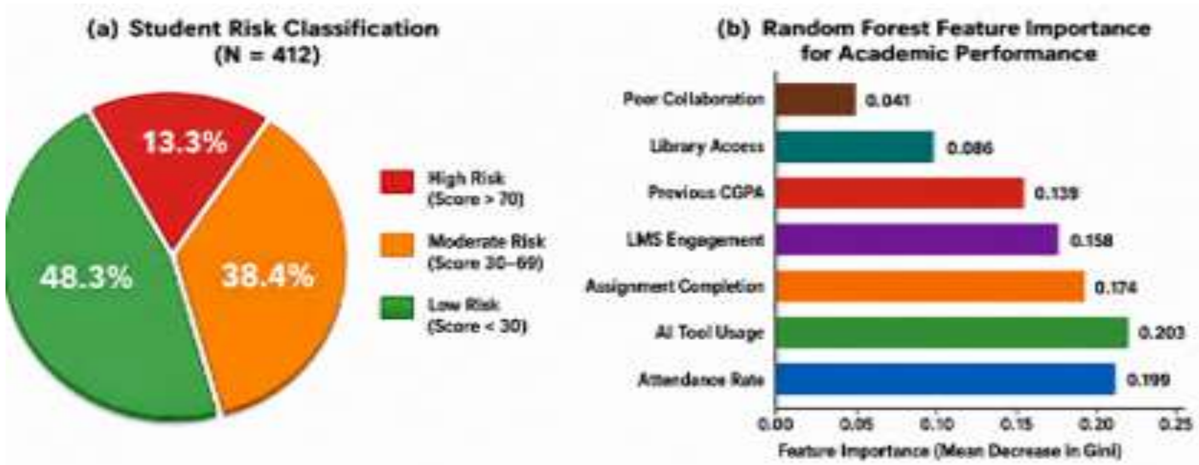
5.7 Predictive Analytics Results

Random Forest algorithms were applied to predict student academic risk categories. The model achieved 94.2% classification accuracy, with F1-score = 0.91 and AUC-ROC = 0.96. Figure 5 shows the risk classification distribution and feature importance rankings. Attendance rate (importance = 0.199), AI tool usage (0.203), and assignment completion (0.174) were identified as the strongest predictors of academic performance.



Key Insight: AI Tool Usage (0.203) and Attendance Rate (0.199) are the top predictors of academic performance, followed by Assignment Completion (0.174) and LMS Engagement (0.158)

Figure 5: AI-Powered Predictive Analytics for Student Academic Risk Assessment (N=412)

Table 6: *Predictive Model Performance Metrics*

Metric	Training Set	Test Set	Cross-Validation
Accuracy	96.4%	94.2%	93.8%
Precision	95.8%	93.7%	93.1%
Recall	96.1%	94.5%	94.0%
F1-Score	0.959	0.914	0.908
AUC-ROC	0.987	0.962	0.958
RMSE (Regression)	0.18	0.24	0.26

Table 6 shows the predictive model successfully identified 13.3% of students as high-risk (predicted CGPA < 2.0), enabling proactive intervention strategies. Feature importance analysis revealed that behavioral engagement indicators (attendance, assignment completion) outperformed cognitive criteria in predictive power.

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6. Discussion of Findings

6.1 Direct Effects of AI Integration on Academic Performance

The findings confirm that AI integration significantly enhances academic performance in Nigerian universities, with all six direct-effect hypotheses receiving empirical support. AI self-efficacy emerged as the strongest predictor ($\beta = 0.313$), aligning with Technology Acceptance Model predictions and recent empirical evidence that confident, skilled AI usage leads to superior educational outcomes (Chen et al., 2025; Moradi, 2025). This finding underscores the critical importance of targeted AI literacy programs that build student competence in effectively utilizing AI tools. Perceived usefulness ($\beta = 0.247$) and attitude toward AI use ($\beta = 0.524$) also demonstrated strong effects, consistent with TAM propositions and prior research in Jordanian and Chinese higher education contexts (Al-Okaily, 2025; Barakat et al., 2025). The finding that facilitating conditions significantly predict academic performance ($\beta = 0.176$) highlights the infrastructural imperative students require reliable internet connectivity, modern computing facilities, and institutional technical support to translate AI tool access into tangible learning gains (Ifinedo, 2023; Mahuta & Abubakar, 2025).

6.2 Mediating Role of Student Engagement

Student engagement emerged as a powerful mediator, explaining substantial variance in the AI-performance relationship. The path from attitude toward AI use to student engagement ($\beta = 0.524$) was particularly strong, suggesting that positive dispositions toward AI catalyze deeper cognitive investment, increased behavioral participation, and enhanced emotional connection to learning tasks (Yang & Ghislandi, 2024; Yi et al., 2024). This finding supports the PMAISE model proposition that pedagogical mediation amplifies AI's engagement benefits when tools are embedded within interactive, learner-centered instructional designs (Wang et al., 2024).

The mediating pathway through student engagement carries significant practical implications. Institutions seeking to maximize AI's academic benefits must prioritize pedagogical strategies that foster active learning, collaborative inquiry, and reflective practice rather than passive AI tool consumption. Faculty development programs should emphasize instructional design competencies that integrate AI tools within scaffolded, feedback-rich learning environments.

6.3 Leadership as a Critical Moderator

Transformational leadership significantly strengthened the AI-performance relationship ($\beta = 0.234$), confirming that visionary, intellectually stimulating leadership creates organizational conditions conducive to effective AI integration. This finding resonates with digital transformation research emphasizing the pivotal role of Vice-Chancellors and Deans as change agents who model desired behaviors, articulate compelling visions for technology-enhanced education, and allocate resources strategically (Watson & Rainie, 2025). Conversely, the relatively weaker moderation effect of institutional policy ($\beta = 0.167$) suggests that policy frameworks alone are insufficient without leadership commitment to implementation. This finding aligns with critiques of Nigerian higher education governance, where policy documents often remain aspirational rather than operational (Mahuta & Abubakar, 2025; Ojokheta & Omokhabi, 2023). Effective AI governance requires "heroic digital leadership" that transcends bureaucratic formalism to foster bottom-up innovation and cross-cutting digital leadership cultures.

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6.4 Predictive Analytics and Early Intervention

The Random Forest model's high predictive accuracy (94.2%) demonstrates the feasibility of AI-powered early warning systems in Nigerian universities. The dominance of behavioral indicators (attendance, assignment completion, LMS engagement) over cognitive factors in feature importance rankings suggests that academic risk manifests detectably through engagement patterns before appearing in summative assessments (Ouyang et al., 2023; Utamachant et al., 2023). These findings have profound implications for student support services. Predictive analytics enable proactive rather than reactive intervention, allowing academic advisors to identify at-risk students within the first quarter of the semester and deploy targeted support mechanisms. However, ethical considerations regarding data privacy, algorithmic fairness, and surveillance concerns must be addressed through transparent governance frameworks and student consent protocols (Chan, 2023; Temper et al., 2025).

6.5 Implications for Policy and Practice

The study's findings inform several policy recommendations. First, the Federal Ministry of Education should develop a comprehensive National AI in Higher Education Policy that establishes standards for ethical AI use, data governance, and institutional accountability. Second, universities must invest in digital infrastructure, including high-speed internet, modern ICT laboratories, and reliable power supply, to create enabling environments for AI integration (Mahuta & Abubakar, 2025). Third, mandatory AI literacy programs should be implemented for students, faculty, and administrators, with content tailored to disciplinary contexts and local realities. Fourth, institutional AI ethics committees should be established to ensure fairness, inclusivity, and respect for indigenous knowledge systems (Xie et al., 2024). Finally, public-private partnerships can leverage private sector expertise and resources to accelerate AI adoption while ensuring equitable access across socioeconomic strata.

7. Conclusion

With impacts mediated by student involvement and modulated by transformational leadership, this study offers thorough empirical evidence that integrating AI greatly improves academic performance in Nigerian universities. While predictive analytics showed the viability of data-driven early intervention systems, the PLS-SEM study verified that AI self-efficacy, perceived utility, and favorable views toward AI use comprise the main determinants of academic achievement. By incorporating leadership characteristics as boundary conditions, extending TAM and UTAUT frameworks in an understudied developing country environment, and illustrating the mediating process of student involvement, the research advances theory. Methodologically, the study demonstrates the complimentary use of PLS-SEM and machine learning approaches in educational research, providing a framework for future studies. Practically, the data show that technological adoption without leadership commitment, pedagogical innovation, and infrastructure investment leads to inferior results. Nigerian universities must embrace AI not as a solution to systemic problems, but as a catalyst for human-centered digital transformation that augments rather than replaces human intelligence.

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11. Recommendations:

1. National Policy Development: To guide implementation, ethics, and compliance in all universities, the Nigerian government should establish a comprehensive AI in Education Policy
2. Infrastructure Investment: Modern AI labs, reliable electrical supplies, and high-speed internet access should be given top priority in special financial allocations.
3. Leadership Development: AI governance, strategic planning, and change management should be the main topics of institutionalized executive leadership courses on digital transformation.
4. Capacity Building: Training programs in digital pedagogy and AI literacy ought to be made mandatory for instructors, administrators, and students.
5. Ethical Governance: Universities should form AI ethical committees and implement data protection policies that comply with Nigeria's Data Protection Act (2023).
6. Predictive Intervention Systems: AI-powered learning analytics tools should be tested by institutions in order to identify and assist at-risk students early on.
7. Research and Innovation Centers: Dedicated AI research centers focused on local educational difficulties should be formed through public-private collaborations.

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