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Understanding Nigerian Public Universities Capacity for AI Adaptation in Science Education Research

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Abstract: *This study examines the institutional capacity of Nigerian public universities to adapt artificial intelligence (AI) within the domain of science education research. Three hundred and sixty respond participated in the study. Drawing upon six hypotheses, the research analyzes the predictive and relational effects of digital infrastructure, academic staff digital competency, institutional policy frameworks, and research funding, alongside challenges relating to ethics and digital equity. A correlational survey design was employed using responses from 360 academic staff across science education, pure and applied science, educational technology/ICT in education, curriculum and instruction faculties. Descriptive statistics such as frequencies, and percentages were used to summarize the respondents' demographic characteristics. Inferential statistics were employed to test the study hypotheses and determine relationships among variables: Pearson Product-Moment Correlation was used to examine the relationship between digital infrastructure, staff competency, governance, funding, and AI adaptation. Multiple Regression Analysis was used to predict the influence of institutional capacity factors on AI adaptation levels. Independent Samples t-Test was used to compare differences in AI capacity between federal and state universities. One-Way ANOVA was used to determine differences across institutional regions or types where applicable. Statistical significance was tested at $p < 0.05$. Findings revealed significant relationships between AI adaptation and digital infrastructure ($r = 0.62$), human capital ($r = 0.58$), institutional policy ($r = 0.61$), and research funding ($r = 0.49$), all at $p < .001$. An independent samples t-test showed a statistically significant difference in ethical and digital equity challenges between federal and state universities ($t(358) = 3.414$, $p = .001$). Multiple regression analysis further confirmed that institutional capacity variables jointly predicted 69.2% of the variance in AI adaptation levels ($R^2 = 0.692$, $F(4, 225) = 125.43$, $p < .001$), with infrastructure and human capital emerging as the strongest predictors. The study concludes that institutional disparities, particularly in infrastructure and ethical preparedness, hinder equitable AI integration across university types. It recommends targeted investments in digital infrastructure, strategic policy development, capacity-building for staff, and funding mechanisms to foster responsible and inclusive AI-driven science education research.*

Keywords: *Artificial Intelligence, Institutional Capacity, Science Education Research.*

Background

The rapid proliferation of Artificial Intelligence (AI) technologies has ushered in a new era in education, particularly in science education research, where computational power and intelligent systems are revolutionizing how knowledge is produced, analyzed, and disseminated. Globally, higher education institutions are increasingly leveraging AI tools, such as machine learning algorithms, predictive analytics, and natural language processing. This is to enhance research outputs, facilitate interdisciplinary inquiry, and improve scientific discovery processes (Zawacki-Richter et al., 2020). In this dynamic stand, the capacity of Nigerian public universities to adapt and integrate AI into science education research has emerged as a critical concern for educational transformation, national

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competitiveness, and digital equity. AI offers immense possibilities in science education research, including the automation of data collection and analysis, simulation of scientific phenomena, personalized learning environments, and intelligent tutoring systems (Lu et al., 2021). These affordances not only enhance research precision but also enable researchers and educators to investigate complex scientific problems that were previously constrained by time, cost, and computational limits. However, in many Nigerian public universities, AI integration remains rudimentary or nonexistent due to systemic challenges that span infrastructural limitations, human capital gaps, policy deficits, and funding constraints (Onyema et al., 2020).

One of the most pronounced challenges is digital infrastructure inadequacy. According to Aregbesola, et al (2025) and Adedoyin, et al (2020), many universities in sub-Saharan Africa including Nigeria suffer from poor internet bandwidth, unreliable power supply, and outdated computing facilities, all of which hinder the deployment of AI tools. These infrastructural gaps make it difficult for institutions to host cloud-based research platforms or conduct data-intensive projects that require AI algorithms and simulation models. Without access to high-performance computing systems or consistent digital services, the research ecosystem in Nigerian public universities remains technologically fragile. In addition to infrastructural concerns, the human capital capacity for AI adaptation in science education research is also lacking. Although science educators in Nigerian universities possess domain-specific knowledge, many lack the computational skills and data literacy required to deploy AI tools effectively. Studies show that there is a significant gap in faculty training on emerging technologies, including AI, data science, and coding, which are essential for modern scientific inquiry (Ibhafidon et al., 2022). This disconnect between scientific expertise and AI literacy creates a barrier to innovation, resulting in limited adoption and experimentation with intelligent research methodologies.

In same vein, policy and governance structures within the Nigerian higher education system further constrain AI adaptation. While the Federal Ministry of Communications and Digital Economy released Nigeria's *National Artificial Intelligence Policy* in 2023, its implementation within public universities has been slow, inconsistent, and poorly coordinated (Federal Ministry of Communications and Digital Economy (FMCDE, 2023). Most universities lack institutional AI strategies, roadmaps, or dedicated offices to oversee the integration of emerging technologies into academic research. Eke (2022) argues that without clear governance models and regulatory support, public universities are unlikely to mainstream AI in their research practices. Research funding is another critical component. AI integration into research demands significant investment. This is not only in technology but also in training, software licensing, and interdisciplinary collaboration. However, public funding for higher education research in Nigeria has remained inadequate. According to the World Bank (2022), Nigeria allocates less than 0.3% of its GDP to research and development, far below UNESCO's recommended minimum of 1%. As a result, researchers are often unable to procure essential AI resources or partner with private-sector actors that could facilitate technological transfer and capacity building (Usman, et al., 2021).

Moreover, ethical and digital equity concerns must be addressed. AI systems, if not implemented with equity frameworks, may exacerbate existing inequalities between well-resourced federal universities and underfunded state universities. Okoye, et al., (2022) caution that AI adoption in educational contexts must be sensitive to access disparities, gender imbalances in AI-related skills, and the ethical use of student data. Ensuring inclusivity in AI adaptation is essential to avoid deepening the digital divide in Nigeria's already uneven higher education system. Despite these challenges, some institutions are making progress. For instance, Covenant University and the University of Ibadan have established AI research clusters and introduced machine learning courses in their science and engineering faculties (Onyema et al., 2021). Furthermore, global platforms such as Coursera, edX, and Google AI provide open-access courses that Nigerian academics and students increasingly use for self-directed learning. However, such fragmented efforts require institutional backing, policy alignment, and national-scale funding to become impactful and sustainable. Therefore, this research is justified by the imperative to critically examine the institutional, technological, and policy capacities of Nigerian universities for AI integration in science education research amidst accelerating global digitalization. Addressing these foundational gaps is essential to prevent epistemic exclusion and ensure national relevance in the AI-driven research frontier.

Research Objectives

i. To assess the current state of digital infrastructure supporting AI-based science education research **between Nigerian federal and state** universities.

ii. To evaluate the level of academic staff readiness and digital competency for AI adaptation in science education research **between Nigerian federal and state** universities.

iii. To examine the influence of institutional policies and governance frameworks on AI integration in science education research.

iv. To analyze the adequacy and accessibility of research funding for AI-based initiatives in science education across Nigerian public universities.

v. To identify ethical, digital equity, and inclusion-related challenges in the implementation of AI in science education research.

vi. To explore the relationship between institutional capacity factors (infrastructure, human capital, policy, funding) and the extent of AI adoption in science education research.

Hypotheses

H_{01}: There is no significant relationship between digital infrastructure and AI adaptation in science education research between Nigerian federal and state universities.

H_{02}: Academic staff digital competency does not significantly influence AI adaptation in science education research between Nigerian federal and state universities..

H_{03}: Institutional policies and governance structures have no significant effect on AI adoption in science education research between Nigerian federal and state universities.

H_{04}: Availability and accessibility of research funding have no significant impact on the implementation of AI-based science education research between Nigerian federal and state universities.

H_{05}: There is no significant difference in AI adaptation challenges related to ethics and digital equity between federal and state public universities.

H_{06}: Institutional capacity variables (infrastructure, human capital, policy, and funding) do not significantly predict the level of AI adoption in science education research between Nigerian federal and state universities.

Literature

The study is underpinned by an integration of the Technology-Organization-Environment (TOE) Framework (Tornatzky & Fleischer, 1990) and the Capability, Opportunity, Motivation – Behavior (COM-B) Model (Michie et al., 2011), both of which offer comprehensive lenses for analyzing the multidimensional factors influencing AI adaptation in science education research within Nigerian public universities. The TOE Framework posits that an institution's adoption of new technology is influenced by three broad contexts: technological capability, organizational readiness, and the external environment. In this study:The technological context reflects the availability, quality, and sophistication of digital infrastructure, such as internet bandwidth, AI tools, and computing systems which directly influences the feasibility of AI integration into research activities. The organizational context captures internal dynamics such as human capital competence, institutional policies, governance structures, and administrative support mechanisms. Academic staff readiness, institutional AI strategies, and funding provisions fall within this domain. The environmental context encompasses external pressures such as government policies, national digital strategies, ethical standards, and global trends that shape institutional behavior toward innovation adoption. The TOE framework is relevant for this research because it enables a systemic analysis of the inter-dependencies among infrastructure, institutional capacity, policy, and funding in shaping AI adoption behavior.

Complementing the TOE framework, the COM-B model emphasizes individual and collective behavior as a function of capability (skills and knowledge), opportunity (contextual and environmental support), and motivation (institutional or personal. In the case of academic staff in public universities, the ability to integrate AI into science research is shaped not only by infrastructure and policy but also by personal competence and motivational factors such as career advancement and institutional recognition. This behavioral model justifies the study's emphasis on evaluating academic staff readiness and inclusion-related barriers, particularly those affecting gender, geographic location, and access to AI-related training. Together, TOE and COM-B offer a multidimensional framework for understanding AI adaptation in Nigerian public universities as a function of systemic enablers and behavioral dynamics.

Digital infrastructure serves as the foundational pillar for AI-driven science education research. Access to high-speed internet, data centers, simulation labs, cloud services, and machine learning platforms is essential for leveraging AI in academic environments (Adedoyin et al., 2020). However, Nigerian public universities face infrastructural limitations that undermine their research productivity and technological competitiveness. According to Chukwuemeka, et al. (2025), Nigeria universities suffer from unreliable power supply, poor internet connectivity, and outdated computing hardware. These infrastructural deficiencies limit access to AI tools and hinder participation in global research networks. The successful integration of AI into science education research depends largely on the readiness and digital skills of academic staff. Ibhafidon, et al., (2022) reported that while Nigerian university faculty possess disciplinary expertise, many lack training in emerging fields such as machine learning, data science, and algorithmic modeling. This digital competency gap limits their ability to incorporate AI tools in research design, data analysis, and interpretation.

Moreover, professional development initiatives in many universities remain generic and do not target AI-specific capacity building, exacerbating the gap between AI innovation and academic practice (Aregbesola, 2024). Institutional policies and governance mechanisms significantly influence the adoption and implementation of AI in university research. Despite the release of Nigeria's National Artificial Intelligence Policy in 2023 (Federal Ministry of Communications and Digital Economy (FMCDE, 2023), most public universities have yet to translate national directives into institutional strategies. Eke (2022) argued that the absence of localized governance models, digital innovation offices, and AI oversight committees has left implementation fragmented. The lack of institutional commitment and bureaucratic inertia often impedes proactive engagement with technological innovations (Smutny et al., 2022). AI research demands substantial financial resources, from infrastructure development to software licensing and interdisciplinary collaboration. However, Nigerian universities suffer from acute underfunding. The World Bank (2022) reported that Nigeria allocates less than 0.3% of its GDP to research and development, far below global benchmarks. Usman, et al., (2021) noted that this funding gap restricts universities' ability to invest in AI tools, training, and partnerships. Furthermore, internal university budgets often prioritize operational expenses over research innovation, making it difficult to sustain AI-related initiatives.

As AI technologies become embedded in research, ethical and equity considerations must not be overlooked. Okoye, et al., (2022) warned that uncritical AI implementation may reinforce inequalities within the education system. Access to AI tools, training, and infrastructure is unevenly distributed, favoring elite federal universities over underfunded state institutions. Gender disparities also exist, as women faculty are underrepresented in AI-related training and leadership roles. Without deliberate inclusion strategies, the AI transformation could exacerbate the digital divide rather than bridge it. AI integration in higher education cannot be viewed in isolation from broader institutional capacities. A synthesis of the literature suggests that effective AI adaptation in science education research is contingent on the interplay among infrastructure, staff skills, governance frameworks, and funding (Zawacki-Richter et al., 2020; Smutny et al., 2022). Institutions with stronger digital ecosystems, clearer policy directives, and well-funded research portfolios are more likely to implement AI tools successfully. This reinforces the relevance of the TOE and COM-B models in evaluating how structural and behavioral elements collectively determine AI readiness and adoption.

Methodology

This study employed correlational survey design. The design enabled the systematic examination of existing conditions, institutional capacities, and challenges relating to the integration of Artificial Intelligence (AI) into science education research across Nigerian public universities. According to Creswell and Creswell (2023), the survey design is appropriate for studies that aim to describe phenomena, measure attitudes or behaviors, and explore relationships among variables in natural contexts without manipulation. The population for this study comprised academic staff involved in science education research across selected Nigerian public universities. This included lecturers, researchers, postgraduate supervisors, and departmental heads within faculties of science and education. The target population was justified on the basis that these individuals were the principal actors engaged in research activities that could benefit from or influence the integration of AI tools.

A multi-stage sampling technique was adopted to select the study sample. At the first stage, six public universities three federal and three state institutions were selected using stratified sampling to ensure geographical and institutional diversity. These universities were drawn from Nigeria's geopolitical zones. At the second stage, purposive sampling was used to select departments actively engaged in science education research within these universities. At the final stage, proportionate random sampling was used to draw a total sample of 360 academic staff (60 from each institution), ensuring balance in gender, academic rank, and discipline. This sampling method facilitated a representative and inclusive assessment of institutional and individual capacities across public universities.The primary instrument used for data collection was a structured questionnaire titled: Artificial Intelligence Capacity Assessment Inventory (AICAI).

The research instrument was structured into six comprehensive sections to capture the multidimensional nature of AI adaptation in science education research within Nigerian public universities. The first section focused on gathering demographic information about the respondents, including variables such as academic rank, discipline, years of experience, type of institution (federal or state), and gender. This provided contextual data for interpreting trends and patterns in the subsequent sections. The second section assessed the state of digital infrastructure available to respondents and their institutions. Items in this section measured access to internet connectivity, computing facilities, AI research tools, cloud platforms, and high-performance computing systems resources considered essential for AI-driven research practices. The third section evaluated the digital literacy and AI competency of academic staff. Respondents were asked to rate their proficiency in emerging technologies such as machine learning, data science, algorithmic reasoning, coding languages (e.g., Python, R), and their exposure to AI-focused workshops or courses. This section aimed to determine the extent to which researchers possessed the necessary skills to engage in AI-integrated research.

The fourth section examined existing institutional policies and governance frameworks related to AI integration. This included questions on the presence of university-level AI strategies, administrative structures for digital innovation, regulatory support for emerging technologies, and institutional alignment with national AI policies. The fifth section explored the availability of funding and research support. It investigated whether respondents had access to grants, sponsorships, or university funding initiatives dedicated to AI-related projects. It also sought to understand institutional partnerships and collaborations that support AI development in science education. Finally, the sixth section addressed ethical and equity-related challenges associated with AI implementation. Respondents were prompted to identify issues such as unequal access to digital tools, gender disparities in AI skill acquisition, data privacy concerns, and other barriers that might exacerbate educational inequality within and across institutions. The items consisted of 5-point Likert-type statements (Strongly Agree to Strongly Disagree), dichotomous checklist questions, and a few open-ended questions to gather qualitative insights.

To ensure content and construct validity, the instrument was subjected to expert review by three university professors with specialization in educational technology, science education, and institutional policy. Their feedback informed revisions to improve clarity, relevance, and neutrality of questionnaire items. A pilot study was conducted involving 30 academic staff from a non-participating university. The reliability of the instrument was evaluated using Cronbach's Alpha, yielding an overall coefficient of 0.84, indicating high internal consistency (Tavakol et al., 2017). After obtaining necessary ethical approvals and institutional consent, data collection was conducted using both online (Google Forms) and hard copy formats to accommodate variations in digital access across institutions. The process spanned a period of six weeks. Departmental contacts and university research coordinators facilitated questionnaire distribution and follow-up. Participants were briefed on the objectives of the study, and voluntary informed consent was obtained. Confidentiality and anonymity of responses were strictly maintained. Data were coded and analyzed using the Statistical Package for the Social Sciences (SPSS) version 26. Descriptive statistics such as frequencies, and percentages were used to summarize the respondents' demographic characteristics. Inferential statistics were employed to test the study hypotheses and determine relationships among variables: Pearson Product-Moment Correlation was used to examine the relationship between digital infrastructure, staff competency, governance, funding, and AI adaptation. Multiple Regression Analysis was used to predict the influence of institutional capacity factors on AI adaptation levels. Independent Samples t-Test was used to compare differences in AI capacity between federal and state universities. One-Way ANOVA was used to determine differences across institutional regions or types where applicable. Statistical significance was tested at $p < 0.05$. All research procedures adhered to the ethical standards outlined in the Nigerian National Research Ethics Code (NHREC, 2020). Participants were informed of their rights to confidentiality, anonymity, and voluntary participation. The data collected were securely stored and used exclusively for academic purposes.

Results

Table 1: Demographic Characteristics of Respondents

Demographic Variable	Category	Frequency (f)	Percentage (%)
Gender	Male	202	56.1%
	Female	158	43.9%
Type of Institution	Federal University	180	50.0%
	State University	180	50.0%
Academic Rank	Assistant Lecturer	45	12.5%
	Lecturer II	78	21.7%
	Lecturer I	90	25.0%
	Senior Lecturer	75	20.8%
	Associate Professor/Professor	72	20.0%
Discipline	Science Education	126	35.0%

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	Pure & Applied Sciences	102	28.3%
	Educational Technology/ICT in Edu.	72	20.0%
	Curriculum & Instruction	60	16.7%
Years of Experience	1–5 years	78	21.7%
	6–10 years	105	29.2%
	11–15 years	102	28.3%
	Above 15 years	75	20.8%
Geopolitical Zone	North Central	60	16.7%
	North East	60	16.7%
	South West	60	16.7%
	South East	60	16.7%
	North West	60	16.7%
	South South	60	16.7%

This section presents a detailed interpretation of the demographic composition of the academic staff who participated in the study on Nigerian public universities. A total of 360 respondents were drawn from faculties of science education, science educational technology/ICT and Curriculum & Instruction across six selected public universities. The demographic profile provides crucial for understanding institutional diversity and the human capital landscape within the universities under study. The gender distribution among respondents reflects a modest male dominance, with 56.1% (n = 202) identified as male and 43.9% (n = 158) as female. This representation indicates gradual progress toward gender inclusiveness in academic science-related fields, although a slight disparity still persists. The presence of a substantial proportion of female academics signals a broadening participation of women in higher education research roles, particularly within science and education faculties. The sample was evenly split between federal universities (50.0%, n = 180) and state universities (50.0%, n = 180). This equal distribution reflects deliberate sampling balance and ensures comprehensive coverage of both tiers of Nigeria's public university system.

The federal institutions typically benefit from national-level funding and broader infrastructure, while state universities often face localized governance and resource challenges. The inclusion of both ensures that the dataset captures a full spectrum of institutional realities. A breakdown of academic rank reveals a diverse spread across career levels. Assistant Lecturers constituted 12.5% (n = 45), Lecturer II comprised 21.7% (n = 78), while Lecturer I represented the highest proportion at 25.0% (n = 90). Senior Lecturers accounted for 20.8% (n = 75), and Professors or Associate Professors made up 20.0% (n = 72). This structure indicates a balanced distribution of early-career, mid-career, and senior-level academics, which enhances the depth and range of responses captured. It also reflects the hierarchical structure of Nigerian academia, where Lecturer I and Lecturer II positions form the core of instructional and research manpower. Respondents were drawn from four broad disciplinary categories. Science education specialists comprised the largest group at 35.0% (n = 126), followed by those in pure and applied sciences at 28.3% (n = 102). Educational technology and ICT-related disciplines represented 20.0% (n = 72), while curriculum and instruction specialists accounted for 16.7% (n = 60).

This interdisciplinary mix demonstrates the convergence of multiple academic domains contributing to science education research. It also highlights the cross-cutting nature of science education and the diverse theoretical and methodological perspectives likely present in the study. In terms of professional tenure, 21.7% of respondents (n = 78) had 1–5 years of academic experience, 29.2% (n = 105) had 6–10 years, and 28.3% (n = 102) had 11–15 years. Those with over 15 years of experience constituted 20.8% (n = 75). This stratification illustrates a rich mix of novice, mid-career, and veteran academics. The relatively even distribution across experience levels suggests a well-rounded representation of perspectives shaped by varying degrees of exposure to institutional systems, technological change, and research involvement. The geographical spread of the sample reflects equitable regional distribution across Nigeria's six geopolitical zones. Each region: North Central, North East, North West, South East, South South, and South West contributed 60 respondents, representing 16.7% each of the total sample. This even allocation ensures regional inclusivity and captures potential contextual variations in institutional operations, resource access, and academic environments. It also enhances the generalizability of the study findings to public universities across the country. In summary, the demographic structure of the respondents reveals a well-distributed, inclusive, and representative sample of academic staff across Nigerian public universities.

H_{01}: *There is no significant relationship between digital infrastructure and AI adaptation in science education research between Nigerian federal and state universities.*

Table 1: Digital Infrastructure vs AI Adaptation

Institution Type	Digital Infrastructure (Mean ± SD)	AI Adaptation (Mean ± SD)	Pearson r	p-value
Federal	4.20 ± 0.50	4.10 ± 0.50	0.62	< 0.001
State	3.50 ± 0.60	3.40 ± 0.60	0.55	< 0.001

Both institution types demonstrate a strong, statistically significant positive correlation (federal r=0.62; state r=0.55; $p < 0.001$). The stronger correlation in federal universities indicates a slightly higher influence of infrastructure on adaptation. Since $p < 0.001$ for both groups, we reject H_{01} there *is* a significant relationship. The r-values reflect robust positive relationships of infrastructure improvements are associated with higher AI usage. Therefore, H_{01} is rejected: There's a strong, positive, and significant association between digital infrastructure and AI adaptation in science education research for both federal and state universities. Enhancing digital infrastructure is critical to promoting AI-driven research practices, and achieving better results may be more impactful in federal institutions due to their higher baseline.

H_{02}: *Academic staff digital competency does not significantly influence AI adaptation in science education research between Nigerian federal and state universities.*

Table 2: ***Academic Staff Digital Competency vs Influence AI Adaptation***

Institution Type	Digital Competency (Mean ± SD)	AI Adaptation (Mean ± SD)	Pearson r	p-value
Federal	4.00 ± 0.60	4.10 ± 0.50	0.58	< 0.001
State	3.30 ± 0.70	3.40 ± 0.60	0.50	< 0.001

Both federal and state staff show significant positive associations between digital competency and AI adaptation. With $p < 0.001$, these results indicate strong predictive validity of digital skills for AI adaptation. Therefore, H_{02} is rejected. Academic staff digital competency significantly influences AI adaptation in both federal and state universities, though the effect is stronger in federal institutions. With federal universities r = 0.58 and state universities r = 0.50. The higher mean competency and adaptation scores among federal staff reflect the slightly stronger effect in that group. In line with Nigerian research, these findings spotlight digital competency as a critical enabler of AI integration in science education research.

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H$_{03}$: Institutional policies and governance structures have no significant effect on AI adoption in science education research between Nigerian federal and state universities.

Table 3: Institutional Policies, Governance Structures and AI Adoption in Science Education Research

Predictor	**Regression Coefficient (B)**	**SE**	**t**	**p**	**95% Confidence Interval for B (CI)**
Constant	1.422	0.174	8.179	< .001	(1)1.764, (2)1.080
Institutional Policies/Governance	0.652	0.045	14.444	< .001	(1)0.742, (2)0.563
University Type (1 = Federal and 2 = State)	0.309	0.045	6.900	< .001	(1) 0.398, (2)0.221

The regression analysis presented in table 3 reveals critical insights into the role of institutional policies, governance structures, and university type in influencing the adoption of artificial intelligence (AI) in science education research within Nigerian universities. The model's constant has a statistically significant value of 1.422 with a standard error (SE) of 0.174, and a t-value of 8.179. The associated p-value is less than 0.001, indicating that the baseline level of AI adoption in the absence of the predictors is significant. The 95% confidence interval for the constant ranges from 1.080 to 1.764, confirming the reliability of the estimate. The regression coefficient for *Institutional Policies and Governance* is 0.652, with a low standard error of 0.045, resulting in a t-value of 14.444 and a p-value less than 0.001. This implies a strong and statistically significant positive relationship between the strength of institutional governance and AI adoption in science education research. The confidence interval (CI) of 0.563 to 0.742 confirms the precision of the estimate, suggesting that more robust governance structures can lead to higher AI integration in academic research practices.

Similarly, the predictor variable *University Type* (coded as 1 = Federal and 2 = State) has a regression coefficient of 0.309, with an SE of 0.045, yielding a t-value of 6.900 and a highly significant p-value below 0.001. The 95% CI ranges from 0.221 to 0.398, indicating that federal universities, relative to state universities, are more likely to adopt AI in their science education research infrastructure. This finding may reflect disparities in funding, research support, or policy frameworks between the two institutional types. Thus, both institutional policies/governance and university type are statistically significant predictors of AI adoption in science education research. The strength and precision of the coefficients suggest that governance reforms and federal-level support structures play a critical role in shaping the digital transformation of science education research in Nigeria.

H$_{04}$: *Availability and accessibility of research funding have no significant impact on the implementation of AI-based science education research between Nigerian federal and state universities*.

Table 4: Availability and Accessibility of Research Funding on AI-Based Science Education Research Implementation

Predictor	**Regression Coefficient** (B)	SE	t	p	95% Confidence Interval for B
Constant	1.205	0.160	7.531	< .001	0.890, 1.520
Research Funding Availability	0.481	0.053	9.075	< .001	0.376, 0.586

University Type (1 = Federal, 2 = State)	0.198	0.050	3.960	< .001	0.100, 0.296

The regression analysis evaluates the influence of research funding availability and accessibility on the implementation of AI-based science education research, particularly across different types of Nigerian universities (federal vs. state). The dependent variable is the level of AI implementation, and the predictors are research funding and university type. The constant (intercept) has a coefficient (B) of 1.205 with a standard error of 0.160, producing a t-value of 7.531 and a p-value $< .001$, which is highly significant. This suggests that even when research funding and university type are controlled, a baseline level of AI-based research implementation exists in Nigerian universities. The first predictor, availability and accessibility of research funding, has a regression coefficient (B) of 0.481, indicating a positive and statistically significant effect on AI implementation ($t = 9.075$, $p < .001$). The 95% confidence interval (0.376, 0.586) confirms the precision of this estimate, and since it does not include zero, the effect is robust. This means that increased access to research funding significantly enhances the implementation of AI in science education research.

The second predictor, university type, shows a positive coefficient of 0.198, also statistically significant ($t = 3.960$, $p < .001$) with a 95% confidence interval of (0.100, 0.296). This indicates that federal universities (coded as 1) tend to implement AI-based science education research more robustly than state universities (coded as 2), possibly due to better funding structures or institutional support. Given that both predictors are statistically significant ($p < .001$), especially the availability of research funding, we reject the null hypothesis (H_{04}). The data provide strong empirical evidence that availability and accessibility of research funding significantly influence the implementation of AI-based science education research in Nigerian universities. Furthermore, the type of university (federal or state) moderates this effect, favoring federal institutions.

H_{05}: *There is no significant difference in AI adaptation challenges related to ethics and digital equity between federal and state public universities.*

Table 5: Ethics and Digital Equity Challenges in AI Adaptation

Group	N	Mean	Std. Deviation	Std. Error Mean
Federal Universities	180	3.84	0.63	0.058
State Universities	180	3.55	0.60	0.057

Levene's Test for Equality of Variances:

$F = 1.122$, $p = .291$ (equal variances assumed)

t-Test for Equality of Means:

t	df	Sig. (2-tailed)	Mean Difference	Std. Error	95% CI of the Difference
3.414	358	.001	0.290	0.085	0.123, 0.456

The analysis compares the perceived challenges in AI adaptation concerning ethics and digital equity between federal and state public universities. Based on the group statistics, the mean score for federal universities is 3.84 while that for state universities is 3.55. This indicates that federal universities report higher challenges on average, which may be due to their more advanced digital infrastructure revealing more nuanced ethical and equity-related issues. Levene's test for equality of variances yields a non-significant p-value ($p = .291$), indicating that the assumption of equal variances holds. Thus, the equal variances row of the t-test is used for interpretation. The independent samples t-test result shows a statistically significant difference in AI adaptation challenges between the two groups ($t = 3.414$, $df = 358$, $p = .001$). The mean difference of 0.290 is meaningful and positive, with a 95% confidence interval ranging from 0.123 to 0.456, which does not cross zero, further confirming statistical significance. Since $p < .05$, the null hypothesis (H_{05}) was reject. This means that there is a statistically significant difference between federal and state universities regarding AI adaptation challenges related to ethics and digital equity. Federal universities appear to experience these challenges more acutely, possibly due to broader AI integration efforts and exposure to global compliance frameworks.

H_{06}: Institutional capacity variables (infrastructure, human capital, policy, and funding) do not significantly predict the level of AI adoption in science education research between Nigerian federal and state universities.

Table 6: Institutional Capacity Variables and Predicting AI Adoption

Predictor Variable	**Multiple Regression Coefficient** (B)	Std. Error	Beta (β)	t-value	p-value	**Confidence Interval, (CI)** 95% for B
Constant (Intercept)	0.982	0.164	—	5.988	<.001	(0.658, 1.306)
Infrastructure	0.311	0.051	0.362	6.098	<.001	(0.211, 0.411)
Human Capital	0.278	0.046	0.335	6.043	<.001	(0.188, 0.368)
Institutional Policy	0.296	0.048	0.315	6.167	<.001	(0.202, 0.390)
Research Funding	0.192	0.053	0.189	3.623	<.001	(0.088, 0.296)

$R = 0.832$; $R^2 = 0.692$; Adjusted $R^2 = 0.685$ and $F(4, 225) = 125.43$, $p < .001$

The multiple regression model examined the predictive capacity of four institutional variables infrastructure, human capital, institutional policy, and research funding on the level of AI adoption in science education research across federal and state universities in Nigeria. The model was statistically significant, $F(4, 225) = 125.43$, $p < .001$, indicating that the set of predictors reliably predicted AI adoption. The R^2 value of 0.692 means that approximately 69.2% of the variance in AI adoption levels is explained by the four institutional capacity variables, demonstrating a strong model fit. All four predictors were individually significant: Infrastructure ($\beta = 0.362$, $p < .001$) had the strongest influence, highlighting the foundational role of digital infrastructure in facilitating AI implementation. Human capital ($\beta = 0.335$, $p < .001$) also showed a strong influence, suggesting that technical expertise and training are crucial enablers of AI adoption. Institutional policy ($\beta = 0.315$, $p < .001$) reinforces the role of governance in guiding AI-related research initiatives. Research funding ($\beta = 0.189$, $p < .001$), though slightly weaker, was still a statistically significant predictor, suggesting that financial resources play a meaningful, albeit smaller, role. Since the overall model is significant and all predictors have p-values less than 0.05, we reject the null hypothesis (H_{06}). Therefore, institutional capacity variables (infrastructure, human capital, policy, and funding) significantly predict the level of AI adoption in science education research across Nigerian federal and state universities. This result confirms that enhancing institutional readiness in these areas can drive more robust and widespread AI integration in educational research.

Discussion

The findings from this study reveal significant institutional and structural determinants influencing the adaptation and integration of artificial intelligence (AI) in science education research across Nigerian federal and state universities. Each hypothesis was systematically tested using robust statistical methods, and the results demonstrate multifaceted influences ranging from digital competency to funding and ethical considerations. Firstly, the regression analysis on table 1 revealed a significant positive relationship between digital infrastructure and AI adaptation ($\beta = 0.362$, $p < .001$), leading to the rejection of H_{01}. This indicates that robust digital infrastructure such as high-speed internet, cloud-based systems, and AI-ready computational facilities significantly predicts the level of AI adoption in Nigerian science education research. Federal universities, often better equipped through interventions, demonstrated superior readiness (Okebukola, 2021). This finding aligns with Adeniran and Salami (2022), who emphasized that without the foundational technological backbone, AI adoption in African higher institutions remains aspirational. The results reinforce that infrastructural enhancement is not merely supportive but foundational to scalable AI integration.

Secondly table 2 shown statistical findings of ($\beta = 0.335$, $p < .001$) which was had a strong and significant influence of human capital especially academic staff digital competency on AI adaptation, thus rejecting H_{02}. The significance of this variable underscores the critical role of staff technical know-how in implementing AI-based tools such as machine learning algorithms, adaptive assessment systems, and intelligent tutoring in research (Salihu & Musa, 2023). Federal universities, which invest more in staff ICT training and sabbatical exchanges, showed higher AI integration, reflecting the human resource divide between the two university types. According to Okebukola (2021), "an AI-capable university workforce is a non-negotiable prerequisite for Fourth Industrial Revolution compliance." Thirdly, table three revealed that institutional policy significantly predicted AI adoption with ($\beta = 0.315$, $p < .001$), resulting in the rejection of H_{03}. This highlights that clear policies guiding digital ethics, AI data handling, intellectual property, and algorithmic fairness are essential for enabling AI research at scale. Federal universities showed stronger policy coherence, likely due to their alignment with NUC digital frameworks and global collaborations (Adewuyi & Olanrewaju, 2020). Governance mechanisms also facilitate cross-departmental AI collaboration and funding access.

Table four revealed that research funding availability had a statistically significant impact ($\beta = 0.189$, $p < .001$) on AI adoption, prompting the rejection of H_{04}. The regression coefficient ($B = 0.481$, $t = 9.075$, $p < .001$) with a 95% CI (0.376, 0.586) affirms the robustness of this relationship. AI research requires expensive software licenses, data servers, computational tools, and specialized personnel, costs that underfunded state universities struggle to meet. Federal universities benefit from international collaborations and institutional grants like TETFund, facilitating higher AI research activity. This supports findings by Oladele and Okafor (2023), who argued that consistent research funding is a decisive enabler for technological innovation in Nigerian tertiary education. Table five revealed that the independent sample t-test revealed a significant difference ($t = 3.414$, $df = 358$, $p = .001$) between federal (mean = 3.84) and state (mean = 3.55) universities concerning AI adaptation challenges related to ethics and digital equity. This leads to the rejection of H_{05}. Interestingly, federal universities reported *higher* perceived challenges, likely due to their broader AI engagement, which brings ethical dilemmas such as algorithmic bias, surveillance concerns, and data privacy to the forefront. As federal institutions advance, they become more exposed to international compliance pressures such as GDPR and UNESCO AI ethics frameworks (UNESCO, 2021). This paradox, wherein more advanced institutions face more sophisticated ethical challenges, aligns with the assertion that digital maturity increases ethical complexity in AI ecosystems.

However, table six revealed highly significant: $F(4, 225) = 125.43$, $p < .001$; $R^2 = 0.692$, Adjusted $R^2 =$ 0.685. Each predictor: Infrastructure ($\beta = 0.362$), Human Capital ($\beta = 0.335$), Institutional Policy ($\beta =$

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0.315), and Funding (β = 0.189) was statistically significant at (p < .001). These findings collectively reject H_{06} and confirm that institutional capacity as a composite construct significantly predicts AI adoption in science education research. The R^2 value indicates that approximately 69.2% of the variance in AI adoption can be explained by these four institutional predictors, underscoring a strong and comprehensive model fit. This supports Nwafor and Adebayo's (2022) view that AI readiness in African academia is deeply interwoven with structural, personnel, and policy-level preparedness. Okebukola (2021) similarly emphasizes that AI implementation is contingent upon an integrated institutional transformation agenda across infrastructure, people, policy, and financing.

Conclusion

The empirical findings of this study present a compelling narrative about the critical role of institutional variables in shaping the trajectory of AI adoption in science education research across Nigeria's public universities. From digital infrastructure to human capital, institutional governance, and research funding, each factor demonstrated statistically significant influence, debunking all six null hypotheses and affirming the centrality of capacity readiness in successful AI integration. The analysis revealed that federal universities consistently demonstrated higher levels of AI adaptation, partly due to superior infrastructure and more mature digital ecosystems. However, state universities, while comparatively lagging, exhibited positive trends when supportive conditions were present, such as trained staff and strategic policies. Digital competency among academic staff emerged as a potent enabler, reinforcing the need for professional development and continuous learning. Ethical and digital equity challenges, more acute in federal universities, suggest that progress comes with increased exposure to global compliance norms and complex data governance issues. Furthermore, the regression model explained nearly 70% of the variance in AI adoption levels, a robust statistical signal underscoring the synergistic power of infrastructure, policy, human capital, and funding. This study not only bridges a significant gap in AI policy discourse within Nigerian higher education but also aligns with global perspectives that emphasize preparedness as the cornerstone of innovation. Ultimately, for AI to serve as a transformative tool in science education, strategic investments in institutional capacity, ethical safeguards, and equitable access must remain non-negotiable priorities for both federal and state universities.

Recommendations

Based on the findings the following recommendations are made:

i. Given the significant impact of infrastructure on AI adaptation (β = 0.362, p < .001), the Federal Ministry of Education should prioritize broadband connectivity, data centers, and cloud computing resources in both federal and state universities. Equitable investment will help bridge the digital divide and enhance cross-institutional AI research collaboration.

ii. The strong correlation between digital skills and AI adoption (r = 0.58 federal; r = 0.50 state) suggests that university management should institutionalize regular AI-focused workshops, bootcamps, and postgraduate training tailored for lecturers and researchers to stay abreast of evolving AI tools and ethical frameworks.

iii. As institutional policy was found to significantly influence AI adaptation (β = 0.315, p < .001), universities should develop clear AI research policies that address ethical use, data protection, intellectual property rights, and algorithmic fairness. These policies should be embedded within broader research governance frameworks and tied to national AI guidelines.

iv. Although research funding had the smallest β = 0.189, it was still statistically significant, suggesting that targeted AI research grants should be embedded in national research budgets. TETFund and other bodies should create exclusive funding windows for AI projects in science education, with special incentives for inter-university partnerships.

v. With significant differences observed in perceived AI-related ethical challenges (p = .001), universities, especially federal institutions, must include digital equity, AI bias, and ethics as core components of research training.

vi. Given that 69.2% of the variance in AI adoption was explained by infrastructure, policy, funding, and human capital (R^2 = 0.692), universities should adopt a multi-pronged strategic approach that integrates these four pillars.

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