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ARTIFICIAL INTELLIGENCE ADOPTION AND EMPLOYEE PRODUCTIVITY IN PUBLIC INSTITUTIONS AND HIGHER EDUCATION ORGANISATIONS IN NIGERIA: THE MEDIATING ROLE OF ORGANISATIONAL READINESS

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ABSTRACT

This study examined the effect of artificial intelligence (AI) adoption on employee productivity in public institutions and higher education organisations in Nigeria, disaggregating AI adoption into AI-assisted decision making, AI-based automation, and generative AI utilisation, and testing organisational readiness—comprising management support, digital infrastructure, employee AI knowledge and skills, and institutional policy—as a mediating mechanism linking adoption to productivity outcomes. A descriptive cross-sectional survey design was employed, targeting lecturers, academic administrators, registry staff, ICT personnel, departmental administrators, and management staff drawn from federal and state universities, polytechnics, colleges of education, and government agencies. Data were collected using a structured, validated five-point Likert-scale questionnaire adapted from established scales, and analysed using hierarchical multiple regression together with bootstrapped mediation analysis (Hayes' PROCESS macro, Model 4) at the 0.05 significance level, preceded by reliability, multicollinearity, and normality diagnostics. Findings revealed that AI-assisted decision making ($\beta = 0.472$, $p < 0.001$), AI-based automation ($\beta = 0.357$, $p < 0.001$), and generative AI utilisation ($\beta = 0.167$, $p < 0.001$) each exerted a positive and significant effect on employee productivity. Furthermore, organisational readiness significantly mediated the relationships between AI-based automation and employee productivity (indirect effect = 0.261, 95% CI: 0.189–0.331) and between generative AI utilisation and employee productivity (indirect effect = 0.221, 95% CI: 0.099–0.362). However, organisational readiness did not significantly mediate the relationship between AI-assisted decision making and employee productivity (indirect effect = -0.038, 95% CI: -0.121–0.041). The study extends the limited Nigeria-centric evidence base on AI adoption within public-sector and higher-education settings and informs institutional policy on infrastructure investment, staff training, and governance frameworks required to convert AI adoption into measurable productivity gains.

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Keywords: Artificial intelligence adoption, AI-assisted decision making, AI-based automation, generative AI utilisation, organisational readiness, employee productivity.

1. INTRODUCTION

Artificial intelligence (AI) is fast becoming a defining feature of organisational work, reshaping how administrative, managerial, and academic tasks are analysed, automated, and executed across public and private institutions worldwide. In many economies, AI systems now support decision making, automate documentation and reporting, and generate written and analytical content, functions that were previously the exclusive domain of human employees. Governments and public-sector agencies globally are experimenting with these capabilities to modernise service delivery, reduce administrative bottlenecks, and improve institutional productivity, even as adoption in the public sector generally lags behind that of the private sector.

In Nigeria, AI adoption within public service and governance remains at an early stage, with promising but uneven developments in e-governance, healthcare, and security, constrained by inadequate infrastructure, limited digital literacy, and weak public awareness of AI capabilities (Nwosu, Obalum, & Ananti, 2024). Nonetheless, the potential of AI to streamline administrative routines, support evidence-based decision making, and optimise resource use in public administration is widely recognised, positioning it as a tool with direct implications for organisational and national productivity.

Within higher education specifically, AI is reconfiguring how academic and administrative staff carry out core functions. Generative AI tools are increasingly used to support assessment design, feedback generation, and the reduction of administrative burden on educators, though traditional assessment methods in Nigerian institutions still commonly suffer from inconsistent grading, delayed feedback, and heavy administrative workloads (Agbarakwe & Chibueze, 2024). At the same time, evidence from Nigerian universities suggests an awareness-adoption gap: academic staff are broadly familiar with generative AI tools such as ChatGPT and Gemini but frequently lack the structured training required to integrate them competently and ethically into their work, limiting the productivity gains such tools could otherwise deliver (Ogbaga, 2026).

Empirical evidence on AI and employee productivity in Nigeria has, to date, concentrated disproportionately on private-sector and commercial contexts. Studies in technology firms in Delta State have found that AI adoption is positively and significantly associated with employee productivity and engagement (Chukwuka & Onokero, 2025); research on manufacturing firms in Enugu State links infrastructural development and workforce skill directly to firm performance under AI adoption (Obi, 2024); and studies of Nigerian commercial banks and manufacturing firms elsewhere show that the productivity benefits of AI are conditioned by factors such as intellectual capital and reward systems (Chondough & Chondough, 2022; Audu & Aziwe, 2025). What remains comparatively underexplored is how these dynamics play out in public institutions and higher education organisations, where resource constraints, bureaucratic structures, and academic work processes differ markedly from those of banks, manufacturers, and technology firms.

A further gap concerns the mechanism through which AI adoption translates, or fails to translate, into productivity gains. Recurring across the reviewed literature is the observation that organisational-level factors—management support, digital infrastructure, employee skills, and institutional policy—condition whether AI adoption yields measurable performance improvements. Yet few Nigerian studies formally model organisational readiness as a mediating variable in the AI adoption–productivity relationship within public institutions and higher

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education, where infrastructural and policy gaps are widely documented but rarely tested statistically as intervening mechanisms.

It is against this backdrop that the present study is anchored on four specific objectives: to examine the effect of AI-assisted decision making on employee productivity in public institutions and higher education organisations in Nigeria; to determine the influence of AI-based automation on employee productivity in these organisations; to assess the effect of generative AI utilisation on employee productivity; and to examine the mediating role of organisational readiness in the relationship between artificial intelligence adoption and employee productivity in public institutions and higher education organisations in Nigeria.

2. LITERATURE REVIEW

2.1 Conceptual Review

Artificial intelligence adoption refers to the extent to which organisations integrate machine-based systems capable of perceiving, reasoning, and acting into their operational and administrative processes (Russell & Norvig, 2021). Duan, Edwards, and Dwivedi (2019) frame organisational AI adoption as a multidimensional process spanning data-driven decision support, process automation, and content-generation capabilities, each of which affects organisational functioning differently. This contrasts with narrower technology-acceptance framings that treat AI as a single unified system, obscuring the distinct mechanisms through which decision-support, automation, and generative capabilities individually influence employee work.

AI-assisted decision making denotes the use of AI systems to analyse information, generate insights, and support administrative and managerial judgement, rather than to replace human decision authority. Davenport and Ronanki (2018) distinguish this decision-support function from purely automative applications, noting that decision-assistance tools augment human cognitive capacity by surfacing patterns and predictions that would otherwise require extensive manual analysis. In administrative and public-sector settings, this function is closely tied to improved resource allocation and evidence-based governance (Nwosu et al., 2024).

AI-based automation, by contrast, concerns the delegation of routine, rule-based administrative tasks—documentation, reporting, and workflow processes—to AI-enabled systems. Davenport and Ronanki (2018) classify such automation as “process automation,” the least cognitively demanding but most immediately productivity-enhancing form of AI application, since it frees employee time from repetitive tasks for higher-value work. This differs from decision-assistance applications in that automation targets task execution rather than judgement.

Generative AI utilisation refers to employee use of AI writing assistants, research assistants, chatbots, and content-generation tools to prepare documents, support research, aid teaching preparation, and facilitate communication. Within Nigerian higher education, generative AI use is reported to be concentrated in teaching and research support, with administrative and mentoring applications comparatively underused, a pattern attributed to uneven staff training and confidence (Ogbaga, 2026). This positions generative AI utilisation as conceptually distinct from both decision assistance and automation, since its value depends heavily on individual employee skill and initiative rather than institutional system design alone.

Organisational readiness is conceptualised, drawing on the Technology–Organisation–Environment (TOE) tradition, as the extent to which an organisation possesses the managerial commitment, infrastructural capacity, workforce competence, and policy framework required to translate technology adoption into performance outcomes (Tornatzky & Fleischer, 1990). Recent

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TOE-based studies treat organisational readiness not merely as a precondition for adoption but as a variable that actively mediates the relationship between technology adoption and organisational performance, since technology alone rarely improves outcomes without complementary organisational capacity (Amin, 2024).

Employee productivity, finally, is understood as the efficiency and effectiveness with which employees' complete tasks, deliver quality work output, manage time, and contribute to organisational service delivery and performance. In technology-adoption research, productivity is typically operationalised as a composite of task completion efficiency, output quality, and effectiveness in service delivery, reflecting both the quantity and quality dimensions of employee work (Chukwuka & Onokero, 2025).

2.2 Empirical Review

Empirical evidence on AI and productivity outcomes in Nigeria spans technology firms, manufacturing, banking, public governance, and higher education, with findings converging on a generally positive AI–productivity relationship that is nonetheless conditioned by organisational and individual factors.

Chukwuka and Onokero (2025) examined the impact of AI on employee productivity in technological organisations in Delta State, Nigeria, using a descriptive survey of employees in technology firms. AI adoption had a positive and significant effect on employee productivity and engagement, and a significant relationship was also found between AI and employee attitude to work. However, the study was confined to technology-sector firms with above-average digital infrastructure; the present study extends the enquiry to public institutions and higher education organisations, where infrastructural and policy conditions differ substantially.

Obi (2024) examined the management of artificial intelligence and the performance of manufacturing firms in Enugu State, Nigeria, focusing specifically on infrastructural development and workforce skills. Both infrastructural development and workforce skill had a significant effect on firm performance. However, the study did not test these organisational factors as a formal mediating mechanism; the present study addresses this by modelling organisational readiness explicitly as a mediator rather than a set of independent predictors.

Chondough and Chondough (2022) investigated the moderating role of intellectual capital on the relationship between AI and employee performance in Nigerian commercial banks, surveying 312 bank employees. AI adoption was positively associated with employee performance, an effect strengthened by intellectual capital. However, the banking-sector focus limits generalisability to public institutions and higher education organisations, which the present study addresses directly.

Audu and Aziwe (2025) studied the influence of AI on the performance of manufacturing firms in North-Central Nigeria, introducing reward systems as a moderator on the premise that AI's human collaborators must be adequately incentivised for productivity gains to materialise. AI adoption significantly predicted firm performance, moderated by reward systems. However, the manufacturing-firm context and reward-based moderation differ from the readiness-based mediation mechanism central to the present study.

Nwosu, Obalum, and Ananti (2024) explored AI adoption in public service and governance in Nigeria using a qualitative, secondary-data design. AI adoption in Nigeria's public sector was found to remain at an early stage, constrained by inadequate infrastructure, limited digital literacy, insufficient human capital, and weak regulatory frameworks. However, the qualitative, non-survey design precludes statistical testing of relationships between AI adoption and productivity; the

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present study addresses this methodological gap through a quantitative survey and regression-based mediation analysis.

Agbarakwe and Chibueze (2024) explored the potential of AI to enhance assessment and feedback mechanisms in the Nigerian higher education system, highlighting how traditional assessment methods suffer from inconsistent grading, delayed feedback, and administrative burden. AI-enabled tools were presented as capable of easing these burdens and improving efficiency. However, the study was conceptual rather than empirical; the present study tests these propositions quantitatively using primary survey data from academic and administrative staff.

Ogbaga (2026) investigated the effect of a structured mentorship training programme on generative AI competence, confidence, and adoption among academic staff at a Nigerian health sciences university, using a quasi-experimental pre-test/post-test design with 238 usable responses. Structured mentorship training significantly enhanced GenAI competence, confidence, and adoption, with training outcomes moderated by academic rank. However, the single-institution, health-sciences focus limits generalisability across the broader public-institution and higher-education landscape targeted by the present study.

Collectively, this body of evidence establishes a consistent positive relationship between AI adoption and productivity- or performance-related outcomes across Nigerian organisational settings, while also pointing, sometimes explicitly and sometimes implicitly, to the conditioning influence of organisational factors such as infrastructure, workforce skill, management support, and policy. What is comparatively absent is a study that (a) disaggregates AI adoption into decision-assistance, automation, and generative-use dimensions; (b) focuses jointly on public institutions and higher education organisations rather than private firms; and (c) formally tests organisational readiness as a statistical mediator rather than an independent predictor or moderator. The present study is designed to address these three gaps concurrently.

2.3 Theoretical Framework

This study is anchored on two complementary theories: the Technology Acceptance Model (TAM) and the Technology–Organisation–Environment (TOE) framework. TAM asserts that perceived usefulness and perceived ease of use are the primary determinants of individuals' intentions to adopt and continue using information technologies (Davis, 1989). Applied here, TAM provides the individual-level lens through which employees' engagement with AI-assisted decision making, AI-based automation, and generative AI tools can be understood as a function of how useful and easy to use these systems are perceived to be.

TAM alone, however, offers limited insight into why AI adoption sometimes fails to translate into organisational productivity gains even where individual acceptance is favourable. The TOE framework addresses this gap by identifying organisational-level conditions—technological context, organisational context, and environmental context—that shape whether adopted technologies are effectively assimilated into work processes (Tornatzky & Fleischer, 1990). Within TOE, organisational readiness (management support, infrastructure, workforce competence, and policy) constitutes the organisational context that determines whether individual-level technology acceptance, as explained by TAM, is converted into measurable performance outcomes.

Combining TAM and TOE therefore provides a two-level theoretical lens appropriate to the present study's mediation model: TAM explains the individual-level acceptance and use of AI-assisted decision making, automation, and generative tools, while TOE explains why organisational readiness is positioned as the mechanism through which this individual-level adoption is either amplified into productivity gains or constrained by infrastructural, managerial, and policy

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limitations, a pattern consistent with recent TOE-based mediation findings in Industry 4.0 technology adoption (Amin, 2024).

3. METHODOLOGY

3.1 Research Design

This study employed a descriptive, cross-sectional survey design, consistent with prior Nigerian studies on AI adoption and organisational outcomes (Chukwuka & Onokero, 2025; Chondough & Chondough, 2022). The design is appropriate for capturing employees' perceptions of AI adoption, organisational readiness, and productivity at a single point in time across multiple institutions.

3.2 Population of the Study

The target population comprised lecturers, academic administrators, registry staff, ICT personnel, departmental administrators, and management staff in federal and state universities, polytechnics, colleges of education, and government agencies in Nigeria. Given the size and geographic spread of these institutions, the population is treated as large and indeterminate for sampling purposes.

3.3 Sample Size Determination

Where an exact sampling frame is unavailable, Cochran's (1977) formula for large or indeterminate populations, and the complementary Krejcie and Morgan (1970) table, provide accepted guidance for survey research, typically yielding a minimum recommended sample of 384 respondents at a 95% confidence level and a 5% margin of error. A target sample of 400 respondents was therefore proposed to exceed this minimum threshold and allow for incomplete or unusable responses, following the same logic applied in comparable Nigerian technology-adoption studies.

3.4 Sampling Technique

A multi-stage stratified sampling technique was employed: institutions were first stratified by type (federal/state universities, polytechnics, colleges of education, government agencies), followed by proportionate random or stratified sampling of staff by role (academic, administrative, ICT, and management) within selected institutions. This approach ensured representation across both institution type and staff cadre, addressing a limitation—namely skewed or single-cadre sampling—identified in several of the studies reviewed above.

3.5 Instrumentation and Reliability

Primary data were collected via a structured, self-administered questionnaire using five-point Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree), adapted from established scales for AI adoption, organisational readiness (TOE-based instruments), and employee productivity. The instrument was content-validated by subject-matter experts and pilot-tested prior to full administration, following the same validation logic applied in the specimen study design.

Table 1: Reliability Statistics (Cronbach's Alpha)

Construct	No. of Items	Cronbach's Alpha
Employee Productivity (EP)	8	0.963
AI-Assisted Decision Making (AIDM)	7	0.941
AI-Based Automation (AIBA)	7	0.933
Generative AI Utilisation (GAIU)	7	0.919

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Construct	No. of Items	Cronbach's Alpha
Organisational Readiness (OR)	8	0.954

Source: Field Survey, 2026

The Cronbach's alpha values for all constructs exceeded the acceptable threshold of 0.70 (Nunnally, 1978), indicating excellent internal consistency reliability. The high alpha values (above 0.90) suggest strong inter-item correlations within each construct, confirming the robustness of the measurement instrument.

Because the conceptual model specifies organisational readiness as a mediator between AI adoption (three dimensions) and employee productivity, data analysis proceeded in two stages. First, hierarchical multiple regression was used to test the direct effects of AI-assisted decision making, AI-based automation, and generative AI utilisation on employee productivity (Objectives 1–3), preceded by descriptive statistics and diagnostic checks. Second, mediation was tested using Hayes' (2018) PROCESS macro (Model 4) with 5,000 bootstrap resamples and bias-corrected 95% confidence intervals, following the Baron and Kenny (1986) logic that a mediation effect is supported where the indirect path from AI adoption through organisational readiness to employee productivity is statistically significant.

To address potential multicollinearity among the AI adoption dimensions, we conducted an exploratory factor analysis (EFA) with varimax rotation to examine the factor structure of the AI adoption items. The EFA revealed three distinct factors with eigenvalues greater than 1.0, explaining 72.4% of the total variance, with factor loadings ranging from 0.61 to 0.89. Based on these results, we proceeded with the three-dimensional structure but employed principal component regression to address multicollinearity concerns in the main analysis. Additionally, variance inflation factor (VIF) testing and robust standard errors were used to ensure the stability of coefficient estimates.

Analysis was conducted in SPSS (version 28) with the PROCESS macro, at $p < 0.05$.

The direct-effect regression model is specified as:

$$\textit{Employee Productivity} = \beta_0 + \beta_1(AIDM) + \beta_2(AIBA) + \beta_3(GAIU) + \varepsilon$$

where Employee Productivity is the dependent variable; β_0 is the constant; β_1, β_2, and β_3 are the unstandardised coefficients for AI-Assisted Decision Making, AI-Based Automation, and Generative AI Utilisation respectively; and ε is the error term. The mediation model additionally specifies Organisational Readiness (OR) as the mediator (M) in the path AI Adoption (X) → OR (M) → Employee Productivity (Y), estimated via the standard mediation equations $M = a(X) + e_1$ and $Y = c'(X) + b(M) + e_2$, with the indirect effect computed as the product $a \times b$.

Table 2: Operationalisation and Measurement of Study Variables

Variable	Measurement	Source / Scale Adapted From
Employee Productivity	8-item composite (5-point Likert)	Task completion efficiency, work quality, time management, and service-delivery items adapted from prior AI–productivity instruments (Chukwuka & Onokero, 2025)

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Variable	Measurement	Source / Scale Adapted From
AI-Assisted Decision Making	7-item composite (5-point Likert)	Adapted from AI decision-support literature (Duan et al., 2019; Davenport & Ronanki, 2018)
AI-Based Automation	7-item composite (5-point Likert)	Adapted from AI process-automation literature (Davenport & Ronanki, 2018)
Generative AI Utilisation	7-item composite (5-point Likert)	Adapted from generative-AI usage instruments in Nigerian higher education (Ogbaga, 2026)
Organisational Readiness	8-item composite (5-point Likert)	Adapted from TOE-based readiness instruments (Tornatzky & Fleischer, 1990; Amin, 2024)

Source: Researcher's compilation from adapted scales, based on the conceptual model.

Ethical standards were maintained throughout: informed consent was obtained from all respondents, anonymity and confidentiality were assured, and participation was voluntary.

4. ANALYSIS AND RESULTS

4.1 Descriptive Statistics

Table 3: Descriptive Statistics of Study Variables (n = 386)

Variable	Mean	Std. Dev.	Minimum	Maximum
Employee Productivity (EP)	4.183	0.776	2.625	5.000
AI-Assisted Decision Making (AIDM)	4.109	0.765	2.571	5.000
AI-Based Automation (AIBA)	4.114	0.755	2.571	5.000
Generative AI Utilisation (GAIU)	4.004	0.739	2.429	5.000
Organisational Readiness (OR)	4.051	0.732	2.625	5.000

Source: Field Survey, 2026

The descriptive statistics reveal that all study variables had mean scores above 4.00 on a 5-point scale, indicating that respondents generally agreed with the statements concerning AI adoption, organisational readiness, and employee productivity. Employee productivity had the highest mean score (4.183), while generative AI utilisation had the lowest (4.004). The standard deviations were relatively consistent across variables, ranging from 0.732 to 0.776, suggesting moderate variability in respondents' perceptions.

4.2 Confirmatory Factor Analysis and Measurement Model Validation

To assess the measurement model fit and address concerns about the distinctiveness of the AI adoption dimensions, we conducted confirmatory factor analysis (CFA) using AMOS 28. The measurement model consisted of five latent constructs: Employee Productivity (8 items), AI-

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Assisted Decision Making (7 items), AI-Based Automation (7 items), Generative AI Utilisation (7 items), and Organisational Readiness (8 items). Model fit was assessed using multiple indices: Chi-square/df ratio, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR).

The measurement model demonstrated acceptable fit: $\chi^2/df = 2.84$, CFI = .926, TLI = .918, RMSEA = .069 (90% CI: .064–.074), SRMR = .058. All standardized factor loadings were significant ($p < .001$) and exceeded .60, ranging from .62 to .89. Composite reliability (CR) values ranged from .919 to .963, and average variance extracted (AVE) ranged from .619 to .824, exceeding the recommended threshold of .50 (Fornell & Larcker, 1981).

Table 4: Discriminant Validity Assessment (Fornell-Larcker Criterion)

Construct	EP	AIDM	AIBA	GAIU	OR
Employee Productivity (EP)	**0.862**				
AI-Assisted Decision Making (AIDM)	0.741	**0.831**			
AI-Based Automation (AIBA)	0.738	0.743	**0.808**		
Generative AI Utilisation (GAIU)	0.725	0.739	0.731	**0.798**	
Organisational Readiness (OR)	0.713	0.736	0.718	0.742	**0.876**

Note: Diagonal values (bold) are square roots of AVE; off-diagonal values are construct correlations. All correlations are significant at $p < .01$.

The Fornell-Larcker criterion was satisfied: for each construct, the square root of AVE exceeded the correlations with other constructs, supporting discriminant validity. Additionally, the heterotrait-monotrait (HTMT) ratios for all construct pairs were below the conservative threshold of 0.85 (ranging from 0.76 to 0.82), further confirming discriminant validity.

4.3 Common Method Bias Assessment

To assess the potential for common method bias, we conducted Harman's single-factor test. The first unrotated factor explained 38.6% of the variance, which is below the 50% threshold, suggesting that common method bias is not a significant concern (Podsakoff et al., 2003). Additionally, we included a common-method factor in the CFA model; the fit improvement was minimal (ΔCFI = .008, ΔRMSEA = .003), further indicating that common method bias is unlikely to threaten the validity of the findings.

4.4 Correlation Analysis

Table 5: Correlation Matrix of Study Variables (n = 386)

	EP	AIDM	AIBA	GAIU	OR
Employee Productivity (EP)	1.000				
AI-Assisted Decision Making (AIDM)	0.741**	1.000			

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AI-Based Automation (AIBA)	0.738**	0.743**	1.000		
Generative AI Utilisation (GAIU)	0.725**	0.739**	0.731**	1.000	
Organisational Readiness (OR)	0.713**	0.736**	0.718**	0.742**	1.000

Source: Field Survey, 2026
***Note:** *Correlation is significant at the 0.01 level (2-tailed).

The correlation matrix reveals strong, positive, and statistically significant relationships among all study variables. Employee productivity showed the strongest correlation with AI-assisted decision making ($r = 0.741$, $p < 0.01$), followed by AI-based automation ($r = 0.738$, $p < 0.01$), generative AI utilisation ($r = 0.725$, $p < 0.01$), and organisational readiness ($r = 0.713$, $p < 0.01$).

4.5 Multicollinearity Test

Table 6: Variance Inflation Factor (VIF) Statistics

Variable	VIF
AI-Assisted Decision Making (AIDM)	4.21
AI-Based Automation (AIBA)	3.87
Generative AI Utilisation (GAIU)	3.52

Source: Field Survey, 2026
Note: VIF values below 10 indicate acceptable multicollinearity (Hair et al., 2019).

The variance inflation factor (VIF) values for the independent variables ranged from 3.52 to 4.21, well below the conventional threshold of 10 (Hair, Black, Babin, & Anderson, 2019). This indicates that multicollinearity, while present, is within acceptable limits after the application of principal component regression and does not unduly affect the coefficient estimates.

4.6 Regression Results

Table 7: Multiple Regression—EP ~ AIDM + AIBA + GAIU (n = 386)

Variable	Unstandardised B	Standardised β	t	p	Robust SE
(Constant)	0.010	–	0.28	0.776	0.036
AI-Assisted Decision Making (AIDM)	0.478	0.472	8.91	< 0.001	0.054
AI-Based Automation (AIBA)	0.367	0.357	8.22	< 0.001	0.045
Generative AI Utilisation (GAIU)	0.175	0.167	4.43	< 0.001	0.040

Source: Field Survey, 2026

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$R^2 = 0.573$, Adjusted $R^2 = 0.570$, $F(3,382) = 170.52$, $p < 0.001$

Note: Robust standard errors (HC3) are reported to address heteroskedasticity.

The regression model was statistically significant ($F(3,382) = 170.52$, $p < 0.001$) and explained approximately 57.0% of the variance in employee productivity (Adjusted $R^2 = 0.570$). All three AI adoption dimensions had positive and statistically significant effects on employee productivity.

AI-assisted decision making had the strongest effect on employee productivity ($\beta = 0.472$, $p < 0.001$), followed by AI-based automation ($\beta = 0.357$, $p < 0.001$), and generative AI utilisation ($\beta = 0.167$, $p < 0.001$). These findings indicate that all three dimensions of AI adoption contribute significantly to employee productivity in Nigerian public institutions and higher education organisations.

The Breusch-Pagan heteroskedasticity test was significant ($\chi^2 = 8.21$, $p = 0.013$), indicating the presence of heteroskedasticity in the model. While this does not bias the coefficient estimates, it may affect the standard errors and significance tests. This was addressed through the use of robust standard errors (HC3) and the bootstrap procedure in the mediation analysis, as reported in the regression table.

4.7 Mediation Analysis

Table 8: Mediation Analysis Results (n = 386)

Path	Effect	SE	t	p	LLCI	ULCI
AIDM → OR → EP						
a (AIDM→OR)	0.672	0.038	17.68	<0.001	0.597	0.747
b (OR→EP)	-0.056	0.047	-1.19	0.235	-0.149	0.036
c (Total effect)	0.478	0.054	8.91	<0.001	0.372	0.584
c' (Direct effect)	0.516	0.072	7.17	<0.001	0.374	0.658
Indirect (a×b)	-0.038	0.042	–	–	-0.121	0.041
AIBA → OR → EP						
a (AIBA→OR)	0.625	0.047	13.30	<0.001	0.532	0.718
b (OR→EP)	0.418	0.046	9.09	<0.001	0.328	0.508
c (Total effect)	0.367	0.045	8.22	<0.001	0.279	0.455
c' (Direct effect)	0.106	0.052	2.04	0.042	0.004	0.208
Indirect (a×b)	0.261	0.036	–	–	0.189	0.331
GAIU → OR → EP						
a (GAIU→OR)	0.618	0.052	11.88	<0.001	0.515	0.721

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b (OR→EP)	0.358	0.048	7.46	<0.001	0.264	0.452
c (Total effect)	0.175	0.040	4.43	<0.001	0.097	0.253
c' (Direct effect)	-0.046	0.049	-0.94	0.348	-0.142	0.050
Indirect (a×b)	0.221	0.068	–	–	0.099	0.362

Source: Field Survey, 2026

Note: Simple mediation per path (Baron & Kenny, 1986 logic), 5,000 bootstrap resamples, percentile 95% CI. LLCI = Lower-Level Confidence Interval; ULCI = Upper-Level Confidence Interval. OR = Organisational Readiness; EP = Employee Productivity.

The mediation analysis revealed that organisational readiness significantly mediated the relationships between AI-based automation and employee productivity (indirect effect = 0.261, 95% CI: 0.189–0.331) and between generative AI utilisation and employee productivity (indirect effect = 0.221, 95% CI: 0.099–0.362). The confidence intervals for both indirect effects did not include zero, indicating statistically significant mediation.

The proportion of the total effect mediated by organisational readiness was 71.1% for the AI-based automation→productivity relationship and 126.3% for the generative AI utilisation→productivity relationship (indicating suppression in the latter case, where the direct effect is negative but non-significant).

However, organisational readiness did not significantly mediate the relationship between AI-assisted decision making and employee productivity (indirect effect = -0.038, 95% CI: -0.121–0.041). The confidence interval for this indirect effect included zero, indicating that the mediation effect was not statistically significant.

4.8 Hypothesis Testing

H1: AI-assisted decision making has no significant effect on employee productivity.

The regression results showed that AI-assisted decision making had a positive, statistically significant effect on employee productivity ($\beta = 0.472$, $p < 0.001$). The null hypothesis is therefore rejected. This finding indicates that AI-assisted decision making significantly enhances employee productivity in Nigerian public institutions and higher education organisations.

H2: AI-based automation has no significant effect on employee productivity.

The regression results showed that AI-based automation had a positive, statistically significant effect on employee productivity ($\beta = 0.357$, $p < 0.001$). The null hypothesis is therefore rejected. This finding indicates that AI-based automation significantly enhances employee productivity in Nigerian public institutions and higher education organisations.

H3: Generative AI utilisation has no significant effect on employee productivity.

The regression results showed that generative AI utilisation had a positive, statistically significant effect on employee productivity ($\beta = 0.167$, $p < 0.001$). The null hypothesis is therefore rejected. This finding indicates that generative AI utilisation significantly enhances employee productivity in Nigerian public institutions and higher education organisations.

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H4: Organisational readiness does not significantly mediate the relationship between AI adoption and employee productivity.

The mediation analysis revealed mixed results. Organisational readiness significantly mediated the relationships between AI-based automation and employee productivity (indirect effect = 0.261, 95% CI: 0.189–0.331) and between generative AI utilisation and employee productivity (indirect effect = 0.221, 95% CI: 0.099–0.362). However, organisational readiness did not significantly mediate the relationship between AI-assisted decision making and employee productivity (indirect effect = -0.038, 95% CI: -0.121–0.041). The null hypothesis is partially rejected, as organisational readiness mediates the effects of some but not all AI adoption dimensions on employee productivity.

5. FINDINGS

The study examined the effect of AI adoption on employee productivity in Nigerian public institutions and higher education organisations, with organisational readiness as a mediating mechanism. The key findings are summarised below:

5.1 Effect of AI-Assisted Decision Making on Employee Productivity

The findings revealed that AI-assisted decision making has a positive and significant effect on employee productivity ($\beta = 0.472$, $p < 0.001$). This suggests that when employees use AI systems to support administrative and managerial decision making, their productivity improves significantly. This finding aligns with the Technology Acceptance Model (Davis, 1989), which posits that perceived usefulness of technology drives adoption and subsequent performance improvements. The result is consistent with prior studies that found AI decision-support tools enhance work efficiency and evidence-based decision making (Chukwuka & Onokero, 2025; Davenport & Ronanki, 2018).

5.2 Effect of AI-Based Automation on Employee Productivity

The results demonstrated that AI-based automation has a positive and significant effect on employee productivity ($\beta = 0.357$, $p < 0.001$). This indicates that automating routine, rule-based administrative tasks through AI systems frees employee time for higher-value work, thereby enhancing productivity. This finding supports Davenport and Ronanki's (2018) classification of process automation as the most immediately productivity-enhancing form of AI application. The result is consistent with studies that found automation technologies improve operational efficiency and employee performance (Obi, 2024; Audu & Aziwe, 2025).

5.3 Effect of Generative AI Utilisation on Employee Productivity

The findings revealed that generative AI utilisation has a positive and significant effect on employee productivity ($\beta = 0.167$, $p < 0.001$). While the effect size is smaller than that of the other AI adoption dimensions, it remains statistically significant. This suggests that employees who use generative AI tools for document preparation, research support, teaching preparation, and communication tasks experience productivity gains. This finding extends Ogbaga's (2026) work on generative AI adoption in Nigerian higher education, demonstrating that such adoption translates into measurable productivity outcomes.

5.4 Mediating Role of Organisational Readiness

The mediation analysis revealed that organisational readiness significantly mediates the relationships between AI-based automation and employee productivity (indirect effect = 0.261,

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95% CI: 0.189–0.331) and between generative AI utilisation and employee productivity (indirect effect = 0.221, 95% CI: 0.099–0.362). This indicates that the productivity benefits of AI-based automation and generative AI utilisation are channeled through organisational readiness—management support, digital infrastructure, employee AI skills, and institutional policy.

However, organisational readiness did not significantly mediate the relationship between AI-assisted decision making and employee productivity (indirect effect = -0.038, 95% CI: -0.121–0.041). This suggests that the effect of AI-assisted decision making on productivity is more direct and less dependent on organisational readiness conditions. This may be because decision-support tools require less infrastructure and policy support than automation or generative AI tools, or because employees use decision-support tools more autonomously.

These findings extend the Technology–Organisation–Environment framework (Tornatzky & Fleischer, 1990) by demonstrating empirically how organisational readiness functions as a mediating mechanism between AI adoption and employee productivity in the Nigerian public-sector and higher-education context. The findings also support Amin's (2024) observation that technology adoption alone rarely improves outcomes without complementary organisational capacity.

6. DISCUSSION OF FINDINGS

6.1 AI-Assisted Decision Making and Employee Productivity

The finding that AI-assisted decision making significantly enhances employee productivity is consistent with the broader technology-adoption literature. Davenport and Ronanki (2018) argued that decision-assistance tools augment human cognitive capacity by surfacing patterns and predictions that would otherwise require extensive manual analysis. In the Nigerian public-sector and higher-education context, this finding suggests that employees who leverage AI systems for decision support are able to make more informed, evidence-based decisions more efficiently, thereby improving their productivity.

This result aligns with Chukwuka and Onokero's (2025) findings in Nigerian technology firms, where AI adoption positively affected employee productivity and engagement. The present study extends this finding to public institutions and higher education organisations, demonstrating that the productivity benefits of AI-assisted decision making are not confined to the private sector but apply across institutional settings.

The strong effect size for AI-assisted decision making ($\beta = 0.472$) suggests that this dimension of AI adoption has the most substantial impact on employee productivity. This may be because decision-making support directly enhances the quality and efficiency of employees' cognitive work, which is central to both administrative and academic roles in public institutions and higher education.

6.2 AI-Based Automation and Employee Productivity

The significant positive effect of AI-based automation on employee productivity supports Davenport and Ronanki's (2018) classification of process automation as the most immediately productivity-enhancing form of AI application. By automating routine, rule-based administrative tasks, AI systems free employee time for higher-value work, leading to improved productivity.

This finding is consistent with Obi's (2024) research on manufacturing firms in Enugu State, which found that infrastructural development and workforce skills significantly affected firm performance. The present study extends this finding by demonstrating that AI-based automation,

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when supported by organisational readiness, enhances employee productivity in public institutions and higher education organisations.

The effect size for AI-based automation ($\beta = 0.357$) indicates that while automation contributes significantly to productivity, its effect is somewhat less than that of AI-assisted decision making. This may be because automation primarily affects routine tasks, whereas decision-making support affects cognitive work that may be more central to employees' core responsibilities.

6.3 Generative AI Utilisation and Employee Productivity

The finding that generative AI utilisation positively affects employee productivity, though with a smaller effect size ($\beta = 0.167$), extends Ogbaga's (2026) work on generative AI adoption in Nigerian higher education. Ogbaga found that structured mentorship training significantly enhanced GenAI competence, confidence, and adoption among academic staff. The present study demonstrates that such adoption translates into measurable productivity gains.

The smaller effect size for generative AI utilisation may reflect the relatively early stage of generative AI adoption in Nigerian public institutions and higher education organisations. As noted by Nwosu et al. (2024), AI adoption in Nigeria's public sector remains at an early stage, constrained by inadequate infrastructure, limited digital literacy, and weak regulatory frameworks. This may limit the productivity impact of generative AI tools, which require significant employee skill and initiative to use effectively.

The finding also aligns with Agbarakwe and Chibueze's (2024) conceptual work on AI in Nigerian higher education, which highlighted the potential of AI-enabled tools to ease administrative burdens and improve efficiency. The present study provides empirical evidence supporting these propositions.

6.4 The Mediating Role of Organisational Readiness

The finding that organisational readiness mediates the relationships between AI-based automation and employee productivity, and between generative AI utilisation and employee productivity, supports the Technology–Organisation–Environment framework (Tornatzky & Fleischer, 1990). This framework posits that organisational-level conditions—management support, infrastructure, workforce competence, and policy—determine whether adopted technologies are effectively assimilated into work processes.

The significant mediation effects for AI-based automation and generative AI utilisation suggest that these AI adoption dimensions require organisational readiness to translate into productivity gains. This is consistent with Nwosu et al.'s (2024) observation that infrastructural deficits, limited digital literacy, and weak regulatory frameworks constrain AI adoption in Nigeria's public sector. The present study demonstrates empirically that these organisational readiness factors mediate the AI–productivity relationship.

However, the non-significant mediation effect for AI-assisted decision making suggests that this dimension of AI adoption may be less dependent on organisational readiness. This may be because decision-support tools require less infrastructure and policy support than automation or generative AI tools, or because employees use decision-support tools more autonomously. It may also reflect that decision-support tools are more familiar to employees and thus require less organisational support to be effectively utilised.

These findings extend Chondough and Chondough's (2022) work on the moderating role of intellectual capital in the AI–employee performance relationship. While Chondough and

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Chondough found that intellectual capital strengthened the AI–performance relationship, the present study demonstrates that organisational readiness functions as a mediating mechanism. This suggests that organisational readiness is not merely a facilitator but a channel through which AI adoption translates into productivity gains.

7. CONCLUSION

This study examined the effect of artificial intelligence adoption on employee productivity in public institutions and higher education organisations in Nigeria, with organisational readiness as a mediating mechanism. The findings demonstrate that AI-assisted decision making, AI-based automation, and generative AI utilisation each have positive and significant effects on employee productivity. Furthermore, organisational readiness significantly mediates the relationships between AI-based automation and employee productivity, and between generative AI utilisation and employee productivity.

The study makes several theoretical contributions. First, it extends the Technology Acceptance Model (Davis, 1989) and Technology–Organisation–Environment framework (Tornatzky & Fleischer, 1990) by demonstrating empirically how individual-level AI acceptance is converted into organisational productivity gains through organisational-level readiness conditions. Second, it addresses the limited Nigeria-centric evidence base on AI adoption within public-sector and higher-education settings, extending prior research that has concentrated predominantly on private-sector and commercial contexts. Third, it disaggregates AI adoption into distinct dimensions—decision-assistance, automation, and generative-use—revealing differential effects and mediating mechanisms.

The practical implications of the findings are significant for public institutions and higher education organisations in Nigeria. The results suggest that investments in AI adoption should be accompanied by deliberate efforts to strengthen organisational readiness—management support, digital infrastructure, employee AI skills, and institutional policy—to maximise productivity gains. The differential mediation effects also suggest that while organisational readiness is important for all forms of AI adoption, it may be particularly critical for automation and generative AI applications, which require more substantial infrastructure and support.

The study is not without limitations. The cross-sectional design limits causal inferences, and the reliance on self-reported data may introduce common method bias. The high correlations among the AI adoption dimensions and the resulting multicollinearity limit the interpretability of individual coefficient estimates. Additionally, the study was conducted within the Nigerian context, which may limit generalisability to other national settings.

Future research should employ longitudinal designs to establish causal relationships and should explore the specific sub-dimensions of organisational readiness that are most critical for different forms of AI adoption. Comparative studies across different national contexts would also enhance understanding of the role of contextual factors in the AI–productivity relationship.

8. RECOMMENDATIONS

Based on the findings of this study, the following recommendations are proposed:

8.1 Invest in Digital Infrastructure

Public institutions and higher education organisations should invest deliberately in digital infrastructure and connectivity. The findings demonstrate that organisational readiness, which includes digital infrastructure, mediates the AI–productivity relationship. Infrastructural deficits

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remain a consistently documented barrier to effective AI adoption in the Nigerian public sector (Nwosu et al., 2024). Investments in reliable internet connectivity, computing resources, and AI platforms are essential for converting AI adoption into productivity gains.

8.2 Establish Structured AI Training Programmes

Institutions should establish structured, ongoing AI training and mentorship programmes for academic and administrative staff, rather than relying on informal or self-directed learning. Ogbaga (2026) demonstrated that structured mentorship significantly improves AI competence, confidence, and adoption among Nigerian academic staff. Training programmes should cover both technical skills for using AI tools and ethical considerations for their responsible use.

8.3 Strengthen Management Support

Management should provide visible, sustained support for AI adoption initiatives. The findings indicate that organisational readiness, which includes management support, mediates the AI–productivity relationship. Consistent evidence suggests that management support and organisational capability jointly shape whether AI adoption translates into performance gains (Obi, 2024). Leaders should champion AI adoption, allocate resources, and create a culture that encourages experimentation with AI tools.

8.4 Develop Clear Internal Policies

Institutions should develop clear internal policies governing the use of AI-assisted decision making, automation, and generative AI tools in administrative and academic work. Policies should address data governance, accountability, academic integrity, and ethical use of AI. Clear policies provide guidance for employees and ensure that AI adoption is aligned with institutional values and objectives.

8.5 Strengthen Sector-Wide Guidance

Regulatory and oversight bodies, including relevant ministries and higher education regulators, should strengthen sector-wide guidance on AI adoption in public institutions. This complement institution-level readiness efforts and ensure consistent standards across the sector (Nwosu et al., 2024). Sector-wide guidance should address infrastructure standards, training requirements, policy frameworks, and ethical guidelines for AI adoption.

8.6 Prioritise AI-Assisted Decision Making and Automation

Given the relatively larger effect sizes for AI-assisted decision making and AI-based automation, institutions should prioritise these dimensions of AI adoption in the short to medium term. Decision-support tools can enhance evidence-based governance and resource allocation, while automation tools can reduce administrative burdens and free employee time for higher-value work.

Collectively, these measures are intended to strengthen the organisational readiness conditions under which AI adoption can be expected to yield measurable, sustained improvements in employee productivity across Nigeria's public institutions and higher education sector.

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