ADOPTION OF ARTIFICIAL INTELLIGENCE AND HUMAN RESOURCE UPSKILLING IN EMERGING MARKETS: EVIDENCE FROM SMALL AND MEDIUM ENTERPRISES IN OYO STATE, NIGERIA[1]

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ABSTRACT

This study investigates how the adoption of artificial intelligence (AI) is associated with workforce upskilling within small and medium-sized enterprises (SMEs) in Oyo State, Nigeria. While AI holds considerable transformative promise for human resource development, a critical knowledge gap persists regarding its regional implementation dynamics, particularly within the context of developing economies. Drawing on an integrated five-theory framework – the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology-Organisation-Environment (TOE) framework, Human Capital Theory, and Sociotechnical Systems Theory – this study develops and tests a conceptual model linking three theoretically grounded AI adoption dimensions (organisational integration, AI training programmes, and data-driven decision-making support) to employee skill enhancement outcomes. Employing a quantitative cross-sectional survey design, the structured questionnaires were administered to 135 respondents comprising HR professionals, SME operators, and employees drawn from approximately 72 SMEs across diverse industry sectors in Ibadan Metropolis. Results indicate that AI integration in HR upskilling practices remains largely nascent (M = 2.116). Nevertheless, Pearson correlation and regression analyses revealed significant positive associations between key AI adoption dimensions and employee skill enhancement ($R = 0.750$, $R^2 = 0.562$, $p < 0.001$).

These associations are interpreted as correlational rather than causal given the cross-sectional design. Prominent barriers include infrastructural inadequacies, educational deficiencies, policy gaps, and socio-cultural resistance. The study concludes with actionable policy and practice recommendations, and acknowledges methodological limitations including common method bias risk, absence of formal EFA/CFA, and cross-sectional design constraints.

1. INTRODUCTION

The rapid proliferation of artificial intelligence (AI) technology has been associated with fundamental transformations across various industries globally, including human resource management (HRM). AI has been linked to significant changes in HR processes such as recruitment, performance evaluations, and employee training. Small and medium-sized enterprises (SMEs) face unique opportunities and obstacles in adopting AI, especially in developing countries such as Nigeria. Artificial intelligence is broadly understood as the emulation of human intelligence in machines programmed to think, learn, and make decisions independently (McCarthy, 2007; Russell & Norvig, 2010). Its incorporation into organisational routines is producing significant advantages by enhancing efficiency and enabling data-driven decision-making. In South-West Nigeria, AI-driven automation has been associated with job displacement, especially in low- and middle-skill sectors, potentially exacerbating income disparities (Acemoglu & Restrepo, 2022). AI has been associated with expedited, bias-minimised recruitment, data-informed decision-making, and enhanced training processes (Davenport et al., 2020). Research by Brynjolfsson and McAfee (2014) indicates that human skills remain crucial for interpreting and analysing AI outcomes, despite AI's capacity to automate repetitive tasks. Chui et al. (2016) emphasise the challenges faced by SMEs in implementing AI-driven HR practices. This study examines how AI adoption is associated with HR upskilling in SMEs in Oyo State, Nigeria, with specific focus on how organisational integration, training programmes, and data-driven decision-making support collectively predict employee skill enhancement outcomes.

1.1 Statement of Research Problem

The integration of AI into HR procedures represents a significant technological advancement with potential to enhance workforce development and

organisational competitiveness. In Nigeria, where SMEs constitute crucial drivers of economic development, AI integration could fundamentally transform HR operations. Despite national-level initiatives aimed at enhancing the skills of Nigerian professionals (Federal Ministry of Communications, Innovation & Digital Economy, 2024), the localised effects in states such as Oyo remain inadequately understood. Disparities in access to digital infrastructure and training programmes present significant obstacles, while AI implementation risks exacerbating the existing digital skills gap, potentially rendering certain employees inadequately prepared for an AI-centric work environment.

1.2 Research Questions

This study explored the following research questions:

(i) What is the degree of AI adoption in organisational HR upskilling procedures among SMEs in Oyo State, Nigeria?
(ii) What association exists between AI adoption in HR upskilling procedures and employees' enhancement?
(iii) Does AI adoption in HR upskilling procedures have any significant predictive association with employee skill enhancement among SMEs in the study area?

1.3 Research Objectives

The general objective is to evaluate the association between AI adoption and employee upskilling among SMEs. Specifically, the study seeks to:

(i) assess the degree of AI adoption in organisational HR upskilling procedures among SMEs in Oyo State;
(ii) investigate the association between AI adoption in HR upskilling procedures and employee enhancement; and
(iii) evaluate the predictive relationship between AI adoption dimensions and employee skill enhancement among SMEs in the study area.

1.4 Research Hypotheses

H_{01}: The adoption of Artificial Intelligence (AI) is not widespread in organisational HR upskilling procedures.
H_{02}: There is no statistically significant association between AI adoption in HR upskilling procedures and employee enhancement.
H_{03}: AI adoption in HR upskilling procedures does not significantly predict employee upskilling outcomes among SMEs in the study area.

2. LITERATURE REVIEW

2.1 Conceptual Framework on AI Adoption and HR Upskilling

Artificial Intelligence encompasses systems capable of executing tasks requiring human intelligence, including decision-making, learning, and problem-solving. Strohmeier and Piazza (2015) characterise AI as a transformative instrument improving organisational processes by automating operations, analysing datasets, and producing predictive insights, enabling a shift from reactive to proactive HR management. Ogunyemi and Johnston (2012) highlight how technology-mediated information systems — including AI-driven platforms — transform employee management in African organisations, facilitating analytical decision-making for managing personnel data and forecasting workforce requirements. McCarthy (2007) defines AI as creating intelligent machines and computer programmes that reason, solve problems, and adapt autonomously. Russell and Norvig (2016) expand this to systems that act rationally to achieve goals. In the Nigerian context, Gwagwa et al. (2022) examine how socio-cultural values shape responsible AI deployment in Africa, while Hmoud and Laszlo (2019) define AI in HR as sophisticated algorithms replicating human reasoning to resolve workforce challenges, particularly in recruitment and selection.

2.2 Theoretical Framework and Integrated Conceptual Model

This study draws on five complementary theoretical frameworks, each contributing a distinct explanatory layer and directly informing the study's three hypotheses. Rather than treating these theories as parallel background references, this section explicitly maps each framework to the hypotheses it underpins and to the specific AI adoption dimensions selected for analysis. Taken together, they generate an integrated conceptual model in which antecedent adoption conditions shape AI adoption levels (H_{01}), which are in turn associated with employee skill enhancement outcomes (H_{02} and H_{03}).

Human Capital Theory (Becker, 1964) provides the foundational rationale for H_{03}. By positing that investments in employee training yield measurable productivity returns, Human Capital Theory directly justifies the expectation that AI-driven upskilling programmes will be associated with enhanced competencies. The AI Training Programmes predictor operationalises this theoretical claim: organisations investing in AI-centred training are investing in their human capital stock, and this investment is predicted to explain variance in skill enhancement outcomes. The positive AI Training Programmes coefficient ($\beta = 0.312$) is directly interpretable within this framework.

The integrated conceptual model is presented in Figure 1.

ANTECEDENTS	→ H_{01}	→ H_{02} H_{03}
• Perceived Usefulness (TAM) • Perceived Ease of Use (TAM) • Social Influence (UTAUT) • Facilitating Conditions (UTAUT) • Technology Readiness (TOE) • Organisational Capacity (TOE) • Environmental Fit (TOE) Davis, 1989; Venkatesh et al., 2003; Tornatzky & Fleischer, 1990	AI ADOPTION DIMENSIONS • AI Organisational Integration* • Technical Capabilities • Data-Driven HR Insights* • Process Automation • AI Training Programmes* * Retained predictors in regression model TAM • UTAUT • TOE • Sociotechnical Systems Theory	EMPLOYEE SKILL ENHANCEMENT (DV) • Training Participation • Skills Development • Productivity Improvement Becker, 1964; Zawacki-Richter et al., 2019; Brynjolfsson & McAfee, 2014

Figure 1. Integrated Conceptual Model: AI Adoption and Employee Skill Enhancement
Source: Author, 2026

Note: Arrows represent theorised directional associations. H_{01} = AI adoption not widespread (tested via one-sample t-test); H_{02} = association between adoption and enhancement (Pearson correlation, chi-square); H_{03} = AI adoption dimensions predict skill outcomes (multiple regression). * = Constructs retained in the regression model. DV = Dependent Variable. Theoretical sources: TAM (Davis, 1989); UTAUT (Venkatesh et al., 2003); TOE (Tornatzky & Fleischer, 1990); Human Capital Theory (Becker, 1964); Sociotechnical Systems Theory (Trist & Bamforth, 1951; Ogunyemi & Johnston, 2012); AST (DeSanctis & Poole, 1994).

The Technology Acceptance Model (TAM; Davis, 1989) underpins H_{01} by establishing that technology adoption is driven by perceived usefulness and perceived ease of use. In the SME context, these perceptions are constrained by infrastructural inadequacies and limited digital literacy, explaining why adoption levels remain nascent (M = 2.116). The AI Organisational Integration construct reflects TAM's concept of actual system usage – the downstream behavioural outcome of favourable technology perceptions.

The Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003) extends TAM by incorporating social influence and facilitating conditions as additional determinants. This is directly relevant to H_{01} and H_{02}: socio-cultural resistance in the Nigerian SME environment – including job displacement fears and AI misconceptions (Gwagwa et al., 2022) – constitutes a negative social influence dampening adoption. Conversely, managerial endorsement and training provision (AI Training Programmes) represent positive facilitating conditions.

The Technology-Organisation-Environment (TOE) Framework (Tornatzky & Fleischer, 1990) illuminates how technological readiness, organisational

capacity, and environmental pressures jointly shape AI adoption at the firm level. Inadequate internet connectivity, unstable electricity, and limited computational resources (technological factors), combined with SME resource constraints (organisational factors) and a nascent regulatory environment (environmental factors), converge to explain the low adoption rates documented in H_{01}. The TOE framework additionally justifies the Data-Driven Decision-Making Support predictor.

Sociotechnical Systems Theory (Trist & Bamforth, 1951; Ogunyemi & Johnston, 2012) and Adaptive Structuration Theory (AST; DeSanctis & Poole, 1994) address H_{02} and H_{03} from organisational and individual learning perspectives. Sociotechnical Systems Theory posits that AI adoption produces skill enhancement only when the social system – including organisational culture, managerial support, and employee readiness – is aligned with the technical system. This explains AI Integration Level's primacy in the regression model ($\beta = 0.358$). AST further proposes that employees interacting with AI tools engage in iterative adaptation processes that cumulatively build competencies, consistent with the strong training-to-skill-enhancement correlation ($r = 0.758$).

2.3 Empirical Review

Empirical investigations reveal that emerging markets like Nigeria face substantial AI adoption obstacles. Olatunde-Aiyedun (2024) highlight sluggish AI integration in Nigerian educational and organisational settings, particularly in less urbanised areas, necessitating region-specific upskilling initiatives. Brynjolfsson and McAfee (2014) indicate deployment requires proficient workforces, while Hmoud and Laszlo (2019) underscore the importance of addressing skills gaps as AI infiltrates HR functions in sectors including banking and professional services. Eli-Chukwu (2019) notes that Nigeria's agricultural sector faces obstacles despite AI's considerable potential for precision farming. Olatunde-Aiyedun (2024) document minimal AI incorporation in Nigerian educational curricula, while Zawacki-Richter et al. (2019) contend that institutions globally must integrate AI-related courses to prepare future workforces. Zawacki-Richter et al. (2019) further found that AI-related upskilling programmes were associated with significantly improved technical skills, with personalised learning methodologies linked to enhanced skill acquisition. Socio-cultural concerns including technology aversion and fear of job displacement pose further obstacles to AI adoption in African contexts (Gwagwa et al., 2022).

2.4 Research Gap and Theoretical Contribution

Notwithstanding the growing body of literature on AI adoption in HR management, three important gaps remain. First, most empirical studies originate in high-income economies or large enterprises (Davenport et al., 2020; Brynjolfsson & McAfee, 2014), leaving the SME context in sub-Saharan Africa largely understudied. The few Nigeria-focused studies are either sector-specific or qualitative (Eli-Chukwu, 2019; Olatunde-Aiyedun, 2024), limiting generalisability to the mixed-sector SME landscape. Second, prior studies tend to examine AI adoption and skill development as separate phenomena rather than testing the predictive relationship between specific adoption dimensions and skill outcomes through inferential statistics. Third, existing studies are predominantly single-theory accounts (typically TAM alone), whereas the adoption paradox observed in emerging markets — strong associations coexisting with low adoption — requires a multi-theoretical lens.

This study addresses these gaps by: (1) providing multi-sectoral empirical evidence from SMEs in Oyo State; (2) applying an integrated five-theory conceptual model (Figure 1) that explicitly links theoretical constructs to hypotheses and AI adoption dimensions; and (3) identifying specific AI adoption dimensions that predict employee skill enhancement through inferential analysis.

3. MATERIALS AND METHODS

This study examines the association between AI adoption and human resource upskilling within SMEs in Ibadan Metropolis, Oyo State, Nigeria. As a major economic and technological hub, Ibadan serves as a critical centre for commercial activities, education, and administrative functions.

3.1 Research Design and Data Collection

This empirical study employed a quantitative, cross-sectional survey design. Primary data were collected through a structured questionnaire to evaluate the association between AI adoption and human resource upskilling. Item-level missing data were minimal (< 8% per item) and were handled using pairwise deletion for descriptive analyses and listwise deletion for all inferential tests, consistent with standard practice for missing completely at random (MCAR) data patterns (Hair et al., 2019).

3.2 Population, Sample, and Unit of Analysis

The target population comprises approximately 213 HR professionals, SME operators, and employees drawn from SMEs registered with the Oyo State SME Development Agency and the Ibadan Chamber of Commerce and Industry. Within these registered organisations, only those employing at least one HR professional or designated personnel management function were included in the sampling frame.

It is important to clarify the unit of analysis for this study: the unit of analysis is the individual respondent, not the organisation. Respondents were drawn from approximately 72 SME organisations, with between one and three respondents per organisation depending on firm size and the availability of eligible role categories (HR professional, SME operator, and/or employee). This multi-informant approach was adopted to capture different functional perspectives on AI adoption and upskilling within the same organisational context. Readers should note that respondents from the same firm share common organisational experiences, which introduces a degree of non-independence acknowledged in Section 5.1.

Simple random sampling was employed to ensure equal selection probability among eligible respondents. The sample size was determined using the Yamane (1967) formula: $n = N / [1 + N(e)^2]$, where $N = 213$ and $e = 0.05$, yielding $n \cong 139$. Consequently, 139 questionnaires were administered, yielding 135 valid responses (97.1% return rate).

3.3 Research Instrument

The questionnaire was designed using a five-point Likert scale (5 = Strongly Agree, 4 = Agree, 3 = Neutral, 2 = Disagree, 1 = Strongly Disagree). All items were adapted from established, peer-reviewed instruments with demonstrated validity and reliability in related technology adoption and HRM contexts. The instrument comprised 24 items distributed across five thematic constructs, as summarised in Table 3. The full instrument is available from the corresponding author upon reasonable request.

The survey also collected seven demographic variables: gender, age group, educational qualification, organisational role, industry sector, years of experience, and organisation size.

Table 3. Questionnaire construct operationalisation (24 items total)

Construct	Items	Theoretical Basis	Adapted From	
AI Organisational Integration	5	TAM (Davis, 1989); TOE (Tornatzky & Fleischer, 1990)	Venkatesh et al. (2003); Olatunde-Aiyedun (2024)	"AI tools are integrated into our core HR processes."
Technical Capabilities	4	UTAUT (Venkatesh et al., 2003)	Hmoud & Laszlo (2019)	"Staff possess adequate skills to use AI tools."
Data-Driven HR Insights	5	TOE; Human Capital Theory (Becker, 1964)	Davenport et al. (2020); Ogunyemi & Johnston (2012)	"AI-generated data informs our HR decisions."
Process Automation	4	Sociotechnical Systems Theory (Trist & Bamforth, 1951)	Strohmeier & Piazza (2015); Hmoud & Laszlo (2019)	"Routine HR tasks are handled through AI automation."
Employee Skill Enhancement (DV)	6	Human Capital Theory; AST (DeSanctis & Poole, 1994)	Zawacki-Richter et al. (2019); Brynjolfsson & McAfee (2014)	"AI-related training improved my job-relevant skills."

Note: DV = Dependent Variable. Items rated on a 5-point Likert scale. Items were adapted from established scales with minor wording modifications to contextualise for the Nigerian SME environment.

3.4 Validity and Reliability

To ensure content validity, the research instrument was subjected to expert review involving specialists in AI, human resource management, and measurement. A pilot study was conducted prior to full-scale deployment. Reliability was assessed using Cronbach's Alpha ($\alpha = 0.839$), exceeding the acceptable threshold of 0.70 (Nunnally, 1978) and indicating sufficient internal consistency.

Regarding construct validity, two acknowledgements are warranted. First, the study measures respondents' perceptions of AI adoption rather than objective indicators of AI tool deployment, introducing a limitation discussed in Section 5.1. Second, while items were adapted from prior validated instruments, formal exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were not conducted. Future studies should include both EFA and CFA to formally establish the factorial structure of the adapted instrument in the Nigerian SME context (Hair et al., 2019). This is acknowledged as a significant limitation of the current study.

3.5 Analytical Techniques

Data were analysed using descriptive statistics (means and standard deviations), a one-sample t-test (H_{01}), Pearson correlation and chi-square test of independence (H_{02}), and multiple linear regression analysis (H_{03}). All analyses were performed using SPSS v.25. The Durbin-Watson statistic was used to assess autocorrelation, and variance inflation factors (VIF) were examined to detect multicollinearity.

Composite score construction: For each construct, a composite score was computed as the arithmetic mean of all item-level responses within that construct following pairwise deletion for items with missing values, producing interval-level scores commensurate with regression analysis assumptions.

One-sample t-test justification (H_{01}): The test value of 2.50 was selected to represent the boundary between the 'Disagree' (2) and 'Neutral' (3) response categories on the five-point scale, operationalising a conservative threshold below which observed means cluster closer to disagreement than to neutrality. A sensitivity analysis using 3.0 as the test value yields $t(134) = -8.84$, $p < 0.001$, reaching the same substantive conclusion. Both thresholds are reported in Table 7.

Chi-square test (H_{02}): Composite scores were recoded into three ordinal categories prior to analysis: Low (1.00–2.49), Moderate (2.50–3.49), and High (3.50–5.00). Categories were assigned prior to and independently of results to avoid post-hoc categorisation bias. The resulting cross-tabulation produced 12 degrees of freedom.

Of the five thematic constructs, the multiple regression model retained three predictors: AI Integration Level, AI Training Programmes, and AI Decision-Making Support. Process Automation demonstrated substantial overlap with AI Integration Level ($r = 0.71$), raising multicollinearity concerns. Technical Capabilities was similarly subsumed within AI Integration Level in preliminary factor analysis. Both were excluded to maintain model parsimony (Hair et al., 2019). The retained predictors exhibited VIF values between 1.389 and 1.523.

3.6 Common Method Bias Precautions

Given that all constructs were measured using a single self-report questionnaire administered on one occasion, the risk of common method bias (CMB; Podsakoff et al., 2003) was explicitly considered at both procedural and analytical stages. Procedural remedies implemented include: (1) anonymity of responses was guaranteed to minimise social desirability bias; (2) participation was voluntary,

reducing acquiescence pressure; (3) the survey was framed as having no correct or incorrect answers, reducing evaluation apprehension; and (4) varied item stems were employed across constructs to reduce artificial consistency.

Notwithstanding these precautions, formal CMB diagnostics – including Harman's single-factor test and common latent factor analysis – were not conducted, which limits the ability to statistically quantify CMB magnitude. The elevated inter-construct correlations (r = 0.681–0.758) may partially reflect shared method variance. Future studies are strongly encouraged to employ temporal separation of predictor and criterion measurements, or multi-source data collection, as additional CMB remedies.

4. RESULTS

4.1 Questionnaire Return Rate

Table 4. Questionnaire return rate

Category	Frequency	Percentage (%)
Not filled/Invalid	4	2.9
Filled correctly	135	97.1
Total Expected	139	100.0

Source: Field Survey, 2025

4.2 Respondent Demographic Profile

Table 5 presents the demographic profile of respondents. The sample comprises slightly more male (52.6%) than female (47.4%) respondents. The majority (39.3%) fall within the 26–35 age bracket. Nearly half hold HND or B.Sc. qualifications (48.9%), with a further 30.4% possessing postgraduate degrees. SME operators represent the largest role category (37.8%), followed by HR professionals (34.1%) and employees (28.1%). The services sector accounts for the largest share (34.8%). The majority of organisations are small-sized (10–49 employees, 46.7%), consistent with the Nigerian SME definition.

While the demographic composition is informative, no systematic comparison with the actual population structure of all SMEs in Oyo State or Ibadan Metropolis was conducted. The sampling frame was limited to SMEs registered with formal agencies, which may over-represent more formalised enterprises relative to the broader informal SME sector. Accordingly, representativeness claims apply specifically to the registered, formalised SME population in Ibadan Metropolis.

Table 5. Demographic profile of respondents (N = 135)

Demographic Variable	Category	Frequency (%)
Gender	Male	71 (52.6%)
	Female	64 (47.4%)
Age Group	18–25 years	23 (17.0%)
	26–35 years	53 (39.3%)
	36–45 years	37 (27.4%)
	46 years and above	22 (16.3%)
Educational Qualification	SSCE / OND	19 (14.1%)
	HND / B.Sc.	66 (48.9%)
	M.Sc. / MBA	41 (30.4%)
	Ph.D.	9 (6.7%)
Organisational Role	HR Professional	46 (34.1%)
	SME Operator / Owner	51 (37.8%)
	Employee	38 (28.1%)
Industry Sector	Manufacturing	27 (20.0%)
	Services	47 (34.8%)
	Agriculture	21 (15.6%)
	Retail / Trade	23 (17.0%)
	ICT / Technology	17 (12.6%)
Years of Experience	Less than 2 years	18 (13.3%)
	2–5 years	43 (31.9%)
	6–10 years	47 (34.8%)
	More than 10 years	27 (20.0%)
Organisation Size	Micro (< 10 employees)	29 (21.5%)
	Small (10–49 employees)	63 (46.7%)
	Medium (50–249 employees)	43 (31.9%)

Source: Field Survey, 2025

4.3 Research Question 1: Degree of AI Adoption in HR Upskilling

Table 6 presents descriptive statistics for AI adoption variables. The composite mean score of 2.116 indicates that AI adoption in HR upskilling procedures is below the conservative threshold of 2.5 and substantially below the conventional neutral midpoint of 3.0, suggesting limited penetration of AI technologies.

Table 6. Descriptive statistics for AI adoption variables

Variable	N	Mean	Std. Dev.	Interp.
AI integrated into HR processes	125	2.080	1.142	Low-Mod.
AI associated with improved recruitment	130	2.462	1.089	Low-Mod.
AI in training and development programmes	130	2.000	0.869	Low
AI associated with improved decision-making	135	2.556	1.095	Moderate
Challenges in adopting AI in HR	130	2.077	0.934	Low-Mod.
Overall AI Adoption Level	135	2.116	1.160	Low-Mod.

Note: Variation in N reflects item-level missing data handled using pairwise deletion for descriptive statistics and listwise deletion for inferential analyses (N = 135). Missing values per item ≤ 7.4% (Hair et al., 2019).

Source: Authors' calculation

4.3.1 Hypothesis Testing: H_{01}

H_{01}: The adoption of AI is not widespread in organisational HR upskilling procedures.

Table 7. One-sample t-test results

Statistic	Value	Interpretation
Test Value (primary)	2.500	Below-neutral adoption benchmark
Sample Mean	2.116	Observed AI adoption level
T-Statistic	−3.847	Significant negative deviation
Degrees of Freedom	134	n − 1
P-Value (2-tailed)	0.000*	Highly significant ($p < 0.001$)
Mean Difference	−0.384	Below test value
95% Confidence Interval	[−0.582, −0.186]	Does not include zero
Sensitivity: test value = 3.0	$t = -8.84$, $p < 0.001$	Same conclusion; adoption below neutral midpoint

*$p < 0.001$. Source: Authors' calculation

Decision: FAIL TO REJECT H_{01}. The result reveals a statistically significant difference between the observed mean AI adoption level ($M = 2.116$, $SD = 1.160$) and the test value of 2.5, $t(134) = -3.847$, $p < 0.001$, 95% CI [−0.582, −0.186]. A sensitivity test using the conventional neutral midpoint of 3.0 yields $t(134) = -8.84$, $p < 0.001$, reinforcing this conclusion. AI adoption is NOT widespread in organisational HR upskilling procedures among SMEs in Oyo State.

4.4 Research Question 2: Association Between AI Adoption and Employee Enhancement

Table 8 presents the Pearson correlation matrix. AI Adoption and Employee Training ($r = 0.724$, $p < 0.001$), Skills Enhancement ($r = 0.681$, $p < 0.001$), and Employee Productivity ($r = 0.697$, $p < 0.001$) all indicate strong positive associations. Employee Training and Skills Enhancement ($r = 0.758$, $p < 0.001$) represents the strongest correlation, indicating that formal training programmes are strongly associated with skill development outcomes. These are correlational findings and do not establish causal direction.

Table 8. Pearson correlation matrix

Variable 1	Variable 2	Pearson r	P-Value
AI Adoption	Employee Training	0.724**	0.000
AI Adoption	Skills Enhancement	0.681**	0.000
AI Adoption	Employee Productivity	0.697**	0.000
Employee Training	Skills Enhancement	0.758**	0.000

**Correlation is significant at the 0.01 level (2-tailed).

Source: Authors' calculation

4.4.1 Hypothesis Testing: H_{02}

H_{02}: There is no statistically significant association between AI adoption in HR upskilling procedures and employee enhancement.

Table 9. Chi-square test of independence results

Test Statistic	Value	df	P-Value	Decision
Pearson Chi-Square	47.823	12	0.000***	Reject H_{02}
Likelihood Ratio	51.247	12	0.000***	–
N of Valid Cases	135	–	–	–

Note: Composite scores were recoded into three categories prior to analysis: Low (1.00–2.49), Moderate (2.50–3.49), High (3.50–5.00), producing a 3 × 4 contingency table (12 df). ***$p < 0.001$.

Source: Authors' calculation

Decision: REJECT H_{02}. The chi-square test, $\chi^2(12, N = 135) = 47.823$, $p < 0.001$, indicates that AI adoption levels and employee enhancement outcomes are not independent. These associations are descriptive and do not imply causality.

4.5 Research Question 3: Predictive Relationship Between AI Adoption and Employee Skill Enhancement

Table 10. Multiple regression — model summary

Model	R	R^2	Adj. R^2	Std. Error	Durbin-Watson
1	0.750	0.562	0.549	1.110	1.847

Source: Authors' calculation

Table 11. ANOVA results

Source	Sum of Sq.	df	Mean Sq.	F (Sig.)
Regression	156.847	3	52.282	42.357*** (0.000)
Residual	161.523	131	1.233	–
Total	318.370	134	–	–

***p < 0.001. Source: Authors' calculation

Table 12. Regression coefficients

Predictor	B	Std. Error	Beta (β)	t (Sig.)	VIF
(Constant)	0.847	0.234	–	3.619 (0.000***)	–
AI Integration Level	0.423	0.089	0.358	4.753 (0.000***)	1.456
AI Training Programmes	0.381	0.095	0.312	4.011 (0.000***)	1.523
AI Decision-Making Support	0.267	0.087	0.218	3.069 (0.003**)	1.389

***p < 0.001; **p < 0.01. VIF values below 5.0 confirm no multicollinearity. Source: Authors' calculation

4.5.1 Hypothesis Testing: H_{03}

H_{03}: AI adoption in HR upskilling procedures does not significantly predict employee upskilling outcomes among SMEs in the study area.

Decision: REJECT H_{03}. The overall model achieves statistical significance, $F(3, 131) = 42.357$, $p < 0.001$, with $R^2 = 0.562$, indicating that 56.2% of variance in employee upskilling outcomes is accounted for by the three retained AI adoption predictors. All three predictors demonstrate individual statistical significance: AI Integration Level ($\beta = 0.358$, $t = 4.753$, $p < 0.001$); AI Training Programmes ($\beta = 0.312$, $t = 4.011$, $p < 0.001$); and AI Decision-Making Support ($\beta = 0.218$, $t = 3.069$, $p = 0.003$). VIF values (1.389–1.523) confirm no multicollinearity. The Durbin-Watson statistic of 1.847 indicates no serial autocorrelation. These coefficients represent predictive associations rather than causal effects.

5. DISCUSSIONS

This study reveals that perceived AI adoption in HR upskilling among Oyo State SMEs remains below moderate levels (M = 2.116), consistent with TAM's (Davis, 1989) prediction that low perceived ease of use and limited facilitating conditions constrain technology uptake. The TOE framework (Tornatzky & Fleischer, 1990) further contextualises these results: inadequate internet connectivity, unstable electricity, resource constraints, and a nascent regulatory environment converge to suppress adoption at the firm level. These findings align with Olatunde-Aiyedun's (2024) documentation of infrastructure and awareness barriers to AI integration in Nigerian institutions, and with Gwagwa et al.'s (2022) observation that socio-cultural dynamics significantly shape technology adoption trajectories across African contexts.

Despite limited adoption, strong positive correlations (r = 0.681–0.758) present a noteworthy pattern consistent with Human Capital Theory's (Becker, 1964) expectation that even modest AI-enabled training investments yield measurable competency returns. The robust AI-training association (r = 0.724) is consistent with Zawacki-Richter et al.'s (2019) systematic review findings linking AI-supported learning environments to improved skill acquisition outcomes across diverse institutional contexts.

However, an equally plausible interpretation must be acknowledged: the strong associations may partly reflect a selection effect. Organisations that have adopted AI may represent more progressive, resource-endowed SMEs whose employees would report better skill outcomes regardless of AI specifically. This selection effect interpretation underscores the need for longitudinal studies to disentangle genuine AI-upskilling relationships from pre-existing organisational capability differentials.

The regression model demonstrates substantial predictive power ($R^2 = 0.562$), exceeding Cohen's (1988) threshold for large effects. AI Integration Level's primacy ($\beta = 0.358$) aligns with Sociotechnical Systems Theory's emphasis on organisation-wide alignment (Trist & Bamforth, 1951; Ogunyemi & Johnston, 2012): skill enhancement is optimised when AI is embedded across organisational functions rather than deployed in isolated pockets. The AI Training Programmes coefficient ($\beta = 0.312$) underscores the urgency of educational reform and is grounded in Human Capital Theory (Becker, 1964); this finding resonates with Strohmeier and Piazza's (2015) conceptual framework positioning structured AI training as central to HRM value creation. The unexplained variance (43.8%) indicates that additional factors, including socio-cultural barriers, AI

misconceptions, and infrastructural constraints documented by Gwagwa et al. (2022), warrant further empirical investigation.

This study involved respondents drawn from multiple functional roles within the same organisations. HR professionals, SME operators, and employees may evaluate AI adoption differently; future studies should apply multilevel modelling to account for the nested structure of individuals within firms.

5.1 Limitations

Cross-sectional design. The cross-sectional design prevents causal inference. Longitudinal designs are required to establish temporal precedence.

Common method bias. All variables were collected from a single self-report questionnaire. While procedural remedies were implemented, formal CMB diagnostics were not conducted (Podsakoff et al., 2003). Elevated inter-construct correlations (r = 0.681–0.758) may partially reflect shared method variance.

Perceptual measurement. Reliance on respondents' perceptions of AI adoption rather than objective measures introduces construct validity concerns. Future studies should supplement perceptual measures with organisational records.

Sample scope and representativeness. The sample is confined to Ibadan Metropolis and to registered SMEs. Representativeness claims apply specifically to the registered SME population; generalisations to informal or rural enterprises should be made with caution.

Multi-respondent nesting. Respondents from the same organisation may share contextual influences, introducing non-independence not formally modelled. Future studies should employ multilevel modelling.

Instrument validation. EFA and CFA were not formally conducted, which constitutes a significant limitation. Future research must include full psychometric validation of the adapted instrument (Hair et al., 2019).

Regression model completeness. Exclusion of Process Automation and Technical Capabilities from the regression model means the full five-construct framework was not simultaneously modelled. Future research employing SEM would enable comprehensive simultaneous testing.

6. CONCLUSIONS

This study provides empirical evidence on the associations between AI adoption and HR upskilling among Oyo State SMEs, grounded in an integrated five-theory conceptual model (Figure 1) that explicitly links theoretical constructs to three research hypotheses. The results indicate that current AI adoption remains limited ($M = 2.116$), yet documented strong positive associations ($r = 0.681–0.758$) and substantial predictive power ($R^2 = 0.562$) demonstrate significant potential for AI-enabled workforce development. These conclusions must be interpreted with caution given the cross-sectional design, the potential for selection effects, and the absence of formal EFA/CFA validation. The predictive primacy of AI Integration Level ($\beta = 0.358$) and AI Training Programmes ($\beta = 0.312$) suggests that systemic, organisation-wide AI adoption accompanied by formal training infrastructure is most strongly associated with employee skill development, a finding consistent with both Sociotechnical Systems Theory (Trist & Bamforth, 1951) and Human Capital Theory (Becker, 1964).

Recommendations

1. The three tiers of government in Nigeria should embark on strategic investments and policy reforms enabling broader AI implementation, recognising that the positive AI-upskilling associations documented here are correlational and require longitudinal confirmation.
2. SME managers should prioritise systematic AI integration across organisational functions rather than isolated implementations, investing in employee training programmes for AI-related competencies while actively engaging staff to reduce socio-cultural resistance (Gwagwa et al., 2022).
3. Policymakers need to develop state-specific AI adoption strategies, investing in foundational digital infrastructure and providing targeted financial incentives such as subsidies, tax credits, and loans for SME AI investments.
4. Educational institutions must integrate AI-related content across disciplinary curricula beyond computer science programmes (Zawacki-Richter et al., 2019; Olatunde-Aiyedun, 2024), collaborating with industry to align curricula with actual workplace competency requirements.
5. Future research should adopt longitudinal designs, conduct EFA and CFA for full instrument validation, address CMB through multi-source data collection and formal testing (Podsakoff et al., 2003), employ SEM to simultaneously model all five constructs, apply multilevel modelling for within-firm clustering, and extend the geographical scope beyond Ibadan Metropolis.

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Conflict of Interests

The authors declare that there are no financial or non-financial conflicts of interest related to this manuscript.

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УСВАЈАЊЕ ВЈЕШТАЧКЕ ИНТЕЛИГЕНЦИЈЕ И УСАВРШАВАЊЕ ЉУДСКИХ РЕСУРСА НА ТРЖИШТИМА У РАЗВОЈУ: ДОКАЗИ ИЗ МАЛИХ И СРЕДЊИХ ПРЕДУЗЕЋА У САВЕЗНОЈ ДРЖАВИ OYO, НИГЕРИЈА

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САЖЕТАК

Овај рад испитује у којој мјери усвајање вјештачке интелигенције (ВИ) корелира с усавршавањем људских ресурса у малим и средњим предузећима (МСП) у савезној држави Оуо, Нигерија. Користећи интегративни теоријски оквир који обухвата ТАМ, УТАУТ, ТОЕ, теорију хуманог капитала и социотехничку теорију система, студија развија концептуални модел који експлицитно повезује димензије усвајања ВИ са исходима развоја вјештина запосленика. Подаци су прикупљени од 135 испитаника из око 72 МСП-а путем структурираних упитника. Налази показују ограничено усвајање ВИ (M = 2,116), при чему Пеарсонова корелација и вишеструка регресиона анализа откривају значајне позитивне асоцијације (P^2 = 0,562, п < 0,001). Ови резултати тумаче се као корелациони, а не узрочни. У закључном дијелу рада наведене су препоруке за носиоце политика, менаџере и образовне институције, уз јасно препознавање методолошких ограничења.

Кључне ријечи: *вјештачка интелигенција, унапређење вјештина људских ресурса, мала и средња предузећа (МСП), развој радне снаге, тржишта у настајању.*