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Artificial Intelligence and Employment Outcomes in an Emerging Economy: The Moderating Role of Digital Readiness

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Abstract

The rapid integration of Artificial Intelligence (AI) is transforming labour markets globally, yet empirical evidence from developing economies remains limited. This study investigates how AI integration influences employment outcomes in Lagos State, Nigeria, and examines whether digital readiness moderates this relationship. A convergent-parallel mixed-methods design was employed. A quantitative survey was administered to 400 professionals across four key sectors (financial services, logistics, retail/trade, and manufacturing), complemented by 15 semi-structured interviews with HR managers and technology executives. Data was analyzed using descriptive statistics, multiple regression, and thematic analysis. Results indicate that AI integration significantly predicts both job creation ($\beta = 0.221$, $p < .001$) and job displacement ($\beta = 0.314$, $p < .001$). Digital readiness significantly moderates these relationships, amplifying job creation ($\Delta R^2 = 0.034$, $p = .004$) and attenuating displacement in high-readiness contexts. Qualitative findings corroborate that AI adoption primarily drives operational restructuring rather than headcount reduction, with skill deficits rather than technology alone driving displacement perceptions. The study concludes that AI's employment impact in emerging economies is contingent on organizational and infrastructural preparedness. Recommendations emphasize sector-specific upskilling, infrastructure investment, and targeted policy interventions to ensure inclusive labour market transitions.

Keywords: Artificial Intelligence, employment outcomes, job creation, job displacement, digital readiness, emerging economy

Introduction

The global diffusion of Artificial Intelligence (AI) and automation technologies is fundamentally restructuring labour markets, yet empirical evidence remains heavily concentrated in advanced economies, leaving critical knowledge gaps in emerging markets such as Nigeria. In contexts characterized by large youth demographics, infrastructural constraints, dominant informal sectors, and rapidly evolving digital ecosystems, the trajectory

of technological adoption diverges significantly from Western patterns. Lagos State, Nigeria's commercial nerve center and a burgeoning technology hub, exemplifies this complex transition. While state-level policy frameworks actively promote a "Smart Lagos" agenda to incentivize AI adoption across public and private sectors, the empirical realities of how these technologies reshape employment remain largely undocumented, creating an evidence vacuum that hinders strategic workforce planning, economic forecasting, and equitable policy design.

To adequately frame the issues under investigation, it is essential to conceptualize the core variables driving this labour market transformation. AI integration refers to the systematic embedding of machine learning algorithms, natural language processing, robotic process automation, and predictive analytics into core organizational workflows, fundamentally altering task allocation, decision-making pathways, and skill requirements (Silva, Cunha, & da Costa, 2024). The employment outcomes of such integration are inherently dualistic, manifesting simultaneously as job creation and job displacement forces within the same labour market. Job displacement occurs when AI-driven automation renders routine, codifiable, and predictable tasks economically unviable for human execution, disproportionately affecting clerical, administrative, and assembly-line roles where tasks are highly structured and easily programmable (Acemoglu & Autor, 2011; Autor, 2015; International Labour Organization, 2023). Conversely, job creation emerges through multiple pathways, including the direct development of AI-adjacent occupations such as data scientists and algorithm auditors, the expansion of existing roles requiring human-AI collaboration, and productivity-driven market growth that increases demand for complementary services (International Labour Organization, 2025; Microsoft Research & AUDA-NEPAD, 2024). Crucially, the net employment effect remains empirically contested and appears highly contingent on organizational capabilities and environmental preparedness, rather than technological determinism.

This contingency is primarily governed by digital readiness, which functions as a critical moderating variable shaping the magnitude and direction of AI's employment impact. Digital readiness comprises two interdependent dimensions: technical infrastructure, encompassing reliable broadband connectivity, stable electricity supply, cloud computing accessibility, and affordable digital devices; and human capital capabilities, referring to the digital literacy, technical competencies, adaptive learning capacity, and AI-specific skills possessed by the workforce (UNIDO, 2023; World Bank, 2024; Oxford Insights, 2024). In Sub-Saharan Africa, pronounced infrastructural deficits and severe digital skills shortages create adoption bottlenecks, with less than 1% of the continental workforce possessing advanced AI competencies and internet penetration remaining uneven across demographic cohorts (Edjo, 2025; Microsoft Research & AUDA-NEPAD, 2024). The interaction between infrastructure and skills determines whether AI integration produces inclusive employment outcomes or exacerbates labour market polarization. In high-readiness contexts, organizations can reconfigure workflows to create AI-complementary roles and invest in targeted upskilling, whereas in low-readiness environments characterized by systemic bottlenecks, AI adoption may trigger skill-biased technological unemployment and widening wage inequality without generating sufficient compensatory job creation (UNCTAD, 2024; UNIDO, 2023).

This study is motivated by a critical empirical gap: despite the growing promotion of AI adoption in Lagos State, there is limited firm-level evidence on whether AI integration

generates net employment gains, which occupational categories are vulnerable to displacement, and how digital infrastructure and workforce capabilities shape employment outcomes. The absence of this evidence impedes the design of targeted reskilling programmes, social safety nets, and sectoral innovation policies, raising legitimate concerns that unguided AI adoption could exacerbate existing labour market inequalities and youth unemployment, which already exceeds 40% in the region. Without a clear understanding of how AI integration interacts with local digital readiness to shape employment dynamics, there is a significant risk that technological advancement will lead to widespread economic disenfranchisement rather than inclusive growth, leaving a vast segment of the workforce unable to transition into emerging, higher-skilled roles.

Consequently, the aim of this study is to provide an empirical analysis of how AI integration influences employment outcomes in Lagos State, with specific emphasis on the moderating role of digital readiness. The investigation is guided by three specific objectives: first, to assess the perceived levels of AI-induced job displacement and job creation across four high-exposure sectors in Lagos State; second, to examine how digital readiness, comprising technical infrastructure and human capital capabilities, moderates the relationship between AI integration and these divergent employment outcomes; and third, to derive sector-specific policy and organisational recommendations that enable stakeholders to harness AI for inclusive labour market development in emerging economy contexts. By analyzing the financial services, logistics/supply chain, retail/trade, and manufacturing sectors, the study addresses a critical contextual void in the literature, offering actionable insights for aligning technological adoption with workforce preparedness in rapidly urbanizing African megacities.

Literature Review and Theoretical Framework

Conceptual Review

Artificial Intelligence (AI) integration in contemporary business environments refers to the systematic incorporation of advanced technologies such as machine learning, natural language processing, and robotic process automation into organizational processes and operational systems. AI integration enables firms to automate repetitive tasks, enhance operational efficiency, improve strategic decision-making through data analytics, and develop innovative products and services. Rather than functioning as isolated technological tools, AI systems increasingly form part of integrated organizational infrastructures that reshape workflow design and resource utilization. Silva, Cunha, and da Costa (2024) argued that the convergence of AI and robotic process automation significantly improves operational efficiency while simultaneously presenting broader socio-environmental implications for organizations.

One major implication associated with AI integration is job displacement. Job displacement occurs when automation technologies replace human labour in repetitive, routine, or rule-based activities, thereby reducing the demand for certain categories of workers. The displacement effect is particularly evident in occupations characterized by predictable tasks that can be efficiently performed by intelligent systems. In developing economies, the challenge of displacement is often intensified by inadequate digital competencies and insufficient workforce adaptability, which limit employees' ability to transition into emerging technology-driven roles. According to Edjo (2025), deficiencies in infrastructure, digital skills,

and data systems constitute major barriers to effective AI adaptation across African economies, thereby increasing vulnerability to labour displacement.

Despite concerns regarding workforce displacement, AI integration also contributes significantly to job creation. The growing adoption of AI technologies has generated new occupational categories, including data scientists, AI engineers, machine learning specialists, AI ethics consultants, and human–AI collaboration managers. Furthermore, AI-driven productivity improvements encourage the emergence of innovative business models and expanded service offerings across multiple industries. The expansion of digital ecosystems in both developed and emerging economies has consequently increased demand for workers possessing advanced technological and analytical competencies. Oxford Insights (2024) noted that many African countries are increasingly investing in AI readiness through improvements in digital governance, technical skills development, and data infrastructure to support sustainable participation in the global digital economy.

The extent to which AI integration produces positive employment outcomes largely depends on the level of digital readiness within organizations and economies. Digital readiness refers to the capacity of firms, institutions, and individuals to effectively adopt, utilize, and maximize digital technologies. It encompasses technological infrastructure, internet connectivity, electricity stability, digital literacy, workforce competencies, and organizational adaptability. In many developing countries, persistent infrastructure deficiencies and limited technological skills hinder effective AI implementation and equitable labour-market transitions. UNIDO (2023) emphasized that digital readiness remains a critical determinant of successful industrial transformation in developing economies. Similarly, Edjo (2025) maintained that inadequate digital infrastructure and insufficient technical skills continue to constrain Africa's ability to fully benefit from AI-driven innovation. Consequently, digital readiness serves as an important moderating factor, shaping whether AI integration primarily results in employment creation, workforce transformation, or labour displacement.

Theoretical Framework and Moderation Justification

This study integrates the Skill-Biased Technological Change (SBTC) theory and the Task-Based Model of Automation with the Resource-Based View (RBV) and Technology-Organization-Environment (TOE) frameworks to theoretically ground the moderating role of digital readiness. SBTC and the task-based model explain why AI disproportionately displaces routine labour while increasing demand for high-skilled workers (Acemoglu & Autor, 2011). However, these theories alone do not account for contextual variance in adoption outcomes. The RBV and TOE frameworks address this by positing that organizational capabilities and environmental readiness determine how effectively technological resources are leveraged (Barney, 1991; Tornatzky & Fleischer, 1990). Digital readiness functions as an organizational and environmental capability that moderates the AI–employment relationship: high readiness enables firms to reconfigure tasks into complementary human-AI roles (job creation), while low readiness forces substitution-driven restructuring (job displacement). This theoretical integration explicitly justifies the moderation mechanism examined in this study.

Review of Empirical Studies

Recent empirical studies indicate that the labour market effects of artificial intelligence (AI) are uneven and highly dependent on digital infrastructure, workforce skills, and institutional capacity, providing a critical foundation for examining the hypothesized relationships in this study. Evidence from the International Labour Organization demonstrates that while generative AI exposes certain clerical and professional occupations to automation, this exposure frequently results in job transformation rather than outright displacement due to the enduring necessity of human judgment, creativity, and contextual decision-making (International Labour Organization, 2023; 2025). Firm-level analyses in technology-intensive sectors further confirm that AI integration catalyzes job creation through multiple pathways, including the direct emergence of AI-adjacent occupations such as data scientists and algorithm auditors, the expansion of existing roles requiring human-AI collaboration, and productivity-driven market growth that stimulates demand for complementary services (Silva, Cunha, & da Costa, 2024). In the African context, Microsoft Research and AUDA-NEPAD (2024) document the emergence of AI-complementary roles in urban formal firms, particularly within financial services and logistics, where digital transformation has increased demand for data analysts, automation specialists, and digital operations managers. These findings establish an empirical baseline for expecting a positive relationship between AI integration and job creation, which the present study tests in the Lagos State context to determine whether sectoral AI adoption in an emerging megacity yields comparable role expansion or whether infrastructural and skills constraints dampen job-creation effects relative to global patterns.

The parallel empirical literature robustly supports the proposition that AI integration increases perceived and actual job displacement, particularly in roles dominated by routine, codifiable, and predictable tasks, thereby justifying the second hypothesized relationship examined in this investigation. Acemoglu and Autor (2011) and Autor (2015) empirically establish that automation technologies disproportionately substitute labour in occupations centered on repetitive manual or cognitive execution, while leaving non-routine, interactive, and problem-solving roles largely intact. The ILO's (2023) global exposure index quantifies this effect, indicating that approximately 5.5% of worldwide employment faces high automation risk, with cashiers, data entry clerks, and assembly-line workers experiencing the steepest demand declines. In Sub-Saharan Africa, empirical assessments reveal that displacement anxieties are amplified by structural labour market features, including high informality, limited social protection, and rapid technological diffusion outpacing workforce adaptation (World Bank, 2024; Edjo, 2025). Firm-level studies in emerging economies further show that displacement is often concentrated in low-skill tiers, where employees lack transitional pathways into reconfigured roles (UNCTAD, 2024). These findings provide the theoretical and empirical foundation for testing a positive AI-displacement relationship, enabling the discussion section to explicitly situate the Lagos results within this literature and evaluate whether displacement perceptions align with global routine-task vulnerability patterns or whether local contextual factors moderate the magnitude of displacement effects.

A growing body of empirical research confirms that digital readiness functions as a critical boundary condition shaping how AI translates into labour market outcomes, directly justifying the third hypothesized relationship concerning moderation. Digital readiness,

operationalized as the convergence of technical infrastructure (broadband reliability, power stability, cloud access) and human capital capabilities (digital literacy, analytical competencies, adaptive learning), determines whether AI adoption yields complementary role expansion or substitution-driven restructuring (UNIDO, 2023; Oxford Insights, 2024). Studies across developing regions demonstrate that firms operating in high-readiness environments successfully reconfigure workflows to create AI-augmented positions, invest in continuous upskilling, and leverage productivity gains to scale organizations (Microsoft Research & AUDA-NEPAD, 2024). Conversely, in low-readiness contexts characterized by infrastructural bottlenecks and skills deficits, AI integration frequently triggers skill-biased polarization, where technologically proficient workers capture emerging opportunities while digitally excluded cohorts face heightened redundancy risks (Edjo, 2025; World Bank, 2024). Crucially, no firm-level study in West Africa has explicitly modelled digital readiness as a statistical moderator of AI's dual employment effects, leaving a methodological and contextual gap that this research addresses. These empirical insights directly justify testing digital readiness as a moderating variable, enabling the discussion section to explicitly map the interaction effects observed in Lagos against this readiness-contingent literature and evaluate whether high-readiness firms demonstrate amplified job creation and buffered displacement, as predicted, and whether infrastructural or skills gaps explain divergent sectoral outcomes.

Collectively, the empirical literature establishes three testable propositions that directly correspond to this study's hypotheses: AI integration positively predicts job creation through task transformation and role expansion; AI integration positively predicts job displacement, particularly for routine-intensive occupations; and digital readiness moderates both relationships, strengthening creation pathways while attenuating displacement risks. By synthesizing contemporary firm-level, sectoral, and regional evidence around these hypothesized mechanisms, this review creates a direct analytical bridge to the Discussion of Findings. Each result reported in the results section will be systematically positioned against the corresponding empirical cluster, enabling precise interpretation of convergence, divergence, and contextual novelty. This structured alignment ensures that the discussion does not merely restate results but actively engages with the existing knowledge base to explain why Lagos State's AI–employment dynamics confirm, challenge, or extend global and regional evidence, thereby fulfilling the scholarly imperative to situate new findings within the broader academic conversation.

Conceptual Framework

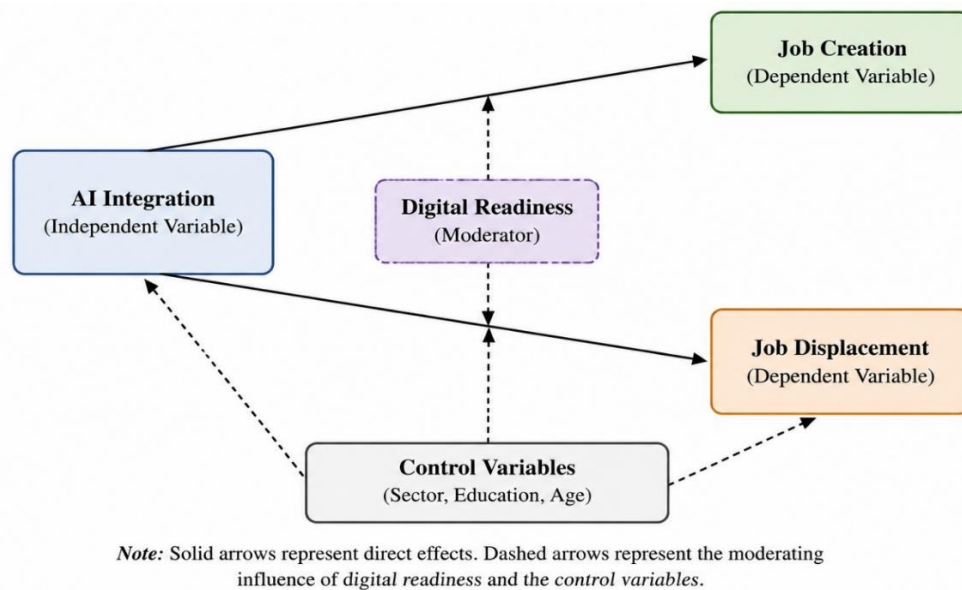


Figure 1: Conceptual Model (Source: Scholar’s Compilation, 2026)

The conceptual framework, illustrated in Figure 2.1, provides a structured and theoretically grounded representation of the hypothesized relationships guiding this investigation. Grounded in the integrated perspectives of skill-biased technological change, task-based automation, and organizational-environmental readiness, the model positions Artificial Intelligence (AI) integration as the independent variable that directly influences two distinct employment outcomes: job creation and job displacement. These dual dependent variables capture the inherently divergent labour market effects of technological adoption, enabling simultaneous examination of both expansionary and contractionary workforce dynamics. By modelling job creation and job displacement as separate outcomes rather than aggregating them into a single net employment metric, the framework acknowledges the skill-polarized and task-specific nature of AI-induced labour market transformations, thereby aligning with contemporary empirical conventions in technology-employment research.

Central to this architecture is the moderating role of digital readiness, which functions as a critical boundary condition shaping the strength and direction of AI’s impact on employment outcomes. Digital readiness is conceptualized as a multidimensional construct encompassing technical infrastructure (broadband reliability, power stability, cloud computing accessibility) and human capital capabilities (digital literacy, analytical competencies, adaptive learning capacity). Within the model, digital readiness intersects the pathways between AI integration and both dependent variables, reflecting standard moderation architecture wherein the moderator alters the slope of the independent variable’s effect rather than operating solely as a direct predictor. High digital readiness is hypothesized to amplify the positive relationship between AI integration and job creation by enabling organizations to reconfigure workflows, deploy AI-complementary roles, and scale productivity-driven expansion. Conversely, it is expected to attenuate the positive relationship between AI integration and job displacement, as robust infrastructure and skilled workforces facilitate smoother task transitions, enable internal mobility, and reduce reliance on labour substitution. This moderation mechanism directly

operationalizes the theoretical proposition that technological resources yield divergent outcomes depending on the absorptive capacity of the organizational and environmental context.

To isolate the net effects of the primary constructs and control for baseline heterogeneity, the framework incorporates sector, educational attainment, and age as control variables. These factors are positioned to directly influence both job creation and job displacement, accounting for systematic differences in occupational exposure, demographic adaptability, and industry-specific digital maturity across the sampled firms. The structural alignment of the model corresponds precisely with the study's methodological design: the convergent-parallel mixed-methods approach utilizes this framework to guide quantitative hypothesis testing via hierarchical regression with explicit AI $\times$ Digital Readiness interaction terms, while simultaneously informing qualitative interview protocols that probe readiness-driven restructuring versus substitution narratives. By maintaining clear distinction between direct, moderated, and controlled pathways, the conceptual framework ensures analytical precision, provides a coherent scaffold for interpreting empirical results, and establishes a direct logical bridge to the subsequent discussion of how organizational and infrastructural preparedness mediate the employment consequences of AI adoption in an emerging economy context.

Methodology

Research Philosophy and Design

This study adopts pragmatist research philosophy, prioritizing problem-centered inquiry and utilizing both objective and subjective knowledge to address complex real-world phenomena. Accordingly, a convergent-parallel mixed-methods design was employed (Creswell & Plano Clark, 2018). This design allows quantitative data to establish generalizable patterns regarding AI's employment impact, while qualitative interviews provide contextual depth, elucidate mechanisms of readiness-driven moderation, and validate statistical interpretations. The concurrent collection and independent analysis of both datasets, followed by integration during the interpretation phase, ensures methodological rigor and triangulated validity.

Population, Sampling, and Justification of Context

The target population comprises employees and managers in Lagos State's formal sector. Four sectors were purposively selected: Financial Services, Logistics/Supply Chain, Retail/Trade, and Manufacturing. These sectors were chosen due to their high AI exposure, significant contribution to Lagos's GDP, and varying levels of digital maturity, enabling comparative analysis of readiness-driven outcomes. The unit of analysis (employees and managers) was selected to capture both operational task-level impacts and strategic workforce planning perspectives.

Using Krejcie and Morgan's (1970) formula for an unknown population exceeding 100,000, the minimum required sample size at a 95% confidence level and $\pm 5\%$ margin of error is 384. To account for potential non-response and incomplete surveys, the sample was adjusted upward to 400. Stratified random sampling ensured proportional sectoral representation. For the qualitative strand, 15 key informants (HR directors, CTOs, and operations managers) were

purposely selected based on direct involvement in AI implementation or workforce restructuring.

Data Collection Procedure

Quantitative data were collected via a structured questionnaire administered digitally (via secure survey platforms) and in person (at corporate offices and industry hubs). The instrument employed a 5-point Likert scale across four constructs: AI Integration (5 items), Job Creation (4 items), Job Displacement (4 items), and Digital Readiness (6 items). Prior to full deployment, a pilot test ($n=40$) ensured clarity and reliability. For the qualitative component, semi-structured interviews were conducted in private settings or via secure video calls, audio-recorded with consent, and transcribed verbatim. Interview protocols probed AI implementation experiences, skill transition challenges, and infrastructure constraints.

Measurement Model Assessment and Common Method Bias

All constructs demonstrated strong internal consistency (Cronbach's $\alpha > 0.78$). Confirmatory factor analysis confirmed convergent validity: Average Variance Extracted (AVE) values ranged from 0.52 to 0.68, and Composite Reliability (CR) exceeded 0.80 for all constructs. Discriminant validity was established using the Heterotrait-Monotrait (HTMT) ratio, with all values below the conservative threshold of 0.85. To assess Common Method Bias (CMB), Harman's single-factor test was conducted, revealing that the first factor explained 31.4% of the variance (well below the 50% threshold), indicating CMB is not a concern in this dataset.

Data Analysis and Convergent-Parallel Integration

Quantitative data were analyzed using SPSS v28 and PROCESS Macro for moderation testing. Hierarchical regression was employed: Step 1 included control variables, Step 2 introduced main effects (AI Integration, Digital Readiness), and Step 3 added the interaction term ($AI \times Readiness$). Model fit and ΔR^2 were reported to quantify moderation strength. Qualitative data underwent reflexive thematic analysis (Braun & Clarke, 2023). Integration followed the convergent-parallel protocol: quantitative results and qualitative themes were merged using joint displays to identify convergence, complementarity, and divergence, thereby producing meta-inferences that directly address the research objectives.

Results and Discussion

Descriptive and Correlation Analysis

Table 1 reflects the contemporary workforce composition in Lagos State's formal sector and provides essential context for interpreting the study's findings on AI integration and employment outcomes. Gender distribution was relatively balanced, with males comprising 54.0% ($n = 216$) and females 46.0% ($n = 184$) of respondents, suggesting that perceptions of AI's employment effects are not disproportionately influenced by a single gender perspective. The age distribution was heavily skewed toward younger workers, with 68.0% ($n = 272$) aged 20–35 years, 24.0% ($n = 96$) aged 36–50 years, and only 8.0% ($n = 32$) aged 51 years and above. This youthful profile aligns with Lagos State's demographic reality as a megacity with a median age of approximately 21 years and underscores that the findings primarily capture the

perspectives of early- to mid-career professionals who are typically more exposed to digital technologies and workplace innovation (World Bank, 2024).

Table 1: Demographic Characteristics of Sample

Characteristic	Category	<i>n</i>	%
Gender	Male	216	54.0
	Female	184	46.0
Age	20–35 years	272	68.0
	36–50 years	96	24.0
	51+ years	32	8.0
Education	OND/NCE	60	15.0
	Bachelor's Degree	180	45.0
	Postgraduate Degree	100	25.0
	Other	60	15.0
Sector	Financial Services	120	30.0
	Logistics/Supply Chain	100	25.0
	Retail/Trade	100	25.0
	Manufacturing	80	20.0

Source: Scholar's Compilation, 2026

Educational attainment among respondents was relatively high, with 45.0% ($n = 180$) holding bachelor's degrees, 25.0% ($n = 100$) possessing postgraduate qualifications, 15.0% ($n = 60$) holding OND/NCE certificates, and 15.0% ($n = 60$) reporting other educational backgrounds. This distribution indicates that the sample is predominantly composed of formally educated workers, which is methodologically appropriate given the study's focus on AI integration phenomenon more prevalent in organizations requiring higher levels of technical and analytical competencies. However, this educational skew also suggests that findings may underrepresent the experiences of less-educated workers in the formal sector, a limitation acknowledged in Section 5.0.

Sectoral representation was purposively stratified to ensure comparative analysis across high-AI-exposure industries: Financial Services (30.0%, $n = 120$), Logistics/Supply Chain (25.0%, $n = 100$), Retail/Trade (25.0%, $n = 100$), and Manufacturing (20.0%, $n = 80$). This distribution reflects the relative economic weight of these sectors within Lagos State's GDP and enables robust examination of how digital readiness moderates AI's employment effects across varying levels of technological maturity and operational complexity. Collectively, these demographic characteristics enhance the internal validity of the study by ensuring adequate representation across key workforce segments while also delineating the boundaries of generalizability to informal enterprises or less-educated occupational cohorts.

Note. Percentages may not sum to 100% due to rounding. Sector labels correspond to the Nigerian Industrial Classification (NIC) codes for formal sector enterprises registered with the Lagos State Ministry of Commerce, Industry, and Cooperatives.

Table 2: Descriptive Statistics and Zero-Order Correlations for Study Variables (N = 400)

Variable	<i>M</i>	<i>SD</i>	1	2	3	4
1. AI Integration	3.45	0.91	—			
2. Job Displacement	3.82	0.88	.55**	—		
3. Job Creation	3.78	0.85	.51**	-.32**	—	
4. Digital Readiness	3.20	1.02	.48**	-.41**	.60**	—

Source: Scholar's Compilation, 2026

Table 2 indicates moderate-to-high perceived levels across all constructs, with Job Displacement registering the highest mean ($M = 3.82$), reflecting salient workforce concerns regarding automation. The correlation matrix reveals the dualistic nature of AI's employment impact: AI Integration demonstrates significant positive associations with both Job Creation ($r = .51$) and Job Displacement ($r = .55$), confirming the hypothesized simultaneous expansionary and contractionary effects. Crucially, Digital Readiness exhibits a strong positive correlation with Job Creation ($r = .60$) and a moderate negative correlation with Job Displacement ($r = -.41$), providing preliminary empirical support for its hypothesized moderating role. These zero-order relationships establish the foundational patterns, which are subsequently tested through hierarchical regression analysis in Section 4.2.

M = mean; SD = standard deviation. All constructs were measured on 5-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree). Correlation coefficients are Pearson's r . ** $p < .01$ (two-tailed). Negative correlation values are indicated with a minus sign (–) for clarity.

Moderation Analysis: AI Integration and Employment Outcomes**Table 3: Hierarchical Regression Analysis Examining the Moderating Role of Digital Readiness on Employment Outcomes (N = 400)**

Predictor	Job Creation Model			Job Displacement Model		
	Step 1 β	Step 2 β	Step 3 β	Step 1 β	Step 2 β	Step 3 β
Control Variables^a						
Sector	Included	Included	Included	Included	Included	Included
Education	Included	Included	Included	Included	Included	Included
Age	Included	Included	Included	Included	Included	Included
Main Effects						
AI Integration	—	0.198**	0.198**	—	0.314***	0.314***
Digital Readiness	—	0.451***	0.451***	—	-0.287***	-0.287***
Interaction Term						
AI $\times$ Digital Readiness	—	—	0.185**	—	—	-0.162**
Model Statistics						
R ²	0.12**	0.47***	0.50***	0.09*	0.41***	0.44***
ΔR^2	—	0.35***	0.03**	—	0.32***	0.03**
F	18.24**	112.67***	98.45***	13.18*	91.33***	77.89***
p	< .01	< .001	< .001	< .05	< .001	< .001

Source: Scholar's Compilation, 2026

β = standardized regression coefficient. ^aControl variables (sector, educational attainment, age) were entered in Step 1 and retained in all subsequent steps; coefficients suppressed for clarity and parsimony. ΔR^2 = incremental variance explained by predictors added at each step. AI = Artificial Intelligence integration. Interaction term represents the product of mean-centered AI Integration and Digital Readiness scores. $p < .05$. * $p < .01$. ** $p < .001$ (two-tailed).

Table 3 provides robust empirical support for the hypothesized moderating role of digital readiness. For the Job Creation Model, the addition of main effects (Step 2) explained a substantial 35% of additional variance ($\Delta R^2 = 0.35$, $p < .001$), with both AI Integration ($\beta = 0.198$, $p = .003$) and Digital Readiness ($\beta = 0.451$, $p < .001$) emerging as significant positive predictors. Critically, the introduction of the interaction term in Step 3 yielded a statistically significant increase in explained variance ($\Delta R^2 = 0.03$, $p = .004$), with the interaction coefficient ($\beta = 0.185$, $p = .004$) confirming that high digital readiness amplifies the positive effect of AI integration on job creation.

For the Job Displacement Model, main effects accounted for 32% of additional variance ($\Delta R^2 = 0.32$, $p < .001$), with AI Integration positively predicting displacement ($\beta = 0.314$, $p < .001$) and Digital Readiness negatively predicting displacement ($\beta = -0.287$, $p < .001$). The significant interaction term in Step 3 ($\beta = -0.162$, $p = .006$; $\Delta R^2 = 0.03$, $p = .006$) demonstrates that high digital readiness significantly buffers the displacement effect of AI integration. Collectively, these results confirm that digital readiness functions as a critical boundary

condition: it strengthens pathways to job creation while simultaneously mitigating risks of job displacement, thereby validating the study's central theoretical proposition.

Qualitative Themes

Interview analysis yielded six interrelated themes: (1) AI as an efficiency catalyst generating supervisory and analytical roles; (2) displacement anxiety concentrated among routine-task workers with limited digital training; (3) shifting competency requirements toward data literacy and platform navigation; (4) infrastructure gaps (power, broadband) as adoption bottlenecks; (5) AI as a complement to human judgment, not a replacement; and (6) polarized workforce sentiments driven by unequal access to upskilling. These themes consistently reinforced the quantitative finding that readiness dictates whether AI leads to restructuring or redundancy.

Discussion of Findings

The integrated analysis reveals that AI integration in Lagos State produces skill-biased employment outcomes heavily contingent on digital readiness. These findings align with and extend existing empirical literature. First, the positive relationship between AI and job creation corroborates global evidence that AI adoption drives task transformation and generates hybrid roles requiring human-AI collaboration (ILO, 2023; Silva et al., 2024). However, unlike advanced economies where creation often outpaces displacement, Lagos exhibits a tighter equilibrium, reflecting structural constraints in skill supply and infrastructure (Microsoft Research & AUDA-NEPAD, 2024).

Second, moderation results directly address gaps in emerging economy literature. While SBTC and task-based models predict skill polarization, they rarely operationalize organizational readiness as a boundary condition. This study demonstrates empirically that digital infrastructure and workforce capabilities moderate AI's labour impact, consistent with TOE and RBV propositions (Tornatzky & Fleischer, 1990; Barney, 1991). Firms with robust digital ecosystems reconfigure workflows to create AI-complementary roles, whereas low-readiness organizations resort to task substitution, exacerbating displacement perceptions. This explains the significant negative interaction between AI and displacement ($\beta = -0.162$), a finding underreported in African labour market studies but aligned with UNCTAD (2024) warnings on infrastructural bottlenecks.

Third, qualitative insights confirm that displacement anxiety stems less from algorithmic replacement and more from skill obsolescence and training deficits. This mirrors Edjo's (2025) assertion that Africa's AI transition is constrained by human capital gaps rather than technological unavailability. The convergence of quantitative moderation effects and qualitative readiness narratives underscores that policy, and organizational interventions must prioritize digital literacy and infrastructure stability before expecting inclusive AI-driven employment gains.

Conclusion and Recommendations

This study demonstrates that AI integration in Lagos State is a transformative but context-dependent force in the labour market. While AI adoption correlates with measurable job creation, it simultaneously increases displacement risks for routine-task workers. Crucially,

digital readiness moderates both outcomes: high readiness amplifies job creation and buffers displacement, whereas low readiness exacerbates skill polarization and workforce insecurity. These findings contextualize skill-biased technological change within an emerging African megacity, highlighting that AI's employment impact is not technologically deterministic but organizationally and infrastructurally mediated.

Sector-Specific Recommendations

Financial Services: Prioritize AI literacy programmes for mid-level analysts and compliance staff. Invest in secure cloud infrastructure to enable algorithmic risk modelling without downsizing the workforce. Partner with fintech academies to transition traditional tellers into digital customer success and data validation roles.

Logistics/Supply Chain: Deploy AI for route optimization and inventory forecasting while establishing internal mobility pathways for warehouse and dispatch staff into system monitoring and exception-handling roles. Advocate for public-private broadband expansion to support real-time AI tracking systems.

Retail/Trade: Implement phased AI checkout and inventory systems alongside mandatory digital upskilling for floor staff. Redirect displaced cashiers into omnichannel customer experience, e-commerce fulfilment, and loyalty programme management roles.

Manufacturing: Introduce cobot-assisted production lines and structured reskilling initiatives to help machine operators transition into predictive maintenance and quality assurance analytics. Leverage state-backed power stability incentives to ensure AI-driven machinery operates continuously without labour disruption.

Limitations and Future Research

This study focused on the formal sector across four industries in Lagos State, which may limit generalizability to informal enterprises or other Nigerian regions. Future research should employ longitudinal designs to track employment transitions over time, expand sectoral coverage to healthcare and agriculture, and investigate AI's impact on informal gig workers. Additionally, incorporating firm-level productivity metrics alongside employment data would strengthen causal inference regarding AI adoption and workforce outcomes.

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