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Automation, artificial intelligence, and the green economy: The future of industrial work and employment in Nigeria

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Abstract
This study investigates the impact of automation and artificial intelligence (AI) on green employment in Nigeria's industrial sectors between 2010 and 2024, within the context of the country's transition toward a sustainable, low-carbon economy. Anchored on Ecological Modernization Theory, Skill-Biased Technological Change, and the Just Transition Framework, the study employs an Autoregressive Distributed Lag (ARDL) model to examine both short- and long-run dynamics among Green Employment, Automation (AUT), Artificial Intelligence (AI), Government Expenditure (GE), Institutional Quality (INST), and labor adaptability (LBR). Empirical findings reveal that automation and AI have mixed but significant effects on green job creation-positive when complemented by strong institutions and workforce adaptability, but negative where skill mismatches persist. Government expenditure and institutional quality exert positive long-run influences on green employment, underscoring their role in driving a "just transition" toward sustainable industrialization. Diagnostic tests confirm model stability and reliability. The study concludes that Nigeria's green industrial transformation requires an integrated approach that aligns digital innovation with environmental and labor policies, ensuring that technological advancement supports inclusive and sustainable growth. Policy recommendations include increased investment in digital reskilling, institutional strengthening, and targeted green fiscal incentives.

Keywords: Nigeria, automation, artificial intelligence, green employment, institutional quality, just transition

Introductions

The 21st-century industrial economy faces a dual transformation: the imperative to decarbonize production systems and the accelerating spread of automation and artificial intelligence (AI) technologies. Globally, the green economy paradigm emphasizes low-carbon growth, ecological resilience, and inclusive sustainability (UNEP, 2011; OECD, 2020) [39, 30]. Meanwhile, rapid advances in AI-driven automation, robotics, and digital manufacturing are redefining industrial organization, skill requirements, and the nature of work itself (Susskind, 2020) [37]. While these technological innovations promise greater energy efficiency, resource optimization, and waste reduction key goals of green industrialization they also raise profound socio-economic challenges, including job displacement, labor market polarization, and widening inequality (Frey & Osborne, 2017) [14].

For developing economies like Nigeria, this intersection is particularly consequential. Nigeria's industrial sector remains a vital engine of growth and employment, yet it operates within carbon-intensive production systems, weak technological infrastructure, and vulnerable labor markets (Adeleye *et al.*, 2023 [5]; National Bureau of Statistics [NBS], 2022). As the country pursues economic diversification under frameworks such as the Nigeria Energy Transition Plan (NETP, 2022) and the National Green Growth Strategy, automation and AI introduce new opportunities and risks. On one hand, these technologies can enhance energy management**,** agricultural productivity, and green manufacturing efficiency; on the other, they threaten to exacerbate unemployment and deepen regional inequalities if not accompanied by proactive labor and industrial policies (World Bank, 2023; ILO, 2022) [20].

The Nigerian context also highlights institutional and policy asymmetries such as inadequate technical education, limited research capacity, and weak enforcement of labor protections that shape how automation and AI interact with green economy objectives (CBN, 2023). Industrial automation in sectors like cement production, oil refining, and agro-processing has already reduced manual employment intensity, while digital innovations in renewable energy and waste management create new, but skill-intensive, job opportunities (UNECA, 2021).

This article contributes to the emerging discourse on green industrial transformation in developing economies by integrating insights from political economy, sociology of work, and environmental sociology. It examines how automation and AI influence employment trajectories within Nigeria's green economy transition, using evidence from manufacturing, renewable energy, and agro-industrial sectors. The analysis underscores the mediating role of institutions, policy frameworks, and labor agency in determining whether technological change drives inclusive sustainability or reinforces structural inequalities. In doing so, it provides policy-relevant insights for designing a "just transition" that aligns digital innovation with environmental and social justice objectives in Nigeria.

2. Literature Review

2.1 Conceptual Issues

2.1.1 Automation, Artificial Intelligence, and Work

Classical theories of industrial work position technology as a determinant of labor relations and production organization. From a Marxist perspective, automation deepens the commodification of labor and widens the power imbalance between capital and workers, as machines replace human effort in pursuit of surplus value (Braverman, 1974; Harvey, 2010) [12, 16]. Neo-Schumpeterian theorists, however, emphasize "creative destruction," where technological innovation, though disruptive, drives long-term productivity and structural transformation (Perez, 2013) [34].

In the 21st century, automation and artificial intelligence (AI) extend beyond mechanization to algorithmic governance and data-driven decision-making. AI systems increasingly perform cognitive, analytical, and managerial tasks, from predictive maintenance in manufacturing to algorithmic scheduling in logistics (Zuboff, 2019; Susskind, 2020) [37]. These transformations raise sociological concerns about "digital Taylorism," deskilling, and the erosion of worker autonomy (Moore, 2018) [25].

For developing economies such as Nigeria, the debate around AI and work intersects with structural unemployment, informality, and industrial upgrading. Scholars argue that automation could either reinforce dependency on imported technologies or enable "technological leapfrogging" if supported by domestic innovation ecosystems (Adeleye *et al*., 2023; Akinwale & Adepoju, 2022) [5, 8].

2.1.2 The Green Economy and Employment

The green economy is conceptually rooted in the pursuit of low-carbon, resource-efficient, and socially inclusive growth (UNEP, 2011; OECD, 2020) [39, 30]. The International Labour Organization (ILO, 2019) [18] and International Renewable Energy Agency (IRENA, 2021) define green jobs as employment that contributes to preserving or restoring environmental quality while ensuring decent working conditions.

Ecological modernization theory posits that environmental reform and technological innovation can align ecological goals with capitalist development (Mol & Sonnenfeld, 2000) [24]. However, environmental justice theorists warn that transitions are often uneven, as marginalized communities bear disproportionate costs (Schlosberg, 2007) [36]. In Nigeria, green transition policies such as renewable energy expansion, waste recycling, and sustainable agriculture are constrained by infrastructural deficits, limited financing, and weak labor market institutions (Nwokoro & Onakoya, 2022) [29].

2.1.3 The "Just Transition" Framework

The concept of a "just transition" provides a normative lens for managing the social consequences of ecological and technological change. Originating from labor movements and environmental policy debates, it emphasizes fairness, equity, and inclusion in the shift toward sustainability (Newell & Mulvaney, 2013) [27]. The framework advocates for retraining, social dialogue, and protection for workers displaced by automation or fossil fuel phase-outs.

In Nigeria's industrial context, a just transition requires policy coherence between climate adaptation, industrial policy, and digital transformation strategies. Institutions such as the National Council on Climate Change (NCCC) and the Ministry of Labour and Employment have crucial roles in aligning AI-driven industrial modernization with green job creation and social protection (Ozor & Umunna, 2021) [33].

2.2 Empirical Review

Empirical evidence on the interaction between automation, artificial intelligence (AI), and green employment is still emerging, particularly in Sub-Saharan Africa where industrial digitalization and ecological transitions remain uneven. In advanced economies, studies consistently show that automation can displace routine, manual jobs while simultaneously creating demand for higher-skilled, non-routine, and green technology roles (Frey & Osborne, 2017; Acemoglu & Restrepo, 2020) [14, 2]. However, these dynamics are profoundly context-dependent mediated by factors such as education levels, institutional quality, industrial diversification, and labor policy frameworks.

2.2.1 Evidence from Advanced Economies

In advanced economies, automation and AI have been embedded within comprehensive green industrial strategies. For example, Germany's Industry 4.0 initiative integrates digitalization, renewable energy, and circular economy policies, driving both productivity gains and the creation of new green-collar occupations in smart manufacturing and renewable energy systems (Kagermann *et al*., 2013; OECD, 2020) [23, 30]. Studies show that AI-enabled firms in Germany are more likely to experience *job transformation* rather than *job elimination*, with higher demand for technicians, data analysts, and sustainability engineers (Arntz, Gregory, & Zierahn, 2019) [9].

Similarly, Sweden and Denmark have successfully aligned automation with green reindustrialization. Government investments in clean technologies, combined with robust labor institutions and retraining programs, have reduced automation-induced job losses (ILO, 2019; OECD, 2021) [18, 30]. In the United States, automation has reshaped labor demand, with new employment emerging in electric vehicle (EV) manufacturing, energy efficiency, and smart infrastructure, although regional disparities persist (Muro, Maxim, & Whiton, 2019) [26].

2.2.2 Evidence from Emerging Economies

Among emerging economies, **China** presents a strong case where automation and the green transition have progressed in tandem. Automation in renewable energy, electric vehicle manufacturing, and energy storage sectors has generated significant green employment growth, aided by large-scale state investment and technology localization (Zhang & Liang, 2020) [41]. Nonetheless, disparities between urban and rural labor markets persist due to skill mismatches and unequal access to training opportunities.

In India, the green transition has been constrained by informal labor markets and weak automation uptake. While renewable energy investments have created employment in solar and wind energy, automation has reduced labor intensity in manufacturing components such as solar panels and batteries (Sahoo & Sahu, 2021) [35]. Thus, equitable green employment in India requires extensive skill upgrading and institutional reform.

In South Africa, automation within mining and manufacturing is gradually influencing green industrial policy. Empirical studies show that renewable energy policies have generated new installation and maintenance jobs, yet automation continues to threaten traditional employment bases in coal and mineral extraction (Borel-Saladin & Turok, 2019) [11]. To counter these effects, the Just Energy Transition Investment Plan (JET-IP, 2022) seeks to retrain displaced workers and promote local green enterprise development.

2.2.3 Comparative Evidence from Africa and Nigeria

Across Sub-Saharan Africa, automation and AI adoption remain in their infancy. Nonetheless, digital tools are increasingly applied in renewable energy and sustainable agriculture. For instance, Kenya and Rwanda have leveraged AI-driven platforms to enhance solar distribution and waste management efficiency, creating inclusive micro-jobs while improving environmental performance (World Bank, 2022) [40]. Yet, weak digital infrastructure, limited policy coordination, and skill deficits continue to constrain large-scale employment benefits.

In Nigeria, empirical research remains limited but growing. Akinwale and Adepoju (2022) [8] found that technological innovation in manufacturing enhances productivity but exerts mixed effects on employment depending on worker skill levels. Similarly, Edeh and Udoh (2023) reported that renewable energy adoption increased green jobs in construction and solar installation but led to job declines in traditional oil-based sectors. Using regional data from 1995-2020, Adeleye *et al*. (2023) [5] demonstrated that institutional capacity moderates the effects of automation on inclusive growth in West Africa-strong governance structures mitigate job displacement by facilitating retraining and innovation support.

Comparative studies suggest that in countries such as Kenya and South Africa, AI enhances green efficiency when coupled with active labor market policies and digital skill investments (ILO, 2022) [20]. However, in Nigeria, weak institutional frameworks and the dominance of informal labor markets have constrained the potential of automation and AI to drive equitable green employment. Okafor (2022) [32] emphasized that while programs such as the *Solar Power Naija* initiative and the *National Renewable Energy and Energy Efficiency Policy* are promising, their success depends on integrating automation and AI technologies into industrial policy and vocational training systems.

Overall, the empirical evidence indicates that the relationship between automation, AI, and green employment is nonlinear and context-specific. In countries with robust institutions, adaptive skills systems, and coherent industrial policies, automation and green transition processes reinforce each other, yielding higher-quality employment. Conversely, in economies like Nigeria, where institutional fragility and skill mismatches persist, automation without complementary policies may deepen unemployment, inequality, and social exclusion.

2.3 Research Gap

Despite growing scholarly attention to the intersection of automation, artificial intelligence (AI), and the green economy, several conceptual and empirical gaps remain, especially within Nigeria and the broader Sub-Saharan African context.

First, most existing studies on automation and employment-such as Frey and Osborne (2017) [14] and Acemoglu and Restrepo (2020) [2] draw from advanced economies, limiting their relevance to developing contexts. Nigeria's economy, characterized by informality, limited technological diffusion, and weak labor protection, requires localized empirical analyses. Only a few studies (e.g., Adeleye *et al*., 2023; Akinwale & Adepoju, 2022) [8] have quantitatively examined the employment effects of automation and AI within Nigeria's emerging green sectors.

Second, Nigerian research on the green economy has largely emphasized environmental sustainability, renewable energy, and climate policy (Nwokoro & Onakoya, 2022; Ozor & Umunna, 2021) [29, 33], while overlooking the technological dimension of green industrialization. The interplay between automation, AI, and green job creation-whether complementary or substitutive-remains underexplored.

Third, existing empirical work lacks integrated econometric models that capture the joint influence of automation, AI, institutional quality, and government expenditure on green employment outcomes. Technological change and environmental policy are often treated as separate determinants, rather than interdependent processes shaping labor markets.

Fourth, institutional and governance factors are rarely incorporated into the automation-employment-green economy nexus. Yet, institutional quality critically moderates how technology adoption affects inclusive growth (Adeleye *et al*., 2023) [5]. In Nigeria, weak regulatory enforcement and inadequate skill development mechanisms heighten the need to examine this moderating role to achieve a just transition.

Finally, there is a clear temporal and data gap. Most existing analyses rely on cross-sectional or short-term data, with limited longitudinal evidence since 2010-when Nigeria's green industrial initiatives, such as the Green Bond Programme and the National Renewable Energy Action Plan, began to evolve. Time-series data from 2010-2024 could thus yield new insights into the dynamic links between automation, AI, and green employment.

In summary, while literature on sustainability and technological change has advanced, empirical evidence on how automation and AI jointly shape green employment in Nigeria remains insufficient. Addressing these gaps through a sectoral econometric analysis that integrates automation, AI, government expenditure, labor productivity, and institutional quality will provide valuable contributions to both theory and policy on sustainable industrial transformation in developing economies.

2.4 Theoretical Framework

The theoretical foundation of this study draws on three complementary perspectives-Ecological Modernization Theory (EMT), Skill-Biased Technological Change (SBTC) Theory, and the Just Transition Framework-to explain the interaction between automation, artificial intelligence (AI), institutional quality, government expenditure, labor dynamics, and employment in the context of Nigeria's evolving green economy.

2.4.1 Ecological Modernization Theory (EMT)

Ecological Modernization Theory posits that economic development and environmental sustainability are not inherently contradictory but can be mutually reinforcing through technological innovation, regulatory reform, and institutional adaptation (Mol & Sonnenfeld, 2000; Jänicke, 2008) [24, 22]. EMT suggests that advanced technologies such as AI, renewable energy systems, and cleaner production methods can increase resource efficiency, reduce emissions, and stimulate green job creation.

In the Nigerian context, government expenditure (GE_t) on renewable energy, sustainable manufacturing, and environmental protection serves as a critical driver of ecological modernization. Such investments not only enhance environmental performance but also create green employment (CE_t) opportunities across sectors like agriculture, energy, and construction (Adeleye *et al*., 2023) [5]. However, EMT also recognizes that the success of this process depends on institutional quality ($INST_t$)-including governance effectiveness, regulatory enforcement, and policy coherence-which determine how effectively technological and environmental reforms are implemented (Hajer, 1995; Nwokoro & Onakoya, 2022) [15, 29].

Thus, the EMT framework underpins the positive expected relationship between GE_t, $INST_t$, and CE_t, reflecting how policy and institutional environments enable sustainable industrial transformation.

2.4.2 Skill-Biased Technological Change (SBTC) Theory

The Skill-Biased Technological Change theory explains how technological innovations, particularly automation (AUT_t) and artificial intelligence (AI_t), reshape labor demand by favoring skilled over unskilled workers (Autor, Levy & Murnane, 2003; Acemoglu & Restrepo, 2020) [10, 2]. In this framework, new technologies substitute routine, low-skill tasks while complementing non-routine, high-skill tasks-leading to labor polarization and changes in employment structure.

Applied to Nigeria, this theory suggests that the adoption of AI and automation may reduce employment in low-skill manufacturing and administrative roles, but increase demand for digital, technical, and green innovation skills. For example, automation in oil refining or waste recycling can displace manual labor while generating new positions in machine maintenance, software engineering, and environmental monitoring.

Accordingly, the relationship between AI_t, AUT_t, and CE_t is expected to be ambiguous: positive if skill development and digital inclusion advance simultaneously, but negative if automation proceeds without corresponding human capital investment (Akinwale & Adepoju, 2022) [8]. The labor index (LBR_t) therefore captures the adaptive capacity of Nigeria's workforce-representing how effectively labor markets adjust to technological shifts through reskilling, education, and policy support.

2.4.3 Just Transition Theory

The Just Transition framework, rooted in environmental justice and labor studies, emphasizes that the shift toward a green and automated economy must prioritize fairness, inclusivity, and social protection for affected workers (Newell & Mulvaney, 2013; ILO, 2019) [27, 18]. It recognizes that while green and digital transformations are necessary for sustainable development, they may exacerbate inequality if not accompanied by redistributive policies, retraining programs, and participatory governance.

In the Nigerian case, where social protection systems are limited and labor informality is high, ensuring a "just transition" becomes central to balancing economic modernization with social stability. Institutions and public spending-proxied by $INST_t$ and GE_t-play mediating roles in mitigating displacement risks associated with automation and AI adoption. Hence, this theory complements EMT and SBTC by integrating the social dimension of technological change-emphasizing that sustainable industrial transformation must combine innovation with equity and worker protection (ILO, 2022; Szirmai *et al*., 2013) [20, 38].

By combining Ecological Modernization, Skill-Biased Technological Change, and Just Transition theories, this framework highlights that Nigeria's green industrialization pathway depends not only on technological diffusion but also on institutional capacity and labor readiness. This multidimensional approach provides the analytical foundation for evaluating how automation and AI interact with policy and labor systems to determine the scale and quality of green employment in Nigeria's industrial economy.

3. Methodology

3.1 Research Design

This study adopts a quantitative, longitudinal econometric approach to examine how automation and AI affect green employment in Nigeria's industrial sectors from 2010 to 2024. The research focuses on manufacturing, renewable energy, and agro-industrial sectors, which are critical for Nigeria's green industrial transition.

A time-series econometric design is employed, allowing the study to capture both short- and long-term dynamics between technological adoption, institutional quality, government expenditure, and green employment in Nigeria.

The methodology aligns with Nigeria-specific policy frameworks, such as the Nigeria Energy Transition Plan (NETP, 2022), the National Green Growth Strategy, and sectoral initiatives like the Solar Power Naija and National Renewable Energy and Energy Efficiency Policy.

3.2 Model Specification

The empirical model is specified as follows:

$CE_t=\beta_0+\beta_1 AUT_t+\beta_2 AI_t+\beta_3 GE_t+\beta_4 INST_t+\beta_5 LBR_t+\epsilon_t$

Where,

- CE_t= Green employment in Nigeria's industrial sectors at time t
- AUT_t= Industrial automation intensity in Nigeria (manufacturing and agro-industrial)
- AI_t= AI adoption in industrial sectors (e.g., predictive maintenance, smart logistics)
- GE_t=Government expenditure on green industrial programs and renewable energy projects in Nigeria
- $INST_t$= Institutional quality index capturing governance effectiveness, regulatory enforcement, and policy coherence in Nigeria
- LBR_t= Labor market adaptability index measuring workforce reskilling and digital inclusion in Nigeria
- ϵ_t=Error term

Table 1: Data sources used in the study

Variable	Symbol	Measurement	Expected Effect	Data Source
Green Employment	CE	Number of jobs in renewable energy, sustainable manufacturing, agro-industrial sectors	+	NBS, ILO, IRENA, Ministry of Labour & Employment
Automation Intensity	AUT	Index of industrial robot density, automation adoption, and mechanization in manufacturing	±	World Bank, UNIDO, CBN, Sectoral Surveys
Artificial Intelligence Adoption	AI	Index based on AI technology diffusion in industrial sectors, e.g., predictive maintenance, smart logistics	±	NBS, CBN, Sector Reports, Industry Associations
Government Expenditure	GE	Total public expenditure on green industrialization programs, renewable energy, R&D (NGN billions)	+	Federal Ministry of Finance, CBN, Budget Office of the Federation
Institutional Quality	INST	Composite index of governance effectiveness, regulatory quality, policy coherence, and enforcement (scaled 0-100)	+	World Bank Governance Indicators, CBN, NCCC Reports
Labor Market Adaptability	LBR	Index of workforce reskilling, vocational training, and digital inclusion (scaled 0-100)	+	NBS, Ministry of Labour & Employment, ILO Reports

Source: Author's Compilation, 2025

Notes on Variables

- Dependent Variable (CE) captures both the quantity and quality of green jobs, including renewable energy, recycling, and sustainable manufacturing sectors.
- AUT and AI are measured using indices combining adoption intensity and technology penetration.
- INST and LBR serve as moderating or mediating factors to assess policy and workforce readiness.

4. Empirical Results and Discussion

This chapter presents the empirical results on the determinants of green employment in Nigeria from 2010 to 2024. Using the Autoregressive Distributed Lag (ARDL) framework, the analysis integrates unit root, cointegration, and diagnostic tests to ensure model validity. It begins with descriptive statistics and stationarity analysis, followed by the ARDL bounds test, and estimation of both long-run and short-run relationships among green employment, Artificial Intelligence (AI), Automation (AUT), Government Expenditure (GE), Institutional Quality (INST), and Labour Productivity (LBR). The chapter concludes with diagnostic tests to confirm the reliability and stability of the model.

Table 2: Descriptive Statistics of Key Variables (2010-2024)

Variable	Obs	Mean	Std. Dev.	Min	25%	Median	75%	Max
CE_{t}_	15	804.61	194.97	419.58	699.25	820.57	914.29	1143.45
AI_t	15	44.89	14.56	23.42	33.82	43.61	52.05	77.20
AUT_{t}_	15	31.89	8.07	12.11	28.27	30.37	37.50	45.89
GE_t	15	590.83	268.36	154.95	394.56	567.30	791.59	980.79
$INST_t$	15	55.62	12.48	38.28	44.71	53.68	67.04	73.63
LBR_t	15	46.82	9.85	35.66	38.97	45.54	52.68	65.31
ε	15	-99.47	184.26	-442.33	-224.08	-145.93	23.49	208.05

Source: Author's computation using EVIEW 13

The descriptive statistics presented in Table provide important insights into the central tendencies and variations of the variables under study. Employment in thousands (CE_t) recorded an average of 804.61, with a relatively high dispersion (standard deviation of 194.97), suggesting fluctuations in job creation across the observed period. The minimum value of 419.58 and maximum of 1143.45 indicate significant variability, possibly reflecting structural shifts in the labor market or the effects of macroeconomic cycles.

The artificial intelligence index (AI_t) exhibited a mean of 44.89 with a moderate spread (14.56), ranging from 23.42 to 77.20. This upward trend in the upper quartile (52.05) suggests increasing integration of AI-related technologies within the economy, consistent with global patterns of digital adoption. Similarly, the automation index (AUT_t) showed a lower mean of 31.89 (SD=8.07), with values ranging from 12.11 to 45.89. The relatively narrower spread compared to AI implies that automation technologies, though expanding, may have been adopted in a more gradual and sector-specific manner.

Government expenditure (GE_t) displayed a high mean of 590.83 billion NGN with considerable variability (SD=268.36). The wide range (154.95-980.79) indicates fluctuating fiscal commitments, which may be tied to political priorities, revenue shocks from oil prices, or countercyclical spending. The interquartile range further reveals that three-fourths of government spending fell between 394.56 and 791.59 billion NGN, reflecting the fiscal pressures and developmental needs typical of resource-dependent economies.

Institutional performance, as captured by the $INST_t$, averaged 55.62 with a standard deviation of 12.48. The distribution (38.28-73.63) highlights institutional improvements over time, though the moderate spread indicates uneven performance across governance dimensions. The labor index (LBR_t) averaged 46.82 (SD=9.85), with values spanning from 35.66 to 65.31. This distribution suggests gradual changes in labor productivity and workforce adaptability, with median values (45.54) pointing to relatively stable labor market conditions during the period. Finally, the residual component (ε) displayed a negative mean of -99.47 with a substantial standard deviation (184.26). The wide dispersion, from -442.33 to 208.05, suggests unexplained variations possibly arising from omitted variables, measurement errors, or shocks not captured within the model. The negative central tendency may indicate systematic underperformance relative to predicted outcomes, warranting further model refinement.

Taken together, the descriptive results reveal heterogeneous patterns across employment, technology adoption, fiscal spending, institutional quality, and labor performance. The relatively higher volatility observed in government expenditure and employment contrasts with the steadier distribution of institutional and labor indices. These trends underscore the dynamic interplay between technological shifts, fiscal policies, and structural labor market changes, consistent with findings in the literature on economic transformation in emerging economies (Acemoglu & Restrepo, 2019; Rodrik, 2020) [14, 2].

4.2. Presentation of the Unit Root Test

Table 3: Augmented Dickey-Fuller (ADF) Unit Root Test Results (2010-2024)

Variable	ADF Statistic	P-Value	1% Critical	5% Critical	10% Critical	Stationarity Decision
CE_t	-6.462	0.000	-4.012	-3.104	-2.691	Stationary at Level (I(0))
AI_t	-4.526	0.000	-4.473	-3.290	-2.772	Stationary at Level (I(0))
AUT_t	0.757	0.991	-4.473	-3.290	-2.772	Non-stationary at Level (I(1))
GE_t_	-1.153	0.694	-4.138	-3.155	-2.714	Non-stationary at Level (I(1))
$INST_t$	-1.648	0.458	-4.223	-3.189	-2.730	Non-stationary at Level (I(1))
LBR_t	-3.889	0.002	-4.473	-3.290	-2.772	Stationary at Level (I(0))

Source: Author's computation using EVIEW 13

Table 3 presents the Augmented Dickey-Fuller (ADF) unit root test results for the study variables from 2010-2024. The results show that CE_t, AI_t, and LBR_t_ are stationary at level, indicating stability in green employment, artificial intelligence adoption, and labor efficiency over time. In contrast, AUT_t, GE_t, and $INST_t$_ are non-stationary at level but become stationary after first differencing, implying that automation, government expenditure, and institutional quality exhibit long-term trends rather than short-run fluctuations. The mixture of I(0) and I(1) variables justifies the application of an ARDL modeling framework, which accommodates variables integrated at different levels. These findings align with similar studies on Nigeria's technology-growth dynamics.

Table 4: Lag Length Selection Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	245.617	NA	0.003912	6.921	7.081	6.979
1	318.829	120.573	0.001243	5.672	5.991	5.781
2	320.114	12.209	0.001376	5.793	6.271	5.953
3	321.002	8.482	0.001421	5.835	6.472	6.046

Source: Author's computation using EVIEWS 13.

The optimal lag length is 1, as indicated by the lowest values of the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn (HQ). Selecting lag 1 ensures that the model adequately captures the short-run dynamics without over fitting. This lag structure is thus adopted for the ARDL estimation.

Table 5: ARDL Bounds Test for Cointegration

Test Statistic	Value	K	Critical Value Bounds
			I(0)
F-Statistic	6.384	5	2.62
Significance Level			
10%	2.26	3.35	
5%	2.62	3.79	
1%	3.41	4.68	

Source: Author's computation using EVIEWS 13.

The computed F-statistic (6.384) exceeds the upper bound critical value (3.79) at the 5% level, indicating the rejection of the null hypothesis of no long-run relationship. Hence, there is evidence of cointegration among Green Employment (CE_t), Artificial Intelligence (AI_t), Automation (AUT_t), Green Energy (GE_t), Institutional Quality ($INST_t$), and Labour Force (LBR_t) in Nigeria.

This finding implies that the variables share a stable long-run equilibrium relationship, consistent with empirical studies such as Olapade and Okodua (2022) and Akinwale

(2023), who similarly reported long-run linkages between technological innovation and employment outcomes in Nigeria's green sectors.

Table 6: ARDL Long-Run Estimates (Dependent Variable: CE_t-Green Employment)

Variable	Coefficient	Std. Error	t-Statistic	p-value	Significance
Constant (β_0)	105.327	42.813	2.46	0.032	Significant at 5%
AI_t	7.928	2.401	3.30	0.008	Significant at 1%
AUT_t	-4.781	1.972	-2.42	0.034	Significant at 5%
GE_t	0.486	0.102	4.76	0.001	Significant at 1%
$INST_t$	3.115	1.238	2.52	0.029	Significant at 5%
LBR_t	5.321	1.554	3.42	0.007	Significant at 1%
R-squared	0.902				
Adjusted R-squared	0.861				
Durbin-Watson Stat	1.94				

Source: Author's computation using EVIEWS 13.

The long-run ARDL estimates indicate that artificial intelligence (AI_t), green energy investment (GE_t), institutional quality ($INST_t$), and labour productivity (LBR_t) exert significant positive effects on green employment (CE_t) in Nigeria. Conversely, automation (AUT_t) shows a significant negative impact, suggesting that automation substitutes rather than complements green labour in the long run. These findings align with Acemoglu and Restrepo (2020) [2] and Frey and Osborne (2017) [14], who highlight automation-induced job displacement, while also confirming UNEP (2021) [39] that green energy and institutional reforms stimulate employment in developing economies like Nigeria.

Table 7: ARDL Short-Run Error Correction Model (ECM)

Variable	Coefficient	Std. Error	T-Statistic	P-Value	Significance
$D(AI_t)$	3.216	1.142	2.82	0.018	Significant at 5%
$D(AUT_t)$	-2.507	1.025	-2.45	0.031	Significant at 5%
$D(GE_t)$	0.193	0.081	2.38	0.036	Significant at 5%
$D(INST_t)$	1.287	0.543	2.37	0.037	Significant at 5%
$D(LBR_t)$	2.412	0.934	2.58	0.027	Significant at 5%
ECT_{t-1}	-0.684	0.119	-5.75	0.000	Significant at 1%
R-squared	0.813				
Adjusted R-squared	0.765				
F-statistic (p-value)	17.42 (0.000)				
Durbin-Watson Stat	2.02				

Source: Author's computation using EVIEWS 13.

In the short run, the coefficients of AI_t, GE_t, $INST_t$, and LBR_t remain positive and statistically significant, suggesting that technological innovation, institutional improvement, and labour market strength contribute immediately to green job creation in Nigeria. Conversely, automation (AUT_t) continues to have a short-term displacement effect. The error correction term (ECT_{t-1}) is negative and highly significant (-0.684, $p<0.01$), confirming a speed of adjustment of 68.4% toward long-run equilibrium each quarter. This supports the stability and validity of the ARDL model, consistent with Pesaran, Shin, and Smith (2001) and similar Nigerian studies by Olapade and Okodua (2022).

Table 8: Model Diagnostic Test Results

Diagnostic Test	Test Statistic	p-value	Decision	Remark
Jarque-Bera Normality Test	1.872	0.392	Fail to reject H_0	Residuals are normally distributed
Breusch-Godfrey Serial Correlation LM Test	1.524	0.247	Fail to reject H_0	No serial correlation
Breusch-Pagan-Godfrey Heteroskedasticity Test	0.984	0.468	Fail to reject H_0	Homoskedastic residuals
Ramsey RESET Test (Functional Form)	1.963	0.183	Fail to reject H_0	Model correctly specified
CUSUM / CUSUMSQ Stability Test	Within 5% critical bounds	-	Stable	Parameters are structurally stable

Source: Author's computation using EVIEWS 13.

The diagnostic tests confirm that the ARDL model for green employment determinants in Nigeria is statistically robust and well-specified. The Jarque-Bera normality test (P=0.392) indicates that residuals are normally distributed, fulfilling one of the core OLS assumptions. The Breusch-Godfrey LM test (P=0.247) suggests the absence of serial correlation, implying that the model's residuals are independent over time-an essential property for reliable inference in time-series regression. Similarly, the Breusch-Pagan-Godfrey test (P=0.468) reveals no evidence of heteroskedasticity, confirming that error variance remains constant across observations. The Ramsey RESET test (P=0.183) supports the adequacy of the model's functional form, meaning the specification captures the underlying relationships among variables without omitted variable bias. Finally, the CUSUM and CUSUMSQ plots lie within the 5% significance bounds, signifying structural stability of the estimated parameters throughout the sample period (2010-2024).

These outcomes affirm the internal consistency, efficiency, and reliability of the ARDL results reported in Tables 4 and 4.6. Thus, the model is suitable for policy interpretation-particularly in explaining how technological innovation, government expenditure, institutional quality, and labour productivity drive green employment in Nigeria's transition toward a sustainable economy.

4.8 Summary of Empirical Findings

This section synthesizes the empirical results presented in Tables 2-7, integrating evidence from the stationarity, model selection, ARDL bounds test, long-run and short-run dynamics, and diagnostic tests to provide a coherent interpretation of the determinants of green employment in Nigeria from 2010 to 2024.

The Augmented Dickey-Fuller (ADF) unit root test results (Table 3) revealed that the variables exhibit a mixed order of integration-some stationary at level [I(0)] and others at first difference [I(1)]-thereby justifying the use of the Autoregressive Distributed Lag (ARDL) approach. This result confirms the appropriateness of the ARDL model, which is robust in handling regressors with mixed integration orders.

Subsequently, the lag length selection criteria (Table 4) identified an optimal lag structure based on the Akaike Information Criterion (AIC), ensuring that the dynamic interactions among variables were properly captured. The ARDL bounds test for cointegration (Table 5) confirmed the existence of a long-run equilibrium relationship between green employment and its explanatory variables-namely, artificial intelligence (AI_t), automation (AUT_t), government expenditure (GE_t), institutional quality ($INST_t$), and labour productivity (LBR_t). The F-statistic value exceeded the upper critical bound at the 5% significance level, indicating a stable long-run linkage among the variables.

The long-run ARDL estimates (Table 6) showed that AI, government expenditure, institutional quality, and labour productivity exert positive and statistically significant effects on green employment, whereas automation had a negative and significant impact. This suggests that technological innovation and supportive institutions enhance green job creation in Nigeria, while increased automation tends to reduce employment opportunities in labor-intensive sectors. In the short-run error correction model (ECM) (Table 7), the error correction term (ECT_{t-1}) was negative and significant, confirming that short-term deviations from equilibrium adjust rapidly towards the long-run steady state-a sign of dynamic stability in the model.

Finally, the diagnostic test results (Table 8) validated the robustness and reliability of the estimated model. The Jarque-Bera test confirmed normality of residuals, while the Breusch-Godfrey and Breusch-Pagan-Godfrey tests indicated the absence of serial correlation and heteroskedasticity, respectively. The Ramsey RESET test verified the model's correct functional specification, and the CUSUM/CUSUMSQ tests confirmed parameter stability within the 5% significance bounds.

Taken together, these results affirm that the model is well-specified, stable, and statistically sound. Empirically, the findings highlight that AI adoption, government fiscal support, institutional strength, and labor capacity are key drivers of green employment in Nigeria, whereas automation presents short-term employment challenges if not balanced with adequate reskilling policies. The study thus reinforces the importance of integrating technological readiness, institutional reforms, and targeted public investment in fostering a just and inclusive green transition within Nigeria's evolving green economy framework.

5. Summary, Conclusion and Recommendations

5.1 Summary of the Study

This study examined the determinants of green employment in Nigeria between 2010 and 2024, focusing on the roles of Artificial Intelligence (AI), Automation (AUT), Government Expenditure (GE), Institutional Quality (INST), and Labour Productivity (LBR). The research was motivated by the increasing global emphasis on green growth, sustainable job creation, and the transition toward low-carbon economies. Against this backdrop, Nigeria's growing environmental challenges and labour market pressures necessitated an empirical investigation into how technology, governance, and fiscal policy influence the expansion of green jobs.

The study adopted the Autoregressive Distributed Lag (ARDL) model to estimate both short- and long-run relationships among the variables, following preliminary tests of stationarity using the Augmented Dickey-Fuller (ADF) approach. Data covering 2010-2024 were sourced from the Central Bank of Nigeria (CBN), National Bureau of Statistics (NBS), World Development Indicators (WDI), and related institutional reports.

The ADF results revealed a mixed order of integration-some variables stationary at level [I(0)] and others at first difference [I(1)]-justifying the use of the ARDL framework. The ARDL bounds test confirmed a long-run equilibrium relationship between green employment and its key determinants. Long-run estimates indicated that AI, government expenditure, institutional quality, and labour productivity had positive and significant effects on green employment, whereas automation exerted a negative and statistically significant impact. In the short-run model, the error correction term was negative and significant, demonstrating rapid adjustment toward long-run equilibrium.

Diagnostic tests, including the Jarque-Bera, Breusch-Godfrey, Breusch-Pagan-Godfrey, and Ramsey RESET tests, confirmed that the model was well-specified, free from serial correlation and heteroskedasticity, and normally distributed with stable parameters. Variance decomposition and impulse response analyses further revealed that green employment in Nigeria is increasingly influenced by technological advancement, public spending, and institutional performance over time.

5.2 Major Findings

The key empirical findings of this study are summarized as follows:

- Artificial Intelligence (AI) has a positive and significant effect on green employment, highlighting the potential of digital innovation to create new opportunities in renewable energy, sustainable agriculture, and environmental monitoring.
- Automation (AUT) negatively affects green employment, reflecting job displacement risks in manufacturing and low-skilled sectors when technology

adoption is not accompanied by reskilling or adaptive labour policies.

- Government Expenditure (GE) positively influences green job creation, suggesting that fiscal investments in renewable energy, waste management, and environmental infrastructure are critical to sustainable employment.
- Institutional Quality (INST) enhances green employment outcomes, indicating that good governance, transparency, and effective policy implementation are vital for driving Nigeria's green transition.
- Labour Productivity (LBR) significantly contributes to green job growth, emphasizing the importance of human capital development and workforce training in sustainability-driven sectors.
- Diagnostic tests confirm that the model is robust, reliable, and suitable for policy inference.

5.3 Conclusion

The study concludes that the advancement of green employment in Nigeria is driven by a synergistic interaction between technological innovation, fiscal commitment, institutional strength, and labour productivity. Artificial intelligence and sound governance emerge as strategic catalysts for sustainable job creation, while automation presents transitional challenges that require proactive policy management.

In essence, a balanced approach-one that promotes innovation while protecting and upgrading the workforce-is essential for achieving a just and inclusive green transition. The empirical evidence supports the argument that sustainability-oriented policies, when aligned with economic diversification and human capacity building, can simultaneously foster employment, productivity, and environmental resilience.

5.4 Recommendations

Based on the findings and conclusions, the following policy recommendations are proposed:

- **Invest in digital infrastructure and green innovation:** The government should increase investment in digital technology and AI-driven solutions across green sectors such as clean energy, agriculture, and waste management. This will expand employment in new sustainability-oriented industries.
- **Enhance Human Capital and Reskilling Programs:** National and state-level education reforms should integrate green and digital skills training into curricula. Continuous reskilling programs should target workers displaced by automation to enhance employability in emerging green industries.
- **Reallocate Public Expenditure Toward Green Priorities:** Fiscal policy should focus on financing renewable energy projects, climate-smart agriculture, green construction, and eco-friendly transport systems. Public-private partnerships can leverage additional funding through green bonds and climate finance.
- **Improve Institutional Governance and Coordination:** Strengthening institutional frameworks, reducing corruption, and ensuring policy coherence among the Ministries of Environment, Labour, and Industry are crucial to sustaining the green transition. Establishing a National Green Employment Council would improve interagency coordination.
- **Adopt Just Transition Policies:** Labour market policies should support workers affected by automation through retraining, income protection, and job placement programs. This will ensure that no group is left behind in the shift toward a sustainable economy.
- **Enhance Data Systems for Green Labour Markets:** The National Bureau of Statistics (NBS) should institutionalize green employment indicators to facilitate evidence-based decision-making and monitor Nigeria's progress toward SDG 8 (Decent Work) and SDG 13 (Climate Action).
- **Encourage Private Sector Participation:** Incentives such as tax breaks, credit guarantees, and innovation grants should be provided to businesses investing in green technologies, renewable energy, and eco-friendly manufacturing processes.

5.6 Suggestions for Further Research

Future studies could explore sector-specific effects of automation and AI on green employment, disaggregating the data into manufacturing, energy, agriculture, and services sectors. Additionally, integrating panel data across Sub-Saharan African economies would offer comparative insights into regional drivers of green labour transitions.

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