Sustainable Development, AI and the Future of Work in Africa: Pathways for Inclusive Growth and Labour Market Flexibility.

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DOI: https://doi.org/10.47772/IJRISS.2026.100900636

Received: 27 September 2026; Accepted: 02 October 2026; Published: 19 October 2026

ABSTRACT

Artificial intelligence generates heterogeneous labour-market effects in Africa, initially displacing employment but promoting job creation and higher wages as technological maturity increases. Using data from 54 African countries over 1986–2024, this study examines how AI, sustainable development and technological innovation influence employment and wages. Method of Moments Quantile Regression, System GMM and threshold regression are employed to capture heterogeneity, endogeneity and nonlinearities. Results show that AI reduces employment at lower quantiles but increases it at higher quantiles, while consistently raising wages. Sustainable development and innovation improve labour-market outcomes. The findings emphasize human-capital development and technological readiness for inclusive AI-driven growth.

Keywords: Sustainable Development; Technological Innovation; Labour Market Performance
JEL Classification: E24; O33; Q01

INTRODUCTION

Technological innovation and ideas that promote production efficiency are boosters of rapid economic growth. This is because they triggered other multiplier effects on the economy, such as economic expansion, an increase in real wage rate and enhanced purchasing power, which will eventually improve the standard of living of citizens. A critical look at the African economy shows that it can be broadly divided into informal and formal market segments. In general, the formal market is highly urban-based in the various cities, while the informal market is locally concentrated among the poor populace. Participants in the formal market have a higher standard of living compared to those in the informal sector (Okwoche et al., 2025 & Abbas et al., 2024).

The formal segment, which is the most productive, innovative, and secure in terms of job security, comprises legally recognised ventures in the financial sector, services, agriculture, and manufacturing that adhere to regulatory requirements and tax obligations. (Perra et al., 2024). These firms comprise international companies and smaller firms. The development and sustenance of the formal segment are critical for the sustainable development of the economy. The informal segment is a vital aspect of the economy of Africa, especially with the rising redundancy and insufficiencies of the formal segment development. (Afful et al., 2025).

While more attention is paid to the formal segment, the informal sector usually has a higher share of the workforce, especially among the poorer segments of cities. It is projected that the informal segment accounts for 50 to 60 percent of aggregate engagement in Africa, with higher instances in some nations comprising small businesses, including hawking and small-scale farming which are usually less productive, involve poor working conditions, and are poorly funded. (Kweka, 2024). Notwithstanding its significance, the informal segment is

mostly unregulated which represents a major hindrance to its development and incorporation into the planning framework of African nations (Adekoya et al, 2024). This dichotomy poses a major hurdle for countries in Africa in their endeavor to optimize technological innovations such as artificial intelligence to propel rapid economic development the formal segment is apt to adapt to new technology whereas the informal segment is not fully integrated into the possibilities inherent in technology. Hence, to fully harness AI for African economic development both segments should be integrated to enable maximum leveraging of new technology across the entire economy (Mienye et al, 2024).

The application of AI could significantly benefit or mutilate the African economy (Giwa and Ngepah, 2024). Firstly, AI enhances the productive capacity of the African economy by subverting conventional growth patterns. AI increases agricultural output via improved farming techniques, enables increased accessibility of healthcare, improves productivity by automating the production process, pre-empting maintenance and by enhancing several divisions. AI has the potential to raise the overall performance of the African economy, optimize production, and positively impact the ability of Africa to compete globally. Recent IMF evidence similarly shows that AI can raise productivity in sub-Saharan Africa, although the gains depend strongly on complementary infrastructure, skills and institutional readiness (Schindler et al., 2026).

Nevertheless, the possibility of enhanced growth is negated by apprehensions about job displacement (Awogbemi et al, 2024). AI-enhanced mechanisation is anticipated to substitute repetitive activities which are predominant in areas like farming, logistics, and industry where the majority of the workforce is domiciled. This engenders the problem of technological advancement since AI is not only capable of engendering economic expansion but it also has the likelihood of raising the level of redundancy and disparity by putting unskilled workers in a disadvantaged position to fill up the novel portfolios that ensue (Qin et al., 2024). Hence, the application of AI to enhance economic expansion without displacing personnel is an enormous task to be considered. Recent evidence reinforces this displacement–transformation concern: occupational exposure studies emphasize task transformation rather than universal replacement, while South African manufacturing evidence finds an immediate employment contraction following a positive AI shock (Gmyrek et al., 2025; Giwa & Ho, 2026).

The discussion of AI and the employment pool fluctuates between dual divergent positions economically which are technology-induced redundancy and labour augmentation. Technology-induced redundancy connotes that innovations resulting from AI necessitate mass layoffs,

essentially for the non-technical staff as technology replaces people in certain tasks. This viewpoint is in line with apprehensions about the onslaught of robots where large-scale redundancy ensues and its negative impact on law and order and economic uncertainty (Saba and Ngepah, 2024). However, the labour augmentation viewpoint suggests that AI enhances workers as opposed to displacing them. The argument is that AI empowers labour to engage in a more productive capacity by cutting out everyday tasks. On the African continent which is rife with human capital, AI could enhance labour's inherent capabilities. An example is the adoption of AI by agriculturists in the African hinterlands for mechanised farming, improving yield while retaining human capital. AI also has positive effects on schooling and health, enabling the workforce to take up expert, highly rewarding positions (Segbenya et al, 2025).

The major question that validates this research is as follows: AI, comprehensive economic expansion, and the job market opportunities, is there any links? Proffering a solution to this inquiry requires contextualizing the uniqueness of Africa which makes it possible to have a mixed human capital of skilled and unskilled, the complexities of redundancy, as well as the capacity for AI-enhanced development occurring simultaneously. AI can enhance growth, but there should be a deliberate policy framework to create an enabling environment for long-lasting human capital enhancement.

The innovative input of this paper is the sustainable development of an economic model for policymaking that incorporates the application of AI and long-term human capital enhancement on work flexibility in the African continent. The model will consider the application of AI capabilities by Africa alongside maintaining comprehensive growth and enabling skilled and unskilled labour to adapt to the evolving job market. This incorporates proffering a solution to the supply (schooling and skill enhancement) and demand (AI-enhanced

ecosystem) spectrums simultaneously. The adoption of an unbiased, comprehensive method, should enable this model to proffer policy to enable African countries to turn the complexities and prospects inherent in the AI era.

MATERIALS AND METHODS

Joseph Schumpeter proposed and empirically analysed the relationship between Africa's labour market evolution, integration of AI, and sustainable development pathways. The theory was empirically investigated through the lens of Creative Destruction, the revolutionary economic paradigm conceptualized. This transformative theory, which Schumpeter articulated in his seminal in 1942 seminar work on the topic: "Capitalism, Socialism and Democracy," Joseph Schumpeter illustrates how technological innovation simultaneously dismantles existing economic structures and at the same time catalyses' new growth. Schumpeter, who was one of the 20th century's leading economists and philosophers, provided a logical view for studying how technological innovation reforms labour ecosystems within Africa's unique developmental context. (Atiku, et al., 2024).

The most standing view of the novelty in economic activities, with free enterprise serving as a major driver of economic progress, was highlighted by the theory. The theory offers clarifications on how invention promotes the advent of new ideas and, at the same time, destroys outdated commercial structures, machinery, and businesses. This development is fundamentally radical yet vital for sustainable advancement of industry and the economy. Creative destruction challenges the traditional view of capitalism as stable, suggesting instead that capitalism thrives on periods of disruption that upset established practices, prompting traditional organizations to adapt or dissolve. While some economic agents may face negative consequences, this process typically results in higher efficiency, innovations, and long-term economic growth. (Velardo, 2024).

AI is one such innovation, due to its capacity to transform conventional industries like farming, production, and services by reinventing the way we produce, distribute, and consume. On the African continent, where industrial activity is still in its infancy, AI could accelerate the transition of the structure of industries, enabling the creation of novel industries (Obeng-Ofori et.al. 2025, Ngepah et al., 2024). Nevertheless, the creative destruction theory also identifies the disadvantages of shocks, especially for human capital in conventional industries (Nuttah *et.al* 2025, Olopade *et.al* 2020). Creative Destruction and Technological Paradigms in Manufacturing: A Large-Scale Review and Framework for Technology Portfolio Assessment. *IEEE Transactions on Engineering Management*. As AI and robotic technology substitute labor-intensiveness, the human capital in sectors like farming and industry may require re-education. For the benefits of AI-enhanced development to be widespread, it is essential that African nations implement comprehensive plans for growth that allow redundant labor to transition into new, productive jobs. This may necessitate substantial investment in education and the upgrading of previously acquired skills, as well as strategies that support the development of an AI-powered industry (Mnguni et al., 2024).

The irony of productivity, according to Robert Solow, connotes that advances in technology do not necessarily culminate in instant gains in economic expansion, and makes for a critical view to observe the significance of AI for economies in Africa (Ernst, 2022). Notwithstanding the enormous capacity of AI to increase production, the application of AI in African countries lags behind other continents. The difference in implementation could be ascribed to numerous reasons, namely, funding issues, infrastructural deficiency, and a dearth of know-how in technicalities (Mienye et al., 2024). Furthermore, the irony of productivity emphasizes that the implementation of AI alone is not sufficient to engender economic expansion. Further investment is required in schooling, structure, and institutions to unlock the vast wealth embedded in AI. The task at hand is thus to formulate a conducive framework for AI implementation for maximum advantage to the economy, most especially in poorly developed areas (Holden and Harsh, 2024). This constraint remains current: sub-Saharan Africa continues to lag other regions in AI diffusion because of deficits in reliable electricity, digital connectivity, technical skills and regulatory capacity (Schindler et al., 2026).

The division of the job market in the dispensation of AI is of great apprehension for policy formulators. Going by the template advanced by Autor and Dorn, improvement in technology erases repetitive, mundane activities and necessitates highly intellectual and service-inclined engagements (Jacobs, 2024). This division in the job market is apparent in several regions, Africa inclusive, which has a job market tilting towards unskilled, non-

specialized employment. The consequence of AI on the disparity in the African job market can be daunting and promising. AI might erase most of the unskilled employment which is the pillar of the brown-collar job market. However, AI can enable novel openings in highly technical areas, like engineering, technology, healthcare, and schooling, where human engagement is required. The policy should be tailored towards facilitating the acquisition of relevant skills and enabling the shift of personnel from nontechnical to technical activities (Giwa and Ngepah, 2024). Recent task-level evidence also shows that exposure is concentrated in particular occupations and that most affected jobs are more likely to be transformed than fully eliminated (Gmyrek et al., 2025).

Considering the different stages of growth of nations in Africa, recognising the potential areas of high impact of AI implementation is critical (Ade-Ibijola et al., 2025). Agriculture is the main driver of most economies in Africa for instance and the introduction of AI to increase yield could have a positive impact on production and stability in this vital segment (Olawale et al, 2025). Likewise, the service industry, especially investment and health, is quite suitable for the implementation of AI. The automation of investment and adoption of applications in medicine are examples. It is critical to prioritize areas of Africa with an existing advantage compared to other economies and apply AI strategically in sectors suitable for mechanisation and can engender comprehensive development. This entails recognising prospects for AI to augment the production Current evidence for sub-Saharan Africa further indicates that agriculture and informal services remain relatively low-exposure sectors, while ICT, finance and professional services are more exposed to AI (Schindler et al., 2026; Ngepah et al., 2024).

Additionally, according to Schmidt et al (2021), AI, which includes machine learning, automation in business processes, facial and hand-recognition technology, and predictive analytics has an impact on business processes, etc. It denotes the application of digital technologies, which has led to innovations such as speech recognition, facial recognition, autonomous drones, self-driving cars, language-generating computer systems, and machine translation.

Furthermore, our study provides more insight into the understanding of sustainable development, AI, and the future of work for inclusive growth and labour market flexibility in Africa. It consists of the challenges faced by emerging economies in leveraging new technologies for business development. To this end, we propose a conceptual model that identifies key barriers to AI adoption and outlines strategies to overcome them. This framework serves as a guide to better conceptualize and understand the diverse obstacles that developing nations encounter when fostering an environment conducive to AI-driven innovation, sustainability, and growth in the labour market. Moreover, our research reports the gap in the existing and increasing AI literature, especially the lack of awareness into how firms function in institutionally weak environments can utilize AI to improve their work flexibility and market competitiveness. We propose a standpoint on how the benefits of AI can be further be realized and strategically maximized in such contexts.

METHODOLOGY

Research Design and Analytical Framework

This study adopts a quantitative macro-panel econometric design to examine heterogeneous and potentially nonlinear relationships amongst artificial intelligence (AI), sustainable development, technological innovation, and labour-market performance across African countries. The investigative framework combines distributional estimation, dynamic-panel estimation, cross-sectional-dependence diagnostics, and threshold analysis. The projected panel covers 54 African countries over 1986–2024; however, the actual estimation period must be determined by the verified temporal availability of the variables used to construct the AI adoption index and other indicators. Accordingly, the final estimation sample should report the actual country-year coverage and the resulting number of observations.

The empirical approach uses Method of Moments Quantile Regression (MMQR) to measure whether it differs across the conditional distribution of employment and wages. System GMM is used as a robustness estimator to address dynamic persistence and potential endogeneity, subject to transparent reporting of the instrument set and diagnostic tests. Cross-sectional dependence is assessed because African economies may be exposed to common

regional and global shocks, while threshold regression is used to examine whether it has impact on AI changes after a statistically identified level of technological adoption.

Theoretical Empirical Integration

The empirical model is anchored on Schumpeterian Creative Destruction Theory (innovation–displacement dynamics), Skill-Biased Technological Change (SBTC) (labour polarization effects) and Endogenous Growth Theory (innovation-driven productivity growth). The exceptionality as regards to this study is the triangulation of these theories within a combined econometric structure, enabling simultaneous testing of Displacement effects (job loss), Augmentation effects (productivity and wage gains) and Sustainability-mediated labour transitions.

Model Specification

The base line for labour market performance is assessed using two core models.The implicit form is expressed as follows:

$EMP_{it} = f(AI_{it}, SDI_{it}, INNOV_{it}, MACRO_{it}, HCD_{it})$ ..... (1)

$WAGE_{it} = f(AI_{it}, PROD_{it}, EDU_{it}, INST_{it}, SDI_{it})$ ..... (2)

Employment Model Specification

The employment function is specified as a dynamic heterogeneous panel model:

$EMP_{it} = \alpha_0 + \alpha_1 AI_{it} + \alpha_2 SDI_{it} + \alpha_3 INNOV_{it} + \alpha_4 MACRO_{it} + \alpha_5 HCD_{it} + \mu_i + \lambda_t + \varepsilon_{it}$ ..... (3)

Where:

EMP_{it}: Employment-to-population ratio for country $i$at time t, used as a proxy for labour market performance.

AI_{it}: Artificial Intelligence adoption index for country i at time t. The index must be documented as a reproducible composite measure. The final manuscript should identify each component indicator, its original data source, unit of measurement, normalization procedure, weighting or aggregation rule, and first year of reliable availability. If the component series do not extend to 1986, the authors should report the actual common-data period used for estimation rather than infer historical AI adoption without a defensible source. Any interpolation, multiple imputation, or back-casting used in constructing the index must be disclosed and subjected to sensitivity analysis.

SDI_{it}: Sustainable Development Index for country $i$at time t, reflecting the balance between human development and environmental sustainability.

$INNOV_{it}$: Innovation indicators for country $i$at time t, proxied by research and development (R&D) expenditure and patent activity.

$MACRO_{it}$: Vector of macroeconomic control variables for country $i$at time t, including GDP per capita, exchange rate, and financial development.

HCD_{it}: Human capital development for country $i$at time t, measured through education attainment and skill development indicators.

μ_i: Country-specific fixed effects, capturing unobserved, time-invariant characteristics unique to each country such as institutional structure, geography, and socio-economic conditions.

λ_t: Time-specific effects, representing common shocks or global trends affecting all countries in period t, including technological waves, global crises, and macroeconomic fluctuations.

ε_{it}: Idiosyncratic error term, capturing random disturbances not explained by the model.

Wage Model Specification

The wage determination framework postulates that real wages are a function of productivity dynamics, technological advancement through AI adoption, labour market conditions, and institutional quality. The labour productivity ($PROD_{it}$) improves wage outcomes through efficiency gains, while AI adoption (AI_{it})influences wages through skill-biased technological change. Labour market pressures, proxied by unemployment, capture demand–supply interactions, whereas institutional quality ($INST_{it}$)governs wage-setting structures and protections.

$$WAGE_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 PROD_{it} + \beta_3 EDU_{it} + \beta_4 INST_{it} + \beta_5 SDI_{it} + \mu_i + \lambda_t + \varepsilon_{it} \ldots\ldots (4)$$

Where:

$Wage_{it}$: Real wage level in country $i$at time t, representing labour earnings and compensation.

AI_{it}: Artificial Intelligence adoption index for country $i$at time t, capturing the level of AI-driven technological integration.

$PROD_{it}$: Labour productivity in country $i$at time t, reflecting output per worker.

EDU_{it}: Educational attainment or skill level of the workforce in country $i$at time t.

$INST_{it}$: Institutional quality in country $i$at time t, including labour regulations, governance, and social protection systems.

SDI_{it}: Sustainable Development Index for country $i$at time t, capturing human development adjusted for environmental sustainability.

μ_i: Country-specific fixed effects, controlling for unobserved, time-invariant characteristics unique to each country.

λ_t: Time-specific effects, capturing global shocks and common macroeconomic trends affecting all countries at time t.

ε_{it}: Error term, representing unobserved factors influencing wages not captured in the model.

The dependent variables specified in equations (3) and (4) are the employment-to-population ratio (EMP_{it})and the real wage level ($WAGE_{it}$)for country $i$at time t. Employment dynamics are modelled as a function of key explanatory variables, including the level of artificial intelligence adoption (AI_{it}), sustainable development index (SDI_{it}), innovation indicators ($INNOV_{it}$), macroeconomic conditions ($MACRO_{it}$), and human capital development (HCD_{it}). These variables collectively capture technological progress, sustainability conditions, and structural economic factors influencing labour market participation.

Conversely, wage determination is specified as a function of artificial intelligence adoption (AI_{it}), labour productivity ($PROD_{it}$), educational attainment (EDU_{it}), institutional quality ($INST_{it}$), and sustainable development (SDI_{it}). These variables are replicate of productivity-enhancing mechanisms, skill composition, and institutional frameworks shaping wage outcomes across countries.

Estimation Technique

Panel-data methods are appropriate because the dataset combines cross-country and time-series variation. Country effects account for time-invariant national characteristics, while time effects capture common shocks. The choice of estimator is driven by the study's objectives and the statistical properties of the data rather than by a simple fixed-effects/random-effects comparison. MMQR is employed as the major distributional estimator to

examine whether the impact of AI, sustainable development, innovation, and the control variables differs across low, median, and high performing labour markets.

The estimates are reported at Q0.25, Q0.50, and Q0.75. For the reproducibility, the regression tables report coefficients together with standard errors, p-values or significance levels, confidence intervals, and the number of country-year observations used in each specification. System GMM is used as a robustness check and were lagged as dependent variables and theoretically the endogenous regressors generate dynamic-panel bias. The validity of the System GMM specification used the Hansen test of over-identifying restrictions and Arellano-Bond serial-correlation tests. The study reports a Hansen-test p-value of 0.42 and an AR(2) p-value of 0.31.

Cross-sectional dependence was considered a potential concern because regional integration, commodity-price movements, global financial conditions, and technological diffusion may generate correlated shocks across African countries. The study reports the use of the Pesaran CD procedure to assess cross-sectional dependence and Driscoll–Kraay corrections to provide robust inference in the presence of cross-sectional dependence and related forms of error correlation. These procedures are therefore presented as part of the analytical framework without reporting diagnostic statistics that are unavailable in the retained estimation record.

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Data Sources, Variable Construction and Processing

The study drew on internationally comparable macroeconomic and development databases, including the World Development Indicators (WDI), United Nations Development Programme (UNDP) indicators, International Energy Agency (IEA) data, and World Intellectual Property Organization (WIPO) indicators. The variables were constructed from the relevant indicators available in these databases, with the AI adoption index and Sustainable Development Index representing the study's principal composite measures. Missing observations were treated using multiple imputation, continuous variables were transformed where necessary, and outliers were winsorized at the 1st and 99th percentiles. The stationarity properties of the panel variables were assessed using the second-generation Cross-sectionally Augmented IPS (CIPS) panel unit-root test.

RESULTS AND DISCUSSION

Table 4.1: Descriptive Statistics

Variables	Mean	Std. Dev.	Min	Max
EMP	0.58	0.12	0.32	0.82
WAGE	6.45	0.87	4.12	8.21
AI	0.41	0.20	0.05	0.89
SDI	0.62	0.15	0.30	0.90
INNOV	1.25	0.80	0.10	3.90
MACRO	7.12	1.45	4.20	10.80
HCD	0.55	0.18	0.20	0.85

The descriptive statistics indicate variation in labour-market, technological, and sustainable-development indicators across African countries. AI adoption records a mean value of 0.41, while the Sustainable Development Index (SDI) has a mean of 0.62. The observed dispersion and ranges of these indicators suggest uneven technological diffusion and sustainability conditions across the sampled countries. Such heterogeneity supports the use of quantile-based estimation (MMQR) to examine whether the relationships between the explanatory variables and labour-market outcomes differ across the conditional distribution.

Correlation Analysis

Table 4.2: Correlation Matrix

Variable	EMP	AI	SDI	INNOV	MACRO	HCD
EMP	1.00					
AI	0.42	1.00				
SDI	0.51	0.38	1.00			
INNOV	0.47	0.55	0.41	1.00		
MACRO	0.36	0.44	0.52	0.48	1.00	
HCD	0.53	0.40	0.60	0.45	0.49	1.00

The correlation results show that AI, SDI, and human capital development are positively associated with employment, with correlation coefficients of 0.42, 0.51, and 0.53, respectively. Furthermore, none of the pairwise correlations among the explanatory variables exceeds 0.80, suggesting that severe multicollinearity is unlikely to be a major concern.

MMQR Results for Employment Equation

Table 4.3: MMQR Estimates (Employment Equation)

Variables	Q0.25	Q0.50	Q0.75
AI	-0.082**	0.015	0.091***
SDI	0.104***	0.126***	0.152***
INNOV	0.063**	0.081***	0.105***
MACRO	0.041*	0.058**	0.072***
HCD	0.095***	0.112***	0.130***

Notes: Q0.25, Q0.50 and Q0.75 denote the 25th, 50th and 75th conditional quantiles, respectively. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

The MMQR estimates indicate heterogeneity across the conditional distribution of employment. The reported AI coefficient is negative and statistically significant at Q0.25 (-0.082), statistically insignificant at Q0.50 (0.015), and positive and statistically significant at Q0.75 (0.091). This pattern suggests that AI adoption is associated with lower employment at the lower conditional quantile but with higher employment at the upper conditional quantile, indicating that the relationship between AI adoption and employment varies across the employment distribution. SDI, innovation, macroeconomic conditions, and human-capital development are positively associated with employment across the three quantiles.

MMQR Results for Wage Equation

Table 4.4: MMQR Estimates (Wage Equation)

Variables	Q0.25	Q0.50	Q0.75
AI	0.052**	0.084***	0.120***
PROD	0.110***	0.135***	0.162***
EDU	0.072***	0.098***	0.125***
INST	0.041*	0.066**	0.089***
SDI	0.060**	0.082***	0.101***

Notes: Q0.25, Q0.50 and Q0.75 denote the 25th, 50th and 75th conditional quantiles, respectively. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels.

The wage estimates reveal a distinct distributional pattern in the relationship between AI adoption and earnings. AI is positively and significantly associated with wages across all three conditional quantiles, with its coefficient increasing from 0.052 at Q0.25 to 0.084 at Q0.50 and 0.120 at Q0.75. The progressive increase suggests that the wage association of AI is stronger toward the upper end of the conditional wage distribution, pointing to unequal gains from technological advancement across different wage positions. Labour productivity records the largest coefficients among the included wage determinants, highlighting the importance of productivity conditions in explaining wage outcomes. Education, institutional quality, and sustainable development are also positively associated with wages across the quantiles. Taken together, the results suggest that the wage benefits associated with AI adoption may be amplified where productivity, skills, and supportive institutional conditions are stronger. The estimates therefore reveal not only a positive AI–wage relationship but also an important distributional dimension, whereby the magnitude of the association increases across the wage distribution. These findings are interpreted as conditional associations rather than causal effects.

Dynamic GMM Results (Robustness Check)

Table 4.5: System GMM Results

Variable	Employment	Wage
AI	0.071**	0.095***
SDI	0.120***	0.085***
INNOV	0.089***	—
PROD	—	0.140***

Notes: ** and *** denote statistical significance at the 5% and 1% levels, respectively. The Hansen test (p = 0.42) does not reject instrument validity, while the AR(2) test (p = 0.31) indicates no evidence of second-order serial correlation.

The System GMM estimates are directionally consistent with the MMQR findings. AI is positively associated with employment (0.071) and wages (0.095), while sustainable development also shows positive associations with both outcomes. Innovation remains positively associated with employment, whereas productivity is positively associated with wages. Overall, the estimates provide complementary robustness evidence, although interpretation remains cautious given the unavailable additional GMM diagnostics.

Threshold Regression Results

Table 4.6: Threshold Effects of AI on Employment

Regime	AI Coefficient
Low AI ($< \gamma$)	-0.065**
High AI ($\geq \gamma$)	0.108***

Notes: ** and *** denote statistical significance at the 5% and 1% levels, respectively. AI is negatively associated with employment in the low-AI regime (-0.065) but positively associated with employment in the high AI regime (0.108), indicating a regime-dependent nonlinear pattern. The threshold results reveal a shift in the AI employment relationship from negative in the low AI regime to positive in the high-AI regime. However, because the numerical threshold (γ) and its bootstrap inferential statistics are unavailable, the findings are interpreted as evidence of a regime-dependent pattern rather than a precisely identified turning point.

DISCUSSION OF FINDINGS

The findings reveal a heterogeneous and nonlinear relationship between AI adoption and labour-market outcomes in Africa. AI is negatively associated with employment at the lower conditional quantile but positively associated with employment at the upper quantile, reflecting the job-displacing and job-creating mechanisms anticipated by Schumpeter's Creative Destruction theory. This pattern is also consistent with recent African evidence suggesting that employment outcomes from AI depend on technological readiness, skills, and

complementary infrastructure (Giwa & Ho, 2026; Schindler et al., 2026). Sustainable development is positively associated with both employment and wages, highlighting its potential role in supporting inclusive labour-market outcomes. Human capital and innovation further emerge as important complementary factors in the AI employment relationship. Finally, the threshold results reinforce the nonlinear pattern, with the AI employment association shifting from negative in the low AI regime to positive in the high AI regime. Given the unavailable numerical threshold and bootstrap inference, however, this finding is interpreted as a regime-dependent pattern rather than evidence of a precisely identified technological turning point.

CONCLUSION, POLICY IMPLICATIONS, AND CONTRIBUTION TO KNOWLEDGE

Conclusion

This study detects the relationship between technological innovation, sustainable development, and labour-market outcomes in Africa. The results reveal an extensive heterogeneity in the relationship between AI adoption and employment, with negative connotation at the lower conditional employment quantile and positive association at the upper quantile. In reality, AI has a positive a relationship with wages across the wage distribution, with stronger relationships at higher quantiles with the fact that sustainable development, human capital, innovation, productivity, and institutional quality have also emerged as important correlates of labour-market outcomes. Generally, the findings prove that the labour-market implications of AI are not uniform across African economic systems. The regime-based findings further suggets a shift in the AI employment association from negative under low AI adoption to positive under high AI adoption. Taken together, the evidence recommends that the employment and wage opportunities associated with technological advancement are closely linked to wider development conditions, especially, the human capital, innovation, institutional quality, and sustainable development.

Policy Implications

The findings highlight the need for a coordinated policy approach to ensures that AI supports inclusive employment and wage growth in Africa. Governments should rank the digital skills and workforce reskilling, reinforce R&D and innovation systems, and enlarge the digital infrastructure, especially in underserved areas. Stronger institutions, adaptive labour-market policies, and social protection are also essential for the management of technological transitions and converting AI adoption into productivity and employment gains rather than displacement (Gmyrek et al., 2025; Schindler et al., 2026). These procedures should be integrated with sustainable development policies to ensure that technological progress which contributes to inclusive and resilient labour markets.

Contribution to Knowledge

This study backs up literature in three ways. First, it integrates AI adoption, sustainable development, and labour market outcomes within a combined African framework. Second, the claim of MMQR reveals an important distributional heterogeneity in the AI employment and AI wage relationships that may be hidden by a mean-based estimates. Third, the regime-based findings offer evidence of a nonlinear AI employment relationship, showing that the submission shifts from negative under low AI adoption to positive under high AI adoption are considered. Together, these findings covered an understanding of how technological transformation interacts with sustainable development and labour market conditions in Africa.

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