African Journal of Business & Development studies Volume 2 Issue 1 2025
ISSN: 3079-6903
DOI: https://doi.org/10.70641/ajbds.v2i1.162

AFRICAN JOURNAL
OF BUSINESS AND DEVELOPMENT STUDIES
AJBDSresearchjournal@usiu.ac.ke
journals.usiu.ac.ke

Artificial Intelligence: Does it Intensify or Mitigate Unemployment in Kenya's Skilled Labor Market?

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Cite: Murunga P. P. (2025). Artificial Intelligence: Does it Intensify or Mitigate Unemployment in Kenya's Skilled Labor Market? *African Journal of Business & Development Studies*,2*(1)*,539-553. https://doi.org/10.70641/ajbds.v2i1.162

Abstract

The Fourth Industrial Revolution(4IR) is reconfiguring labor markets through artificial intelligence (AI). This study examines the effect of AI investment on skilled employment in Kenya in both short- and long-run dynamics and the role of structural breaks. Quarterly data from 2012Q1 to 2024Q4 were analyzed using the Autoregressive Distributed Lag (ARDL) model, incorporating Chow breakpoint tests, structural dummy variables, and Granger causality. Baseline estimates show AI investment significantly raises skilled employment in the short run (8.83%) and long run (4.81%). With structural breaks included, the short-run effect turns negative coefficient (β =–14.21), while the long-run effect remains positive (β =8.13). The error correction term (–0.65) indicates rapid adjustment to equilibrium. Wages positively affect skilled employment in both horizons (β=0.59; β=6.09) which will call for competitive compensation. Inflation has a strong persistent negative short-run effect (β =–51,250.92) and long-run effect (β =-27,852.28). GDP per capita exerts persistent negative effect (β =–0.47; β =–1.46) attributed to capital-intensive growth that limits labor absorption. The results show AI adoption initially displaces skilled labor but later increases demand for advanced skills. Macroeconomic factors amplify these dynamics: wage growth enhances employment, while inflation and GDP growth exert asymmetric effects. Granger causality tests confirm a bidirectional causal relationship between AI and skilled employment. Kenya may provide education and training programs to mitigate transitional unemployment, align training with AI-intensive sectors, expand broadband in underserved counties, integrate AI curricula in TVETs, and sustain competitive wage structures. Regulatory safeguards and social protection are essential to ensure inclusive AI-driven labor market transformation.

Key Words: Skill, Employment, Artificial Intelligence, ARDL, structural breaks, human capital

1.0 INTRODUCTION

Artificial intelligence (AI) is now central to global technology and is transforming production systems and labor markets. Its capacity to automate routine and repetitive tasks has raised concerns over labor displacement among low-skilled workers (Nguyen & Vo, 2022; Giwa &

Ngepah, 2024). AI-driven efficiency gains further erode employment security by reducing the demand for certain occupations (Zhang & Xu, 2024). Projections from McKinsey & Chui (2024) indicate that by 2030–2060, nearly half of existing jobs will be significantly transformed or eliminated by AI.

AI adoption generates both risks and opportunities for labor markets. Growth in machine learning, data analytics, and data science has created high-demand occupations requiring advanced technical expertise (Guliyev, 2023). These roles provide competitive wages and stronger career trajectories, supporting labor market modernization (Saba & Ngepah, 2024; Chen & Zhang, 2024). The World Economic Forum and Wood (2023) project that AI will generate 12 million more jobs than it displaces globally. Such dual dynamics provide the need for balanced policy approaches that mitigate displacement risks while leveraging long-term gains (Damioli & Vivarelli, 2024).

In Kenya, structural labor market shifts are compounded by regional disparities, informality, and digital diffusion. Currently, AI adoption is evident in agriculture, finance, health, education, and transport. Local innovations include AfyaRekod's health system, FarmDrive's credit scoring, Utu's API, and Angaza Elimu's e-learning. Multinationals such as Google, IBM, Microsoft, and Huawei expand research and training. Policy frameworks indicate strong commitment to adoption and these policy frameworks include Blockchain and AI Taskforce (2018), ICT Policy, and Digital Master Plan (2022–2032) prioritize AI. The Digital Economy Blueprint and Taskforce stress ethics (KICTANet, 2023; OECD, 2022; UNESCO, 2023). The latest policy framework is National AI Strategy (2025–2030) which envisions innovation, skills, and regulation.

This institutional and technological momentum justifies focusing on Kenya for empirical investigation. However, it remains unclear how this transformation will affect skilled labor markets in both the short and long run. While prior studies have analyzed AI's employment effects in advanced and emerging economies (Nguyen & Vo, 2022; Giwa & Ngepah, 2024; Chen & Zhang, 2024), few have examined sub-Saharan Africa using high-frequency data. No study has yet employed autoregressive distributed lag (ARDL) modeling combined with structural break analysis to evaluate the temporal dynamics of AI's effects in an African economy and in a developing country context. This gap is critical, given that AI is projected to contribute \$2.4 billion to Kenya's economy by 2030 (Serrari, 2023).

This paper fills the gap by analyzing the effects of AI on skilled labor in Kenya using an autoregressive distributed lag (ARDL) model. Assessing the impact of artificial intelligence (AI) on skilled employment is critical for policymakers, researchers, and practitioners. It helps identify new competencies, close skill gaps, reduce inequalities, and guide digital policy (Klenert et al., 2023). This study advances the limited African literature on AI and labor with a focus on Kenya. The study examines AI's effect on labor demand and skill gaps. It evaluates how AI adoption generates employment while posing risks of displacement. The study further estimates short- and long-run effects of AI adoption on skilled employment using autoregressive distributed lag (ARDL) modeling. It also identifies structural breaks in Kenya's labor market linked to AI integration.

2.0 LITERATURE REVIEW

Artificial intelligence (AI) is widely recognized as a major determinant of economic growth and human development. However, it's effect on labor markets remain contested. Some scholars argue that AI and robotics generate new categories of work mostly in technology-intensive occupations such as design, management, and system enhancement (Autor, 2015; Acemoglu & Restrepo, 2018; Neves et al., 2019; Vermeulen et al., 2018). Others are concerned with displacement risks posed by automation leading to job losses and long-term social security problems (Caruso, 2018; Pinheiro et al., 2019). Robotics literature is directly relevant to this debate, as robots constitute a primary physical manifestation of AI-driven automation. Findings from robotics research thus provide important evidence into how AI integration transforms labor markets (Tasioulas, 2019).

Empirical evidence indicates the various differentiated effects of robotics adoption across skill categories. Graetz and Michaels (2018), analyzing data from 17 countries between 1993 and 2007, found that robots reduce opportunities for low-skilled labor but simultaneously expand demand for high-skilled workers. Dixon et al. (2021) reported similar findings at the firm level, noting that employment outcomes depend on whether worker skills complement or substitute robot investments. Their study further identified a hollowing-out of middle-skilled jobs, with growth concentrated in both high- and low-skilled segments. Dahlin (2019), examining U.S. data, also found positive effects on high-skilled employment which showed that workers engaged in innovation and programming were most likely to benefit. Collectively, the above studies imply that robotics adoption does not uniformly destroy jobs but rather reconfigures skill demand in unique ways.

Beyond robotics, broader AI-focused research confirms that technology adoption transforms labor demand. Advanced technologies in most cases complement specialized expertise thus creating incentives for skill acquisition while replacing some routine or manual tasks. Studies by Xie et al. (2023), Babina et al. (2023), Plumwongnot and Pholphirul (2022), and Buera et al. (2022) show that AI reduces reliance on low-skilled labor while increasing demand for high-skilled workers. Evidence from the U.S. and China indicates that AI-driven investment in manufacturing and services contributes to labor market polarization, with a distinct bias toward skilled employment.

The consensus imply that AI adoption consistently favors skilled workers, while its effects on low- and middle-skilled employment remain more ambiguous. However, the evidence is mixed on the temporal dynamics of these effects, with little agreement on how short-run adjustments differ from long-run outcomes. No study has examined these dynamics in the context of an emerging African economy using high-frequency data and structural break analysis. This gap motivates the present study, which investigates the short- and long-run effects of AI on skilled labor in Kenya, while identifying points of structural adjustment and their implications for policy.

2.1 Theoretical Framework

This study adopts the Skill-Based Technical Change (SBTC) framework, which explains how technological progress reconfigures labor demand. SBTC entails a shift favoring skilled over less-skilled workers, expanding opportunities in specialized occupations requiring higher education while eroding demand for middle-skill and routine-intensive roles (Wang & Zhang, 2021). Individuals with advanced expertise complement digital technologies by executing complex cognitive tasks, whereas lower-skill labor is increasingly displaced by automation. Violante (2008) stated that computerization substitutes human input, disproportionately affecting less-skilled workers. Job growth thus concentrates in high-skill, adaptable professions (Cooley et al., 1997), while routine-based manufacturing, clerical, and administrative work remains vulnerable to mechanization (Benzell et al., 2019). Displaced workers frequently transition into low-skill service employment requiring limited training but physical adaptability. The framework aligns with human capital and task-based models, where elastic substitution between skilled and unskilled labor governs aggregate productivity dynamics and distributional outcomes (Hutter & Weber, 2021). The model begins with output Y:

$$y = \left[\frac{\sigma - 1}{yj} + \frac{\sigma - 1}{yH}\right]^{\frac{\sigma}{\sigma - 1}} \quad \text{...(1)}$$

Final output Y combines goods from unskilled labor Y_J and skilled labor Y_H, with substitution elasticity σ and incorporating technological. Thus, technology-adjusted production function:

$$y = \left[\frac{\sigma - 1}{yj} + \frac{\sigma - 1}{yH}\right]^{\frac{\sigma}{\sigma - 1}} + \left(\frac{AH}{J}\right)^{\frac{\sigma}{\sigma - 1}} \text{..............................(2)}$$

Technological progress skill bias showing relative productivity growth of skilled labor A_H versus unskilled labor A_J, expressed through SBTC ratio as follows:

$$\frac{AH\prime}{AH} - \frac{AJ\prime}{AJ} = \gamma$$

Where:

$A_H^{\cdot}/A_H$ denotes technology growth favoring skilled labor.

$A_J^{\cdot}/A_J$ denotes technology growth favoring unskilled labor

γ is the skill bias parameter, measures technological bias favoring skilled over unskilled workers.

If $\gamma>0$, technology favors skilled workers raising inequality and demand for high skilled jobs. If $\gamma<0$, technology benefits unskilled labor reducing wage gaps.

A_H and A_J denote endogenous technology in skilled and unskilled production, with progress bias expressed toward skilled labor.

$$\frac{AH}{AJ} = \left(\frac{H}{J}\right)^{\sigma - 1} \text{...(3)}$$

Equation (3) shows workforce drives technological progress sustaining skill premium, defined by Acemoglu (2002) as skilled–unskilled wage gap, expressed through technology integration.

$$L\left(\frac{H}{J}\right) = \frac{\sigma}{\sigma - 1}\left[T\left(\frac{AH}{AJ}\right) + \frac{WH}{WJ}\right] \text{...(4)}$$

where $L(\frac{H}{J})$ represents the labor of both skilled and unskilled workers, $\frac{\sigma}{\sigma - 1}$ reflects the substitution elasticity effect $T(\frac{AH}{AJ})$ indicates the level of technological utilization by skilled and unskilled workers, and $\frac{WH}{WJ}$ denotes the relative wages of skilled and unskilled workers.

SBTC theory asserts technology disproportionally raises demand for high-skill labor while displacing low-skill roles.

3.0 METHODOLOGY AND DATA

Based on SBTC framework, wages and technology directly influence labor allocation. AI investment proxies' skill-biased technology (T), while wages operate as a price mechanism (W). Thus, Equation 5 defines skilled employment (SEMP) as a function of AI and wages consistent with 4IR dynamics (Adendorff & Collier, 2015).

SEMP=f(AI,WG)..(5)

The model integrates inflation and GDP, essential for employment dynamics. Exclusion risks estimation bias (Yildirim et al., 2020; Ayhan & Elal, 2023; Dogan & Inglesi-Lotz, 2020; Adeyemi, 2023).

Therefore, Equation 5 is expanded as follows:

$SEMP=\alpha0+\beta1AIt+\beta2WGSt+\beta3INFt+\beta4GDPt+\varepsilon t$ …………………………(6)

Expressing Equation 6 in logarithmic form gives:

$lnSEMP= \alpha0+ \beta1lnAIt+ \beta2lnWGSt+ \beta3lnINFt + \beta4lnGDPt+\varepsilon t$…………….(7)

SBTC theory predicts AI enhances skilled employment, wages, and GDP. Inflation reduces real income and purchasing power, constraining firms' hiring capacity and negatively affecting skilled employment (Aminu & Ogunjimi, 2019; Adeyemi, 2023).

3.1 Variables and Data Sources

This study uses data from OECD AI Database, KNBS, Economic Surveys, UNESCO, and World Bank covering the period 2012Q1–2024Q4. Annual Venture Capital AI investment data was converted to quarterly frequency using linear interpolation in Stata's ipolate command. The quarterly data underpin the analysis, with annual indicators such as GDP per capita converted to quarterly using Stata. COVID-19 disruptions are embedded in the dataset reflected in GDP contractions, investment declines, consumption shocks, and employment fluctuations. The macroeconomic factors represent pandemic-induced structural distortions in Kenya's labor markets and macroeconomic aggregates.

Table 1

Variable Descriptions

Variable	Definition	Expected Sign	Source
SEMP	Skilled labor requiring formal training	Positive	KNBS/World Bank
AI Investment	Investment in AI technology-based ventures	Positive	OECD
WGS	Skilled labor compensation in millions	Positive	KNBS/World Bank
INF	Inflation in goods and services	Negative	KNBS/World Bank
GDPPC	Economic output per person yearly	Positive	KNBS/World Bank

Note. SEMP = Skilled Employment; WGS = Wages; INF = Inflation; GDPPC = GDP per capita growth.

3.2 Estimation Technique

This study employs the ARDL method (Pesaran et al., 2001) due to key advantages: bounds testing for long-run relationships, suitability for mixed-order datasets excluding I(2), and simultaneous estimation of short- and long-run dynamics.

The ARDL representation of Equation 7 is formulated as follows:

$\Delta lnSEMPt = \alpha 0 + \sum_{t=1}^{n1} \alpha 1i\Delta lnSEMPt - i + \sum_{t=1}^{n2} \alpha 2i\Delta lnAIt - i + \sum_{t=1}^{n3} \alpha 3i\Delta lnWGt - i + \sum_{t=1}^{n4} \alpha 4i\Delta lnINFt - i + \sum_{t=1}^{n5} \alpha 5i\Delta lnGDPt - i$ +β1lnSEMPt−1+β2lnAIt−1+β3lnWGt−1+β4 lnINFt−1+β5lnGDPt−1+μt ……………………………………………………………………………(8)

Where;

Dependent Variable (ΔlnSEMPt): The change in the natural logarithm of skilled employment at time t

Lagged Differences (ΔlnXt−i): The differences in the natural logarithms of variables (e.g., SEMP, AI investment, wages, inflation, GDP) lagged by i periods.

Lagged Levels (lnXt−1): The levels of variables from the previous period (t−1)

Error Term (μt): Captures unobserved influences and random noise at time t

To account for potential structural breaks, the significance of which is discussed in Section 4.3, in the variables being analyzed, we have adjusted the model by incorporating a dummy variable that represents the structural breakpoints, specifically those observed in 2015Q4 and 2021Q1. The skilled employment break aligns with COVID-19, which disrupted labor markets and reshaped skill demands (Amankwah-Amoah et al., 2021). The AI break is a reflection of policy reforms and regulatory shifts that spurred innovation and venture capital investment (Scherer, 2015). The updated model, which includes the ARDL equation along with the dummy variables, is presented in Equation 9.

$\Delta lnSEMPt = \alpha 0 + \sum_{t=1}^{n1} \alpha 1i\Delta lnSEMPt - i + \sum_{t=1}^{n2} \alpha 2i\Delta lnAIt - i + \sum_{t=1}^{n3} \alpha 3i\Delta lnWGt - i + \sum_{t=1}^{n4} \alpha 4i\Delta lnINFt - i + \sum_{t=1}^{n5} \alpha 5i\Delta lnGDPt - i$ +β1lnSEMPt−1+β2lnAIt−1+β3lnWGt−1+β4 lnINFt−1+β5lnGDPt−1+ β6DUMMY2015Q4+β7DUMMY2020Q1+μt …………………………(9)

4.0 EMPIRICAL FINDINGS AND DISCUSSION

This chapter outlines and interprets the key results, starting with descriptive statistics, stationarity checks, selection of optimal lag length, and the ARDL bounds approach. It then proceeds to the outcomes of the autoregressive distributed lag model, followed by Granger causality assessments and model diagnostics.

4.1. Descriptive Statistics

Table 2 below reports descriptive statistics for 49 observations. Mean values were 2,715,294 (skilled employment), 5,608.65 (AI), 714,171.5 (wages), 6.694 (inflation), 190,836.2 (GDP per capita), and 5.31% (GDP growth). Values ranged from 0 to 3,253,079.3. AI and inflation were positively skewed, while GDP growth, wages, and skilled employment showed negative skewness, indicating distributional asymmetry. Jarque-Bera tests confirmed non-normality for AI (JB=10.13, p=0.0063), wages (JB=9.16, p=0.0102), GDP per capita (JB=6.18, p=0.0454), and GDP growth (JB=13.35, p=0.0013). Skilled employment (p=0.1008) and inflation (p=0.4029) followed normality. These findings imply potential need for transformations or non-parametric approaches to ensure robust statistical inference across variables.

Table 2

Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis	Jarque-Bera	p-value
SEMP	49	2715294	301264.9	2155800	3253079	-0.10978968	2.0364803***	4.59	0.1008
AI	49	5608.653	8303.387	0	24024	1.3115673***	3.0059683	10.13	0.0063
WGS	49	714171.5	141501.2	443322.1	933828.5	-0.21804473	1.8252069***	9.16	0.0102
INF	49	6.694	1.174	4.69	9.408	0.41397474	2.6321779	1.82	0.4029
GDPPC	49	190836.2	70372.87	82319.52	321763.7	0.09453486	1.9397512**	6.18	0.0454
GDP Growth	49	5.307	1.65	-0.3	8.4	-1.1901871***	5.2692059***	13.35	0.0013

4.2. Unit Root Test

The ARDL model is appropriate since variables are not integrated of order two, I(2). Bounds testing requires variables at I(0) or I(1). Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests confirm integration at order zero or one, excluding I(2). Tests were conducted at first difference without trend, using four lags for ADF and Newey–West bandwidth of three for PP. Results, shown in Table 3, justify ARDL adoption by confirming stationarity conditions.

Table 3

Stationarity Tests (ADF and PP at First Differences – No Trend)

Variable	ADF Test Statistic	ADF p-value	PP Test Statistic	PP p-value	Stationary?
LSEMP	-4.661	0.0001	-6.633	0	Yes (I(1))
LAI	-3.871	0.0023	-6.635	0	Yes (I(1))
LWGS	-3.451	0.0093	-6.683	0	Yes (I(1))
INF	-4.725	0.0001	-6.689	0	Yes (I(1))
GDPPC	-4.209	0.0006	-6.658	0	Yes (I(1))
GDPGROWTH	-4.657	0.0001	-6.639	0	Yes (I(1))

ADF and PP tests confirm all variables are stationary at first difference, integrated of order one (I(1)). For skilled employment (LSEMP), AI investment (LAI), wages (LWGS), inflation (INF), GDP per capita (GDPPC), and GDP growth (GDPGROWTH), ADF statistics exceeded 1% critical thresholds, with MacKinnon p-values below 0.01, rejecting unit roots. PP results corroborated ADF, showing negative statistics and significant p-values. Thus, variables are non-stationary at levels but stationary after differencing, validating suitability for cointegration and error correction modeling.

4.3. LM Unit Root Test

The study used the Lagrange Multiplier (LM) unit root test to assess structural breaks in skilled employment, AI, wages, inflation, and GDP per capita. The LM test, an extension of the Augmented Dickey-Fuller (ADF) test, enables the detection of multiple structural breaks at unknown points in the data. Results rejected unit roots, confirming stationarity. Lagged level t-values ranged -4.0 to -6.5 with $p<0.001$, evidencing mean reversion. Skilled employment (-6.34) and AI (-5.5) exceeded critical thresholds, validating non-stationarity rejection despite breaks.

The LM test detected breaks in skilled employment (2020Q1) and AI (2015Q4). The former coincides with COVID-19 global disruptions which disrupted labor markets, accelerated remote working, and changed skill demands across industries (Amankwah-Amoah et al., 2021). The latter aligns with policy reforms and regulatory changes that supported innovation and increased venture capital investment in AI technologies (Scherer, 2015). Wage growth, inflation, and GDP per capita remained stationary, with insignificant breaks, confirming shocks are transitory and revert to their long-term trends over time.

4.4 Chow Test

The analysis evaluates Venture Capital AI Investment (AI), Wages (WGS), and Inflation (INF) on Skilled Employment (SEMP) while incorporating a structural break around 2020. Pre-2020, AI had a significant negative effect on SEMP (coefficient = -52.76, p = 0.000), consistent with skill-biased technological change (SBTC) and substitution in labor markets. Wages strongly increased employment (coefficient = 2.64, p = 0.000), while Inflation had a negative impact (coefficient = -14,369.19, p = 0.017). Post-2020, results shifted. AI lost statistical significance (coefficient = 1.73, p = 0.535) as its disruptive effects diminished. One possible explanation is that COVID-19 accelerated digitalization, expanded remote work, and generated complementarities between AI and skilled labor. Policy reforms and regulatory frameworks post-2020 supported innovation ecosystems, while venture capital reoriented toward scalable AI solutions, reducing substitution pressures. Similarly, inflation became insignificant (coefficient =-14,293.2, p = 0.632) due to disrupted pass-through effects amid supply chain disruptions and demand contractions but wages retained a positive, significant effect (coefficient = 3.08, p = 0.004)

The Chow Breakpoint Test confirmed a significant structural break in 2020Q1 ($Chi^2 = 19.26$, p = 0.0002), coinciding with the COVID-19 shock. This break reconfigured the AI–employment nexus macro-labor dynamics. Importantly, the negative long-run GDP per capita coefficient in the model with breaks is counter-intuitive. A plausible explanation is "jobless growth" driven by capital-intensive AI investment, which raises aggregate output without commensurate employment gains. Alternatively, it may indicate the dominance of productivity-enhancing but labor-displacing AI applications in early adoption phases, amplifying inequality between capital and labor returns. Post-2020, however, the reorientation of AI toward service industries, health, and digital platforms may have mitigated these effects, explaining why AI's role became insignificant in the second period.

4.5. Optimum Lag and ARDL Bound Test

The bounds test results, evaluated using Pesaran, Shin, and Smith (2001), indicate strong cointegration. The F-statistic (172.023) and t-statistic (-23.105) exceeded critical bounds for I(0) and I(1). Kripfganz and Schneider (2020) critical values confirmed significance (p = 0.000), rejecting the null hypothesis. Thus, a long-run relationship exists between Skilled Employment (SEMP), AI Investment, Wages (WGS), Inflation (INF), and GDP per capita growth (GDPPC). This equilibrium suggests short-term fluctuations converge toward the long run. Model selection via AIC identified ARDL(1,1,0,1), incorporating one lag of SEMP, AI, and INF, with wages contemporaneous, effectively incorporating short-run dynamics.

4.6. Granger Causality Test

This study applies Granger's (1974) causality test to assess relationship between skilled employment, AI, wages, inflation, and GDP per capita. Results indicate one-way causality at the 10% significance level. AI, wages, inflation, and GDP per capita Granger-cause skilled employment. Thus, the null hypothesis of no causality is rejected. These variables significantly influence skilled employment in Kenya. Economically, this suggests that changes in skilled employment as influenced by AI and GDP may alter income inequality, as skilled workers typically earn more than unskilled workers.

4.7. Estimated ARDL results without structural breaks

Tables 4 and 5 report ARDL estimates for short- and long-run dynamics. Results indicate AI investment significantly enhances skilled employment (SEMP) in Kenya. In the short run, a 1% rise in AI investment increases skilled employment by 8.82%, while in the long run the effect remains positive at 4.81%. These findings define AI's role in increasing skilled labor demand, consistent with Xie et al. (2021) and Babina et al. (2023). In Kenya, venture capital–driven AI expansion increases employment opportunities in data science, machine learning, and programming, confirming structural shifts toward high-skilled employment (Rapanyane & Sethole, 2020).

Table 4

ARDL Short-run Estimate Table- Dependent Variable: Skilled Employment D(InSEMP)

Variables	Coefficients	Std. Error	t-Statistics	Probability*
D(LAI)	8.825646	1.943521	4.54	0
D(LWGS)	5.3628	0.3519	15.24	0
D(INF)	-26968.41	3180.16	8.48	0
GDPPC	1.9466	0.237	8.21	0.066

Table 5

ARDL Long-run Estimate Table

Variables	Coefficients	Std. Error	t-Statistics	Probability*
LAI	4.812234	1.212312	3.97	0
LWGS	5.396386	0.505446	10.68	0
INF	-27065.51	4577.211	5.91	0
GDPPC	-0.55231	0.387245	-1.43	0.153

Wages strongly determine skilled labor demand. A 1% rise in earnings increases skilled employment by 5.35% in the short run and 5.39% in the long run. Competitive pay attracts talent, particularly in technical fields (Slatten et al., 2021). Yet, Kenya faces brain drain, driven by better prospects abroad. Policies that enhance wage competitiveness can mitigate this outflow, strengthening human capital retention (Sheikheldin & Mohamed, 2021; Zakus & Anteh, 2021). Angelopoulos et al. (2017) also link long-run wage trajectories with upward shifts in skilled employment.

Inflation erodes skilled labor growth. A 1% rise reduces employment by nearly 27,000 in both the short and long run. High inflation discourages firm expansion and hiring (Vermeulen, 2015; Salazar, 2022). It increases volatility, weakens confidence, and constrains investment (Reiche & Meyler, 2022). Broader effects include reduced purchasing power, suppressed demand, and delayed hiring (Ha & Ohnsorge, 2022).

GDP per capita generally supports skilled labor growth, with a 1% rise linked to a 1.95% increase. Yet, extended lags reveal a puzzling negative relationship. This anomaly contrasts with prior evidence supporting GDP per capita as a driver of innovation, sectoral growth, and skilled labor demand (Hami & Orhan, 2022; Martinez, 2022; Jahanger et al., 2022) and confirms a critical research gap on growth-employment linkages in Kenya.

4.7 ARDL-ECM Estimation Results

The negative coefficient of the error correction term confirms long-run equilibrium reversion cointegration relationship in skilled employment. Short-run dynamics are instead evaluated by the first-differenced variables (Δ) confirming immediate adjustments. The estimated value of –0.65 indicates that roughly 65% of short-term disequilibria are corrected each period. This is a moderately rapid adjustment speed meaning that Kenya's skilled labor market realigns efficiently aftershocks.

4.8. Estimated ARDL results with structural breaks

The ARDL model is re-estimated after the structural break. Dummy variables, coded 0/1 reflects regime changes such as reforms, shocks, COVID-19, or policy changes. They correct distortions in long- and short-run dynamics. This improves model precision and depicts variable interactions more accurately across periods.

Table 6

ARDL-ECM Estimation Results with Structural Break (Dummy for 2015Q4)

Dependent Variable: Change in Employment (ΔSEMP)

Component	Variable	Coefficient
Error Correction Term (ECT)	L.SEMP	-2.3874
Long-Run (LR) Coefficients	AI	8.1371
	Wages	6.0956
	Inflation	45852.28
	GDP per capita	-1.4623
	Dummy2015Q4	-12577.2
Short-Run (SR) Coefficients	AI (Δ)	-14.2128
	Wages (Δ)	0.5905
	Inflation (Δ)	-51250.9
	GDP per capita (Δ)	-0.4712

Table 6 shows that incorporating structural break dummy variables into the short-run ARDL model alters coefficient estimates. The coefficient for changes in Artificial Intelligence (AI) investment becomes negative (β =–14.2128), implying a short-term decline in skilled employment. However, the long-run coefficient remains positive (β =8.1371) which confirms the beneficial long-term impacts. In contrast, Tables 4 and 5, without dummies, report positive short-run and long-run AI (β=8.8256 and β =4.8122). Therefore, modeling structural breaks is important since ignoring them distorts dynamic interactions between AI investment and skilled employment. Adaptive labor policies must therefore promote technological integration and upskilling during structural shifts.

The negative short-run AI effect implies that initial adoption suppresses skilled employment by automating cognitive and routine tasks. Such substitution displaces roles unless workers adapt through reskilling and redeployment into AI-complementary jobs (Barbieri et al., 2020). Policymakers must design forward-looking education and training programs to mitigate transitional unemployment.

The adverse short-run impact also signals broader labor market transformations. AI-intensive sectors may experience compositional shifts in occupations, rising wage inequality, and diminished mobility for displaced groups (Zarifhonarvar, 2023). These risks demand inclusive policies such as targeted reskilling, social protection, and adaptive regulation to ensure equitable access to evolving opportunities.

Other macroeconomic variables retain significant roles. In the short run, inflation has a large negative effect (β=–51,250.9) and GDP per capita also declines (β =–0.4712) due to cost shocks and capital-intensive growth. In the long run, inflation turns negative (β =-45,852.28), while GDP per capita remains negative (β =–1.4623). Wages consistently exert strong positive effects (β =0.5905 short-run; β =6.0956 long-run). Policies should therefore stabilize inflation and promote inclusive growth, and sustain competitive compensation structures to secure skilled labor markets.

4.9. Diagnostic Test Result with and Without Structural Breaks

The diagnostic tests applied include autocorrelation, heteroscedasticity, and normality, each vital for ARDL model validation. Results show no violations. Probability values exceed the 10% threshold. Residuals are uncorrelated, homoscedastic, and normally distributed. These findings establish statistical reliability and enhance confidence in coefficient estimates. They reinforce the credibility of conclusions and strengthen policy relevance.

5.0 CONCLUSION AND POLICY IMPLICATION

This study examined the determinants of skilled employment in Kenya from 2012Q1 to 2024Q4 using the ARDL framework with structural breaks. The findings had four major results. First, wages are a strong and persistent driver of skilled employment, with positive effects in both the short and long run. Second, the negative long-run GDP per capita coefficient with breaks is counter-intuitive. A plausible explanation is "jobless growth" driven by capital-intensive AI investment, which raises aggregate output without commensurate employment gains. Third, inflation consistently shows a negative effect meaning macroeconomic instability erodes labor absorption and reduces employment opportunities. Fourth, Artificial Intelligence investment had a dual effect: in the short run during structural disruptions, AI adoption is associated with skilled worker displacement; in the long run, AI supports labor demand by improving productivity and developing new employment niches. Therefore, policymakers should invest in forward looking education and training programs to mitigate transitional unemployment. The negative and significant error correction term confirms rapid adjustment toward equilibrium aftershocks thus responds swiftly to deviations caused by economic shocks. Granger causality indicated AI has an important positive influence on skilled employment thus confirming its growing structural role in as Kenya advances through the Fourth Industrial Revolution.

5.1 Policy Implications

The negative impact of inflation indicates the importance of stable macroeconomic management. Targeted fiscal and monetary policies are necessary to stabilize prices and protect real wages. Competency-based training in agriculture, healthcare, and fintech as outlined in the National AI Strategy 2025–2030, will equip youth with market-relevant skills. Partnerships with TVETs and universities in Nairobi, Kisumu, and Eldoret can reduce regional disparities. AI curricula and certifications may be integrated into TVET institutions to innovation hubs like Konza Technopolis, to address skill mismatches. Sector-specific digital adoption units in ministries such as Health and Agriculture can operationalize AI projects, enforce data governance, and track labor impacts. Expanding broadband in underserved counties like Turkana, Wajir, and Marsabit is essential for inclusive participation. Stronger AI regulatory frameworks with expanded social safety nets, will ensure ethical deployment, protect workers, and smooth labor transitions.

5.2 Limitations and Future Research

This study acknowledges several limitations. First, venture capital investment is used as a proxy for AI adoption. Though practical, it may not fully assess the scope of technological diffusion. Firm-level expenditures, patent data, or digital adoption indices may have provided a more accurate measure. Second, the analysis is restricted to formal sector skilled employment. The informal economy, which represents a large share of Kenya's labor market, remains unexamined. Its exclusion limits the breadth of labor market insights. Third, the macro-level approach constrains sectoral granularity. Disaggregated analysis by industry for example agriculture, healthcare, or finance may identify heterogeneous impacts. Firm-level datasets would allow targeted policy recommendations and better insights. Finally, the study's temporal scope identifies structural shifts but cannot forecast long-term technological trajectories. Longitudinal research is needed to trace persistent transformations in labor demand under sustained AI diffusion.

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