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# **Economic Implications of Artificial Intelligence on Labour Markets in Emerging Economies**

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Christopher Nyong Ekong and Emmanuel Ating Onwioduokit Department of Economics University of Uyo, Uyo, Nigeria

### Abstract

This study investigates the relationship between artificial intelligence (AI) adoption and employment outcomes in emerging economies, using regression analysis to explore multiple economic and institutional variables. The findings reveal a statistically significant negative association between AI adoption and employment rates, indicating that increased diffusion of AI technologies is linked to labour displacement, particularly in economies characterized by low-skilled, routine-intensive workforces. This underscores the concerns that, without complementary reforms, AI may exacerbate structural unemployment and inequality. Conversely, ICT infrastructure exhibits a positive and significant effect on employment, highlighting its role in enabling digital entrepreneurship, market access, and platform-based work. Education, proxied by mean years of schooling, shows a marginally positive effect, pointing to the underutilized potential of human capital in mitigating technology-induced job losses. GDP per capita significantly enhances employment, affirming the growth-employment nexus, though its impact is contingent upon the inclusivity and sectoral composition of growth. Foreign Direct Investment (FDI), however, is found to be statistically insignificant, challenging assumptions about its automatic job-creating capacity in the absence of strong domestic linkages. Labour market rigidity also negatively affects employment, suggesting the need for more flexible vet protective regulatory frameworks. The study concludes with critical policy implications: prioritizing human capital development, expanding ICT infrastructure, fostering inclusive growth, maximizing the employment impact of FDI through targeted interventions, and reforming labour regulations. A coordinated policy approach integrating technology, education, and institutional reform is essential to harness AI's potential while mitigating its disruptive effects. Ultimately, emerging economies must align digital transformation with inclusive employment strategies to navigate the challenges and opportunities of the Fourth Industrial Revolution

# Key Words: Artificial Intelligence (AI), Employment Outcomes, Emerging Economies, Labour Market Dynamics, ICT Infrastructure, Human Capital Development

**JEL Classification:** J21; O33; O15; F23; J68; O25

## 1. Introduction

Artificial Intelligence (AI), as a frontier general-purpose technology, is a principal driver of the Fourth Industrial Revolution, with weighty implications for productivity, industrial organization, and labour market dynamics. The transformative potential of AI lies not only in its ability to automate tasks traditionally performed by human labour but also in its capacity to generate new forms of economic activity, reshape value chains, and alter comparative advantages across nations. While a growing body of research has extensively analysed these impacts within the context of advanced economies—highlighting phenomena such as skill-biased technological change, employment polarization, and the hollowing out of middle-skill jobs—the implications for labour markets in emerging and developing economies have received considerably less analytical attention.

Emerging economies are structurally and institutionally distinct from their advanced counterparts. Labour markets in these contexts are characterized by high levels of informality, demographic pressures from youthful and expanding populations, fragile social safety nets, limited access to digital infrastructure, and relatively weak institutions. These features imply that the diffusion and adoption of AI may produce divergent outcomes, both in terms of economic efficiency and distributional effects. For instance, while AI might unlock new productivity frontiers in certain sectors, it could also exacerbate labour displacement in economies where large shares of the workforce are concentrated in low-skill, routine-intensive occupations with limited mobility. The confluence of automation potential and institutional rigidity could further entrench existing labour market dualities and income inequalities. Understanding the distributional and structural impacts of AI is particularly importantl for policy design in contexts where state capacity is limited and labour market institutions are underdeveloped. As Acemoglu and Restrepo (2018) emphasize, the effects of automation technologies, including AI, are not technologically deterministic but mediated by institutional configurations, the pace of task reallocation, and investments in human capital and innovation ecosystems. Thus, the trajectory of AI-induced labour market transformation in emerging economies will depend significantly on the responsiveness of policy regimes and the degree of public and private sector coordination.

Artificial Intelligence (AI) is reshaping economies across the globe, but its influence on emerging markets is especially complex. These regions face a unique mix of structural weaknesses, informal labour dynamics, and youthful demographics—all intersecting with the rise of new technologies. Among the most affected is the labour market, a critical but delicate part of emerging economies. As AI becomes more widespread, it promises both disruption and transformation across sectors, job types, and social outcomes like wages and inequality.

AI's impact is far from uniform—it varies sharply across sectors. In manufacturing, AI accelerates "premature deindustrialization," where countries begin to deindustrialize before reaching high-income status. With robotics and automation reducing the demand for low-cost labour, multinational companies might opt for high-tech factories closer to home, sidestepping labour-intensive production in developing countries. This trend threatens the traditional path of job creation and industrial growth in

regions like Sub-Saharan Africa and South Asia. Yet, for firms that manage to integrate AI—particularly in industries like textiles, food processing, or electronics—there's potential for productivity gains. Still, without strong digital and industrial policies, these gains may remain limited to a few, widening inequality.

In the service sector, the picture is more mixed. AI boosts efficiency in areas like finance, retail, and business process outsourcing (BPO). Countries like India and the Philippines, with large BPO industries, are already adapting to automation through tools like chatbots and AI-driven fraud detection. While routine jobs may decline, new opportunities are emerging in high-skill digital services—like data analysis and AI maintenance. For countries that invest in education and upskilling, AI could be a springboard into the digital economy. But where institutions are weak and digital access is uneven, it may deepen divisions within the workforce.

Agriculture, though less immediately impacted, holds vast potential for AI-driven transformation in the long run. Tools like satellite-based crop monitoring, predictive yield analytics, and AI-enhanced weather forecasting could revolutionize farming practices. However, smallholder farmers often face significant barriers—limited internet access, low digital literacy, and scarce funding. For AI to truly benefit rural populations, it will require coordinated support through government subsidies, infrastructure investment, and digital education.

AI's influence on employment depends largely on the nature of the workwhether it is routine or non-routine, cognitive or manual. Broadly, the labour market is experiencing changes in three main job categories: those most susceptible to displacement, those likely to expand, and those in the informal sector. Jobs most at risk of automation are those that involve routine, predictable tasks and require relatively low cognitive engagement. These include factory workers on assembly lines, clerical staff engaged in data entry, and drivers threatened by autonomous vehicle technologies. These roles are being rapidly replaced by AI systems and robots capable of performing the same tasks more efficiently. In emerging economies, such jobs form a significant part of the employment base. The absence of robust retraining programs or social protection mechanisms in these settings heightens the risk of mass unemployment and social unrest as AI displaces human labour. In contrast, occupations requiring high levels of creativity, emotional intelligence, and technical expertise-such as software development, healthcare, education, and digital content creation-are more likely to expand. AI complements rather than replaces these roles, enhancing human capabilities instead of substituting them. For instance, AI supports doctors in diagnostics and treatment planning, but it does not replace the need for empathetic patient care. However, for emerging economies to benefit from such job expansion, there must be significant investment in education, particularly in STEM disciplines, and digital literacy initiatives. Without a skilled workforce, the opportunities in high-tech sectors may remain out of reach.

The informal sector presents a unique challenge. In many emerging economies, especially in Africa and South Asia, more than 60% of the workforce operates outside formal structures. AI is already beginning to affect informal jobs—for example, ride-hailing platforms are replacing traditional taxi services, and AI-enhanced supply chains

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are sidelining local vendors. Because these workers often lack access to training, financial services, or job security, displacement in the informal sector often means an immediate fall into poverty. Policymakers must therefore develop inclusive AI strategies that incorporate formalization efforts, training hubs, and access to microfinance to cushion the impact on informal workers.

One of AI's most critical and complex effects is its impact on wages and income distribution. As automation spreads, wage polarization is becoming more pronounced. High-skilled workers, especially those with digital and technical proficiencies, command increasingly higher wages, creating a premium for those with the right qualifications. In contrast, those in routine, low-skill roles see stagnating or even declining wages as AI reduces demand for their labour. This trend is particularly acute in emerging economies, where institutional protections are often weak, and large segments of the workforce operate informally or without union representation. This wage gap threatens social cohesion and economic stability. If the benefits of AI accrue only to a technologically literate elite while leaving the majority of the population behind, inequality will deepen. In urban areas where technological infrastructure is concentrated, AI adoption leads to rapid productivity growth and innovation. However, rural areas, often underserved in terms of digital infrastructure and educational resources, lag far behind, exacerbating regional inequalities. This urban-rural divide not only limits inclusive economic growth but can also fuel increased migration to cities, straining urban infrastructure and contributing to the growth of informal settlements and unemployment.

AI also risks reinforcing existing gender inequalities. Women in emerging economies are overrepresented in vulnerable, low-paid, and informal jobs—sectors that are highly susceptible to automation, such as retail, domestic services, and textile manufacturing. Moreover, the underrepresentation of women in STEM fields means they are often excluded from the new job opportunities that AI creates. Worse still, gender biases embedded in AI algorithms, often a reflection of historical and social discrimination, can further marginalize women.

AI's influence on labour markets in emerging economies is complex and multidimensional. While it offers opportunities for new kinds of work and productivity gains, it also poses serious risks—job displacement, wage inequality, rural exclusion, and gender bias. Navigating this transformation requires proactive, inclusive, and well-targeted policy responses. Investments in education, infrastructure, and social protection, alongside gender- and region-sensitive strategies, are essential to ensure that AI drives broad-based, equitable development rather than deepening existing divides.

# 2. Materials and Methods

## Data

We use cross-country panel data from the World Bank Enterprise Surveys, ILOSTAT, and OECD's AI observatory from 2010–2023. The dependent variable is the employment rate (formal sector), and key independent variables include AI adoption index, ICT infrastructure, education levels, and GDP per capita. Control variables include inflation, FDI, and labour market regulation indices.

## Model Specification

In examining the economic implications of Artificial Intelligence (AI) on labour markets in emerging economies, the choice of an appropriate econometric model is crucial to ensuring the reliability and validity of empirical results. This study adopts a fixed effects (FE) panel estimation technique, and the rationale for this choice is both methodological and contextual.

Emerging economies are characterized by considerable heterogeneity in terms of institutional quality, labour market structure, educational systems, levels of technological adoption, and stages of economic development. Many of these country-specific characteristics are unobservable or difficult to measure directly, yet they exert significant influence on both the pace of AI integration and labour market outcomes. Importantly, these factors are often time-invariant or evolve very slowly over time. The fixed effects model accounts for such unobserved heterogeneity by allowing each country in the panel to have its own intercept, effectively controlling for all time-invariant country-specific factors. This ensures that the estimated impact of AI is not biased by omitted variable effects that differ across countries but remain constant over time. Furthermore, the analytical focus of this study is on how AI-driven changes within individual countries affect their respective labour markets over time. In this context, the fixed effects model is particularly suitable as it emphasizes within-country variation, stripping out crosssectional differences to highlight how temporal changes in AI-related variables (such as AI investment, automation indices, or digital infrastructure) correlate with shifts in employment, wages, and labour force participation. This within-country analytical focus aligns well with the policy orientation of the study, as the findings are intended to inform country-specific strategies and interventions aimed at managing AI's impact on the labour market.

Another important consideration is the likely correlation between the unobserved country-specific effects and the explanatory variables included in the model. For instance, countries with better institutional capacity or higher levels of education may be more adept at integrating AI technologies, while also experiencing more favourable labour market outcomes. In such cases, the assumption of zero correlation between the individual effects and regressors—required by random effects models—is unlikely to hold. By contrast, the fixed effects model allows for this correlation, offering more robust and consistent estimates under these conditions. The use of fixed effects is also consistent with empirical precedents in the literature on technology, automation, and labour markets. Numerous studies have employed fixed effects models when analyzing the impact of technological change using panel data across countries or regions, precisely because it helps isolate the dynamic effects of interest from confounding structural characteristics (Chen, Loayza, & Torres, 2021; Choi, Dutz, & Usman, 2020; and Freeman;2009).

In sum, the fixed effects model provides a rigorous framework for analyzing the evolving relationship between AI and labour markets in emerging economies. By controlling for unobserved, time-invariant heterogeneity and focusing on within-country dynamics, this approach enhances the credibility of the empirical analysis and ensures

that the policy recommendations derived from the findings are context-sensitive and actionable.

We employ a fixed effects regression model:  $EMP_{it} = \beta_0 + \beta_1 AIA_{it} + \beta_2 ICT_{it} + \beta_3 EDU_{it} + \beta_4 GDP_{it} + \beta_5 FDI_{it} + \beta_6 LAB_{it} + \varepsilon_{it}$ Where: EMP = Employment rate AIA = AI adoption index ICT = ICT infrastructure index EDU = Mean years of schooling GDP = GDP per capita FDI = Foreign Direct Investment (% GDP) LAB = Labour market regulation index  $\varepsilonit = Error term$ Model Specification and Justification

To empirically investigate the economic implications of artificial intelligence (AI) on labour markets in emerging economies, we specify a model that captures the complex relationships among technological adoption, institutional context, human capital, and macroeconomic factors. The dependent variable is the employment rate (EMP), which serves as a direct indicator of labour market performance. This choice is theoretically grounded in the labour demand framework, where shifts in employment reflect both the displacement and creation effects of new technologies such as AI.

At the core of the model is the AI Adoption Index (AIA), the principal explanatory variable, which quantifies the extent to which AI technologies have been integrated across economic sectors. AI adoption can have varying effects on employment, depending on the nature of tasks within different occupations. While routine and repetitive tasks are more susceptible to automation, AI can also enhance productivity and generate new employment opportunities in emerging sectors. Including this variable allows us to directly assess the net impact of AI on labour market outcomes within the unique structural conditions of emerging economies.

To contextualize AI adoption, we include the ICT Infrastructure Index (ICT) as a complementary variable. Robust ICT infrastructure is a prerequisite for effective AI deployment, especially in sectors that rely on digital connectivity and data flows. ICT serves not only as a proxy for technological readiness but also as an enabling factor that can amplify the pace and depth of AI integration into productive systems.

Given that the impact of AI on employment is often mediated by the skill composition of the labour force, we introduce mean years of schooling (EDU) as a measure of human capital. Education plays a critical role in determining the adaptability of workers to technological change. In the context of emerging economies—where a significant portion of the workforce may lack advanced skills—education can influence whether AI leads to structural unemployment or facilitates workforce transitions into higher-skilled jobs.

To control for the overall level of economic development, GDP per capita (GDP) is included in the model. This variable reflects not only income levels but also broader

macroeconomic conditions that affect both the capacity for AI investment and the absorptive potential of labour markets. Higher GDP per capita may correlate with greater innovation capacity, better labour institutions, and more resilient job markets. Furthermore, we incorporate Foreign Direct Investment (FDI), measured as a percentage of GDP, to capture the role of external capital flows in shaping labour market dynamics. FDI often brings with it advanced technologies, including AI-enabled systems, especially in manufacturing and service sectors. The employment effects of FDI in the presence of AI depend on the sectors targeted and the skill intensity of incoming investments.

Lastly, we account for the institutional framework governing labour market operations through the Labour Market Regulation Index (LAB). Labour regulations influence the flexibility with which firms can adjust their workforce in response to technological change. In highly regulated labour markets, rigidities may constrain both layoffs and hiring, potentially dampening the immediate employment effects of AI. In contrast, more flexible regulatory environments may facilitate quicker reallocation of labour but also expose workers to greater vulnerability.

Overall, the selected model offers a comprehensive framework for understanding the economic implications of AI adoption on employment in emerging economies. It integrates key dimensions of technological capacity, human capital, institutional context, and macroeconomic structure—factors that are especially salient in countries undergoing rapid digital transformation while grappling with persistent development challenges. The relationship among these variables enables us to explore not only the direct effects of AI but also the conditions under which its impact on labour markets may be amplified, mitigated, or reversed.

### 3. Results and Discussion

#### **Descriptive Statistics**

Before estimating the model, we provide summary statistics of all variables used in the analysis, covering 25 emerging economies over the period 2010–2022 (325 country-year observations).

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Variable	Mean	Std. Dev.	Min	Max
EMP (Employment rate, %)	62.43	6.82	48.1	75.9
AIA (AI adoption index)	0.438	0.173	0.102	0.765
ICT (ICT infrastructure index)	0.509	0.197	0.102	0.901
EDU (Mean years of schooling)	8.47	1.94	4.2	12.3
GDP (GDP per capita, US\$)	6,821.57	4,292.11	1,043	18,765
FDI (% of GDP)	2.96	1.84	-1.2	9.3
LAB (Labour market regulation index)	0.542	0.212	0.103	0.888

**Table 1: Descriptive Statistics** 

Table 1 presents the summary statistics for the key variables employed in the empirical analysis. The average employment rate (EMP) across the sampled countries is 62.43%, with a standard deviation of 6.82%, indicating moderate cross-country variation. The AI Adoption Index (AIA) has a mean value of 0.438, with values ranging from 0.102 to 0.765, suggesting heterogeneous levels of AI diffusion among emerging economies.

ICT infrastructure (ICT) similarly exhibits variation, with a mean of 0.509 and a standard deviation of 0.197.

Education, measured by the mean years of schooling (EDU), averages 8.47 years, reflecting substantial disparities in human capital development, with the lowest observed at 4.2 years and the highest at 12.3 years. GDP per capita displays considerable dispersion, averaging US\$6,821.57, with a minimum of US\$1,043 and a maximum of US\$18,765, underscoring the economic heterogeneity among the sample countries.

Foreign Direct Investment (FDI), expressed as a percentage of GDP, averages 2.96%, though the negative minimum value (-1.2%) may reflect net disinvestment episodes in certain contexts. Lastly, the Labour Market Regulation Index (LAB) has a mean of 0.542, with values ranging from 0.103 to 0.888, capturing varying degrees of regulatory rigidity or flexibility in labour markets across the sample. Overall, the descriptive statistics indicate substantial cross-country variation in structural, economic, and institutional indicators relevant to understanding the labour market implications of AI adoption.

## **Correlation Matrix**

To assess potential multicollinearity, we computed the correlation matrix. No pair of independent variables exhibited a correlation coefficient above 0.80, indicating an acceptable level of multicollinearity. Below is the correlation matrix for the variables employed in the study. It provides preliminary insights into the pairwise linear relationships among employment rate, AI adoption, ICT infrastructure, education, GDP per capita, foreign direct investment, and labour market regulation.

Variable	EMP	AIA	ICT	EDU	GDP	FDI	LAB	
EMP	1.00	0.12	0.08	-0.06	0.00	-0.03	-0.14	
AIA	0.12	1.00	0.07	0.06	-0.04	-0.06	-0.12	
ICT	0.08	0.07	1.00	0.12	0.11	0.19	0.04	
EDU	-0.06	0.06	0.12	1.00	-0.08	0.25	0.18	
GDP	0.00	-0.04	0.11	-0.08	1.00	0.13	0.06	
FDI	-0.03	-0.06	0.19	0.25	0.13	1.00	-0.03	
LAB	-0.14	-0.12	0.04	0.18	0.06	-0.03	1.00	

### **Table 2: Correlation Matrix**

The matrix reveals relatively weak correlations among the variables, suggesting limited multicollinearity. Notably, education (EDU) is positively correlated with FDI (0.25) and LAB (0.18), indicating that higher human capital levels may be associated with increased foreign investment and more structured labour regulations. Conversely, the negative correlation between LAB and EMP (-0.14) may point to rigid labour regulations being weakly associated with lower employment rates. These preliminary patterns inform subsequent regression analysis.

## Fixed Effects Regression Results

We estimate the following fixed effects model:

 $EMP_{it} = \beta_0 + \beta_1 AIA_{it} + \beta_2 ICT_{it} + \beta_3 EDU_{it} + \beta_4 GDP_{it} + \beta_5 FDI_{it} + \beta_6 LAB_{it} + \varepsilon_{it}$ Table 3 presents the regression results using fixed effects (within estimator), with robust standard errors clustered at the country level.

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Variable	Coefficient	Std. Error	t-Statistic	p-Value
AIA (AI Adoption Index)	-4.213***	1.123	-3.75	0.000
ICT (ICT Infrastructure Index)	3.187**	1.298	2.46	0.015
EDU (Mean Years of Schooling)	0.764*	0.414	1.85	0.066
GDP (GDP per capita, logged)	2.092***	0.642	3.26	0.001
FDI (% of GDP)	0.148	0.188	0.79	0.431
LAB (Labour Market Regulation	-1.324*	0.792	-1.67	0.098
Index)				
Constant	35.482**	16.309	2.18	0.031
Country Fixed Effects	Yes			
Year Fixed Effects	Yes			
Number of observations	325			
R-squared (within)	0.582			
F-statistic (p-value)	12.37 (0.000)			

 Table 3: Fixed Effects Regression Results (Dependent Variable: Employment Rate)

*Notes:* Robust standard errors clustered at the country level. \*p < 0.10; \*\*p < 0.05; \*\*\*p < 0.01

The empirical results of the regression analysis reveal a complex and multifaceted relationship between artificial intelligence (AI) adoption and employment outcomes in emerging economies. Most notably, the AI Adoption Index is negatively signed and statistically significant at the 1% level. This suggests that, on average, higher levels of AI diffusion are associated with reductions in employment rates. Such a finding reinforces concerns in the extant literature regarding the labour-displacing effects of automation, particularly in developing economies with predominantly labour-intensive production structures and limited absorptive capacity (Acemoglu & Restrepo, 2017).

This result may be attributed to the substitutive rather than complementary nature of AI technologies in these settings. In contexts where the labour market is dominated by low-skilled or routine-intensive occupations, the introduction of intelligent automation systems often leads to displacement effects that are not readily offset by the creation of new tasks or occupations. As Choi, Dutz, and Usman (2020) argue, without proactive policy interventions—particularly in education and labour market reform—AI can exacerbate structural unemployment and deepen existing inequalities. Moreover, unlike advanced economies where AI may augment human productivity, the skill mismatch in emerging markets limits the capacity of displaced workers to transition into higher-value roles, thereby intensifying the adverse short-run effects.

By contrast, the coefficient on ICT infrastructure is both positive and statistically significant, indicating that digital infrastructure contributes positively to employment generation. This result is consistent with findings by Katz and Callorda (2018), who observe that the expansion of ICT infrastructure catalyses job creation across multiple sectors by enabling new business models, fostering entrepreneurial ecosystems, and improving labour market intermediation. ICT infrastructure underpins the growth of the digital economy and enhances access to information, markets, and services, thereby lowering entry barriers and transaction costs for firms and workers alike.

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This positive relationship may also reflect the complementary nature of ICT infrastructure with human capital and institutional development. While AI may substitute for labour in some domains, the broader diffusion of ICT tends to generate employment through its role in enabling platform-based work, online services, and digitally mediated commerce. Empirical studies such as the World Bank (2021) show that investments in broadband and mobile connectivity have a demonstrable impact on employment, particularly among youth and women, by expanding opportunities for remote and flexible work.

Further, education, proxied by mean years of schooling, exerts a positive—albeit only marginally significant at the 10% level—effect on employment. This suggests that human capital accumulation remains a critical, albeit underutilized, factor in cushioning the displacement effects of AI adoption. The result is theoretically consistent with the task-based model of technological change, which emphasizes the role of cognitive and non-routine skills in determining labour market resilience (Autor, Levy, & Murnane, 2003). Workers with higher educational attainment are more likely to adapt to technological disruption, participate in training and re-skilling, and transition into tasks that are complementary to AI technologies.

Nevertheless, the marginal significance of the education variable may point to qualitative deficiencies in the education systems of many emerging economies. Curricular content may not sufficiently reflect the demands of the contemporary labour market, particularly with respect to STEM (science, technology, engineering, and mathematics) competencies, digital literacy, and problem-solving skills. Arntz, Gregory, and Zierahn (2016) underscore that the extent to which education mitigates automation risk depends critically on the alignment between schooling outcomes and the evolving task content of occupations.

Gross Domestic Product (GDP) per capita exhibits a positive and highly significant coefficient, underscoring the well-documented nexus between economic development and employment creation. Higher GDP per capita typically signals an expansion in economic activities across diversified sectors, thereby generating demand for labour across both the formal and informal segments of the economy. This finding is consonant with the neoclassical growth framework, where capital accumulation and productivity enhancements increase labour demand and real wages (Levine & Renelt, 1992). Moreover, the result reinforces the argument that macroeconomic growth provides the fiscal space and institutional capacity required for complementary investments in infrastructure, education, and social protection.

However, the magnitude and inclusivity of growth matter. In economies where growth is concentrated in capital-intensive or resource-based sectors, the employment elasticity of output may remain low, dampening the potential benefits of growth on labour absorption. Therefore, policy efforts must aim at fostering labour-intensive and inclusive growth trajectories, with a focus on sectors such as agriculture, light manufacturing, services, and the green economy.

In contrast, the coefficient on Foreign Direct Investment (FDI) is statistically insignificant, indicating that FDI inflows do not exhibit a robust relationship with

employment outcomes in the sample under study. This result challenges the oftenassumed automaticity of FDI-led job creation in development policy discourse. Several factors may account for this finding. First, FDI in many emerging economies tends to be sectorally concentrated in extractive or capital-intensive industries that generate limited direct employment. Second, foreign firms may rely on imported labour or technology, thereby limiting local employment multipliers. Third, weak institutional linkages between foreign investors and domestic enterprises may reduce technology spillovers and backward integration.

Alfaro (2003) notes that the employment impact of FDI is conditional upon the absorptive capacity of the host economy—particularly the availability of skilled labour, robust infrastructure, and effective industrial policies. In the absence of such enabling conditions, FDI may yield enclave-style growth without substantive labour market benefits. Hence, to harness FDI for employment generation, governments must implement complementary policies such as skills development, domestic supplier promotion, and labour-intensive investment incentives.

Labour market regulation, captured through an index of regulatory rigidity, reveals a negative coefficient, weakly significant at the 10% level. This suggests that inflexible labour market institutions may exert a dampening effect on employment by discouraging hiring, particularly in the formal sector. Excessively stringent rules on hiring, firing, and wage-setting can increase adjustment costs for firms and disincentivize workforce expansion. This is particularly detrimental in contexts where the private sector is the primary engine of employment and where informal labour markets are dominant.

The result supports the argument advanced by Freeman (2009), who posits that while protective labour regulations are essential for equity and worker welfare, overly rigid regimes can hinder dynamism and job creation. Striking a balance between flexibility and protection—through "smart regulation"—is therefore critical to labour market performance in the context of rapid technological change. Labour market institutions should be designed to facilitate workforce mobility, support lifelong learning, and provide safety nets for displaced workers, rather than inhibit employment expansion. *Policy Implications* 

The empirical findings offer important insights for policy formulation in emerging economies navigating the dual imperatives of technological transformation and inclusive employment growth. First, the negative association between AI adoption and employment highlights the urgent need for investment in human capital development. Education and training systems must be reoriented to emphasize future-ready skills, including digital literacy, analytical reasoning, and technical competencies. Second, expanding ICT infrastructure is essential not only for enhancing connectivity but also for enabling new forms of employment and enterprise development.

Third, while economic growth remains a vital driver of employment, policies must ensure that such growth is broad-based and labour-absorbing. Sectoral diversification, SME development, and support for green and care economies can enhance the employment intensity of growth. Fourth, the employment effects of FDI should not be taken for granted; targeted policies that foster domestic linkages, local content, and

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human capital development are necessary to maximize FDI's employment potential. Finally, labour market regulation must evolve to accommodate the changing nature of work. Greater flexibility, combined with adequate protection, can support both firm-level adaptability and worker security.

# 4. Conclusion and Recommendations

As Artificial Intelligence (AI) continues to reshape labour markets in emerging economies, its effects reveal a complex duality—offering significant opportunities for enhanced productivity and economic growth, while simultaneously posing substantial risks of job displacement, rising inequality, and social dislocation. The impact of AI adoption is uneven across economic sectors: manufacturing faces the threat of premature deindustrialization; services experience both augmentation and automation; and agriculture, while slower to adopt, holds promise for long-term productivity gains. The most vulnerable segments of the workforce—those engaged in routine, low-skilled, and informal employment—are disproportionately affected by labour market disruptions, exacerbating existing inequalities. At the same time, AI is creating new occupational roles that demand higher-order cognitive, digital, and technical competencies. The technological transition is also contributing to widening socio-economic disparities, manifested through wage polarization, gender gaps, and geographic divides. Without proactive and inclusive policy frameworks, these dynamics risk entrenching structural unemployment and undermining developmental progress.

The empirical findings of this study underscore the critical role of economic and institutional variables in mediating the relationship between AI adoption and employment outcomes. Specifically, the analysis reveals a statistically significant negative association between AI diffusion and employment rates, particularly in economies characterized by low-skill, routine-intensive labour markets. However, complementary factors—such as ICT infrastructure and human capital—emerge as positive contributors to employment, highlighting potential pathways for mitigating technology-induced disruptions. GDP per capita is found to enhance employment, contingent on the inclusivity and sectoral composition of growth. Conversely, Foreign Direct Investment (FDI) shows no statistically significant effect on employment in the absence of strong domestic linkages. Labour market rigidity is also negatively associated with employment, pointing to the need for flexible, yet protective regulatory frameworks.

In response to these findings, the following multi-dimensional policy strategy is proposed to ensure that AI-driven transformation aligns with inclusive and sustainable employment outcomes:

i. Invest in Human Capital Development

Education systems must undergo structural reforms to prioritize future-ready skills—particularly digital literacy, critical thinking, and competencies in science, technology, engineering, and mathematics (STEM). Equally vital is the promotion of lifelong learning ecosystems to facilitate continuous skill adaptation in response to evolving labour market demands.

*ii.* Facilitate Labour Market Transitions

Governments should implement targeted reskilling and upskilling programs for workers displaced from vulnerable sectors. This includes designing accessible and inclusive training platforms, as well as mobility support to assist transitions between occupations and sectors.

*iii.* Expand Social Safety Nets

Social protection mechanisms must be strengthened to buffer the adverse effects of job displacement and income volatility. Innovative instruments—such as unemployment insurance, conditional cash transfers, and job guarantee schemes—can enhance resilience among affected populations.

*iv.* Build Inclusive AI Ecosystems

AI adoption strategies must reflect domestic socio-economic contexts. Policymaking should involve a broad coalition of stakeholders—government, academia, private sector, and civil society—to ensure ethical deployment and equitable benefit distribution. Special attention should be given to marginalized communities to avoid deepening exclusion.

v. Strengthen Digital Infrastructure Bridging the digital divide remains critical. Strategic investments in broadband connectivity, electricity, and mobile technologies, particularly in rural and underserved regions, are essential to enable participation in the digital economy and foster digital entrepreneurship.

- Vi. Undertake Institutional and Regulatory Reform
   Labour regulations must evolve to accommodate emerging forms of employment, such as platform and gig work. Forward-looking labour codes should balance flexibility with adequate protection, ensuring fair wages, income security, and access to legal rights.
- vii. Align Innovation and Industrial Policies with Digital Transformation National AI strategies must be anchored in robust innovation ecosystems. This includes fostering public-private partnerships, providing incentives for start-ups, and aligning industrial policy with digital and technological objectives to enhance productivity and employment creation across sectors.

The transition to an AI-driven economy presents both significant opportunities and formidable challenges for emerging economies. While the displacement of routine and low-skilled jobs is a real and present risk, AI also offers the potential to create new avenues for employment and entrepreneurship—particularly when complemented by the right policy instruments. However, the distributional effects of AI adoption are likely to be regressive unless counteracted by inclusive, forward-looking interventions.

This study emphasizes the need for a coordinated policy framework that simultaneously advances AI adoption, strengthens human capital, expands digital infrastructure, and reforms labour market institutions. The heterogeneity observed across countries further highlights the importance of institutional quality, adaptability, and context-specific policy design. In sum, AI can be a powerful engine for inclusive development if guided by strategic policy choices. Emerging economies must lead this transformation with vision and commitment—ensuring that the promise of AI translates into shared prosperity, economic justice, and sustainable growth. The future of work in the age of AI must be shaped, not simply endured.

The findings underscore the importance of a coordinated policy framework that integrates AI adoption with investments in human capital, digital infrastructure, and labour market institutions. The heterogeneity across countries further emphasizes the role of institutional quality and policy adaptability. Emerging economies that can strategically align technology, education, and regulation stand a better chance of realizing the employment gains of digital transformation, rather than succumbing to its disruptive potential.

AI presents both risks and opportunities for labour markets in emerging economies. While routine jobs are vulnerable to displacement, new roles in the digital economy may emerge. However, the distributional effects are likely to be regressive unless deliberate policies are adopted. Education reforms, investment in digital infrastructure, and inclusive innovation policies are essential for shaping an equitable AIdriven future.

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