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The Macroeconomic Impact of Artificial Intelligence Adoption on Labour Markets in Emerging Economies: A Literature Review

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Abstract

Artificial intelligence (AI) is rapidly transforming labour markets across the global economy, yet its macroeconomic consequences for emerging economies remain insufficiently examined in the existing literature. This paper presents a systematic review of the current literature on the impact of AI adoption on labour markets in five major emerging economies—India, Brazil, Indonesia, South Africa, and Nigeria—over the period 2015–2024. Drawing on published findings from the International Labour Organization (ILO), the World Bank, the International Monetary Fund (IMF), the Organisation for Economic Co-operation and Development (OECD), and peer-reviewed academic literature, this review synthesizes evidence on three interconnected questions: How has AI adoption affected employment levels and occupational structures in emerging economies?; what are its distributional consequences for income inequality and vulnerable workers?; and what policy frameworks does the literature recommend to manage the transition equitably? The review finds that existing studies consistently identify a dual and asymmetric effect: AI adoption displaces routine and low-skill employment in manufacturing and services while generating new demand for higher-skilled, technology-complementary occupations, thereby widening pre-existing income inequality unless counteracted by deliberate policy intervention. The literature further shows that the magnitude of these effects varies significantly across countries depending on institutional quality, educational endowments, digital infrastructure, and sectoral

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composition. The paper concludes by identifying gaps in the current literature and highlighting the need for firm-level and longitudinal studies in the Global South context.

Keywords: Artificial Intelligence, Labour Markets, Emerging Economies, Technological Unemployment, Income Inequality, Literature Review, AI Policy, Macroeconomics

1. Introduction

Artificial intelligence has transitioned from a domain of speculative science to a pervasive economic force reshaping industries, institutions, and labour markets across the global economy. The automation of cognitive and physical tasks, once considered the exclusive province of human workers, is now increasingly performed by machine-learning algorithms, robotic systems, and large language models. While the productivity-enhancing potential of AI is widely acknowledged in the literature, its distributional consequences—particularly in the context of emerging and developing economies—remain deeply contested (Acemoglu and Restrepo 2018; Brynjolfsson and McAfee 2014).

Emerging economies occupy a paradoxical position in the global AI landscape. On one hand, the literature suggests they stand to benefit enormously from AI-driven productivity gains, potentially leapfrogging traditional stages of industrial development. On the other hand, scholars have highlighted that their labour markets are characterized by large pools of low- and semi-skilled workers whose livelihoods are most vulnerable to automation. Countries such as India, Brazil, Indonesia, South Africa, and Nigeria collectively employ hundreds of millions of workers in sectors such as manufacturing, retail, agriculture processing, and routine services that AI is actively transforming (Chang and Huynh 2016; ILO 2023).

This paper is motivated by three research questions that the existing literature has not comprehensively addressed in a comparative emerging-economy framework: (1) How has AI adoption affected employment levels and occupational structures in major emerging economies? (2) What does the literature reveal about the distributional consequences of AI adoption for income inequality and vulnerable workers? (3) What policy frameworks does the scholarly and institutional literature recommend to manage the AI transition equitably in the Global South?

To address these questions, this paper undertakes a systematic review of published academic literature, institutional reports, working papers, and policy documents published between 2013 and 2024, identified through Google Scholar, JSTOR, SSRN, the ILO's LABORDOC, and the World Bank Open Knowledge Repository. The five sample economies—India, Brazil, Indonesia, South Africa, and Nigeria—were selected to ensure geographic diversity and to cover a range of AI preparedness levels. The review makes three principal contributions. First, it provides a comparative synthesis of AI-labour market findings across five diverse emerging economies. Second, it maps the sectoral and distributional dimensions of AI's impact as documented in the literature. Third, it identifies critical gaps in existing scholarship and offers directions for future empirical research. The paper does not present original econometric analysis; rather, it systematically reviews and critically evaluates the evidence produced by existing studies.

2. Literature Review

2.1 Theoretical Foundations: Technology and Labour Displacement

The intellectual foundations of debates surrounding technology and employment date to the classical economists. Ricardo (1821) acknowledged the possibility of technological unemployment in his chapter on machinery, while Keynes (1930) famously predicted "technological unemployment" as a temporary malady of the transition to an automated future. The post-war consensus, however, leaned toward technological optimism: Solow (1956) and subsequent growth theorists argued that innovations would create new categories of work faster than they destroyed old ones, a position empirically supported through much of the twentieth century (Acemoglu and Restrepo 2018).

The digital revolution revived these debates. The task-based framework developed by Autor, Levy, and Murnane (2003) remains foundational: it distinguishes between routine tasks (susceptible to automation) and non-routine tasks (complemented by technology), predicting a hollowing out of middle-skill employment. Acemoglu and Restrepo (2018;

2020) extended this framework by distinguishing displacement effects (where machines substitute for labour) from reinstatement effects (where new labour-intensive tasks emerge), finding that in U.S. manufacturing, displacement has significantly outpaced reinstatement since 1990. Brynjolfsson and McAfee (2014) further argue that AI constitutes a general-purpose technology with economy-wide transformative potential comparable to electricity, making its labour market effects broader and more persistent than prior technological waves.

2.2 AI Adoption and Labour Markets: Evidence from Emerging Economies

The literature on AI's labour market impact in emerging economies begins most prominently with the World Bank's World Development Report (2016), which estimated that up to 77 percent of jobs in countries such as China and India were susceptible to automation. However, subsequent scholars challenged this estimate. Banga and te Velde (2018) argued that these figures overstate risk by ignoring task heterogeneity within occupations and the fact that low wages in developing countries reduce the economic incentive for automation. Chang and Huynh (2016), in a study of ASEAN economies, estimated that approximately 56 percent of employment was at risk, with garment and textile sectors facing the most acute exposure—a finding directly relevant to Indonesia and other sample countries.

Country-specific literature reveals nuanced patterns. For India, Mehrotra and Parida (2019) document that IT-sector AI adoption has driven rapid growth in high-skill employment while depressing wages and employment in routine back-office roles. For Brazil, studies reviewed by the ILO (2023) indicate that service-sector automation is disproportionately affecting low-income female workers. In sub-Saharan Africa, Cazzaniga et al. (2024) at the IMF find that countries such as Nigeria, with low AI preparedness index scores, face the double jeopardy of limited capacity to benefit from AI productivity gains while remaining exposed to trade-channel automation effects as manufacturing competitors adopt AI.

The IMF's AI Preparedness Index (Cazzaniga et al. 2024) provides a useful cross-country summary. Among the five economies reviewed, India scores highest (0.62), reflecting its technology sector and English-language talent pool, while Nigeria scores lowest (0.38), indicating the weakest institutional and infrastructural foundation for managing an equitable AI transition. These disparities in readiness imply that the impact of AI on labor markets is not uniform even within the 'emerging economy' category, a point emphasized by Rodrik (2016) in the context of premature deindustrialization. Table 1 documents the AI preparedness and investment indicators across sample economies, and Figure 1 in Section 2.4 below illustrates the growing divergence in AI investment as a share of GDP over 2015–2022.

Table 1: AI Preparedness and Investment Indicators for Sample Economies

Country	IMF AI Preparedness Index (2023)	AI Investment (% of GDP, 2022)	Global AI Ranking
India	0.62	1.80%	47
Brazil	0.55	1.20%	58
Indonesia	0.49	0.90%	67
South Africa	0.51	1.00%	63
Nigeria	0.38	0.40%	91

Source: IMF AI Preparedness Index (Cazzaniga et al. 2024); World Bank (2023)

2.3 Distributional Consequences: Inequality and Vulnerable Employment

A consistent theme across the reviewed literature is that AI adoption worsens income inequality in the short to medium term, particularly in contexts with weak redistributive institutions. This is consistent with the skill-biased technological change (SBTC) hypothesis (Autor, Levy, and Murnane 2003), which predicts that technology increases relative demand for high-skill workers while depressing returns to low-skill labour. Cazzaniga et al. (2024) find that across a broad sample of economies, AI adoption is associated with a declining labour income share, consistent with the findings of Acemoglu and Restrepo (2020) for advanced economies. In emerging economy contexts, this effect is amplified by the absence of robust social protection systems that might otherwise cushion displaced workers.

ILO (2023) data on vulnerable employment rates—defined as the share of workers in informal, own-account, or contributing family employment—show that while rates have declined modestly across all five sample economies between 2015 and 2023, the pace of decline has slowed in countries with higher AI adoption intensity, suggesting that AI may be partially offsetting traditional pathways out of vulnerable employment. Table 2, compiled from ILO (2024) and World Bank (2024) data, summarizes vulnerable employment and Gini coefficient trends. Notably, all five economies recorded rising Gini coefficients over the review period, with Nigeria experiencing the sharpest increase (from 35.1 to 38.4). While the literature does not establish direct causation, studies by Cazzaniga et al. (2024) and Rodrik (2016) identify AI-driven labour market polarization as a contributing factor consistent with these observed trends.

Table 2: Vulnerable Employment Rate and Gini Coefficient Trends, 2015–2023

Country	Vulnerable Emp. Rate 2015 (%)	Vulnerable Emp. Rate 2023 (%)	Gini 2015	Gini 2023
India	76.1	71.4	35.7	37.8
Brazil	34.2	31.8	51.3	52.9
Indonesia	58.3	53.7	39	38.2
South Africa	18.4	17.9	63	63.5
Nigeria	81.6	79.3	35.1	38.4

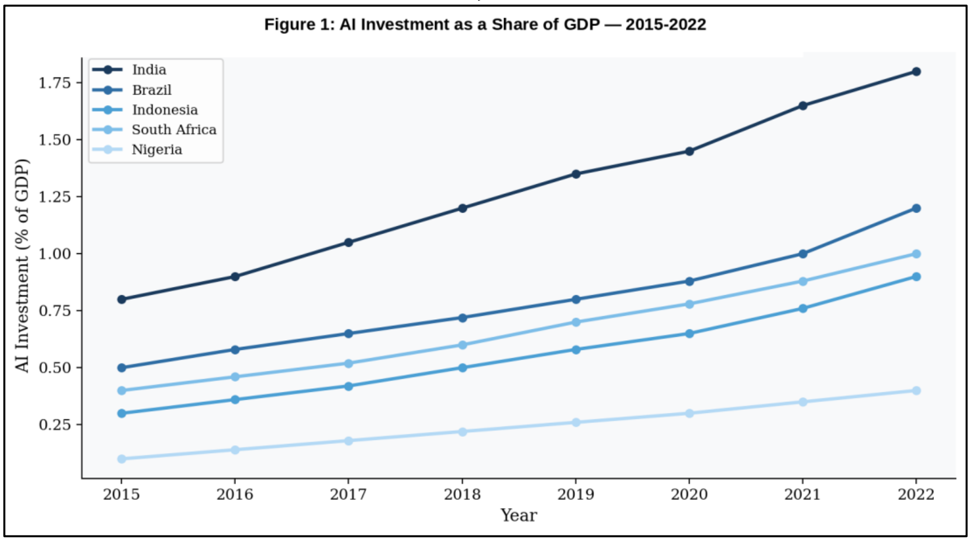
Source: ILO ILOSTAT (2024); World Bank Poverty and Inequality Platform (2024)

2.4 AI Adoption Trends, Investment, and Gender Dimensions

The literature documents substantial and growing AI investment across all five sample economies, though from very different baselines. World Bank (2023) and IMF (2024) data, illustrated in Figure 1 below, show that India's AI investment as a share of GDP grew from approximately 0.8 percent in 2015 to 1.8 percent in 2022, driven largely by the private technology sector and government initiatives such as the National AI Strategy (NITI Aayog 2018). Nigeria, by contrast, saw investment growth from just 0.1 percent to 0.4 percent over the same period, reflecting both lower private sector capacity and limited public investment in digital infrastructure.

Gender dimensions are particularly salient in the reviewed literature. The ILO (2023) reports that in Indonesia and Brazil, women account for a disproportionate share of workers in sectors with high automation risk, including garment manufacturing and retail. Banga and te Velde (2018) further note that women in these sectors tend to have lower digital literacy and less access to retraining programs, compounding their vulnerability. This gender-differentiated impact of AI represents a critical gap in the policy literature, as most national AI strategies reviewed do not explicitly address gender equity in labor market transitions.

Figure 1: AI Investment as a Percentage of GDP — Sample Economies, 2015–2022



Source: World Bank World Development Indicators (2023); IMF (2024)

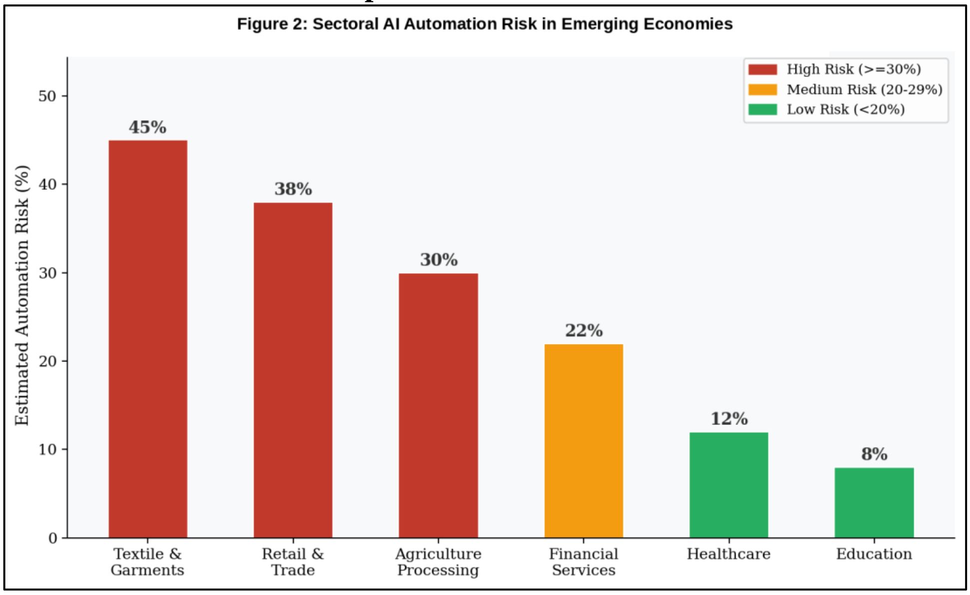
2.5 Sectoral Dimensions of AI Disruption

The reviewed literature consistently identifies significant variation in impact of AI on labour markets across sectors. Chang and Huynh (2016) and the World Bank (2016) estimate that textile and garment manufacturing faces the highest automation risk (estimated at 45 percent), followed by retail and trade (38 percent) and agriculture processing (30 percent). These figures are particularly alarming in the context of Indonesia's garment sector, which employs approximately three million workers, the majority of whom are women with limited access to retraining opportunities (ILO 2023).

Conversely, the literature documents AI complementarity in sectors such as healthcare, education, and personalized services, where technology augments rather than substituting human judgment (Brynjolfsson and McAfee 2014). Agriculture presents a nuanced case:

precision agriculture technologies offer substantial productivity gains for smallholder farmers in Nigeria, India, and Indonesia, yet Banga and te Velde (2018) note that adoption is severely constrained by inadequate rural digital infrastructure and limited access to affordable capital. Figure 2 summarizes the sectoral automation risk estimates reported in the literature.

Figure 2: Sectoral AI Automation Risk in Emerging Economies as Reported in Literature



Source: Chang and Huynh (2016); World Bank (2016)

2.6 AI, Productivity, and the Growth Nexus

A distinct strand of the literature examines the macroeconomic growth effects of AI adoption. Aghion, Jones, and Jones (2017) model AI as a general-purpose technology capable of accelerating long-run economic growth, particularly as AI penetrates knowledge-intensive sectors. IMF (2024) analysis finds a positive association between AI investment and total factor productivity growth across a broad sample of economies, with the effect strongest in countries that combine AI adoption with high human capital endowments. Among the sample economies, India's trajectory is most consistent with this pattern: sustained AI investment alongside strong tertiary education outcomes has contributed to productivity-led growth in the technology services sector.

However, the literature cautions against interpreting AI-led productivity growth as automatically welfare-enhancing. Rodrik (2016) documents "premature deindustrialization"—the contraction of manufacturing employment in developing countries before they have reached the income levels at which advanced economies deindustrialized—and argues that AI-driven automation accelerates this trend. South Africa's case is illustrative: despite moderate AI preparedness and productivity gains in financial services, structural unemployment has remained above 30 percent, reflecting the failure of new job creation to compensate for displacement (ILO 2023; World Bank 2023).

2.7 Policy Responses: What the Literature Recommends

The policy literature reviewed converges on several recommendations. First, investment in education and reskilling is identified as the most critical lever. Cazzaniga et al. (2024) argue that countries with higher AI preparedness scores—which incorporate measures of human capital and digital skills—are better positioned to realize productivity gains while managing displacement. Second, adaptive social protection systems are widely recommended, including portable benefits, unemployment insurance adapted to gig and informal workers, and conditional cash transfers (ILO 2023; World Bank 2016).

Third, the literature increasingly calls for international policy coordination on technology transfer and AI governance. Banga and te Velde (2018) argue that without deliberate knowledge transfer mechanisms, the global AI divide will widen, leaving lower-income emerging economies such as Nigeria increasingly marginalized from AI-driven growth. A notable gap in the reviewed policy literature is the limited attention paid to the political economy of AI policy reform in emerging economies, where vested interests and weak institutions may impede even technically sound recommendations. This represents an important direction for future research, as the feasibility of policy implementation is at least as important as its design.

3. Conclusion

This paper has presented a systematic review of the current literature on the macroeconomic impact of AI adoption on labour markets in five major emerging economies over the period 2015–2024. The review finds that existing scholarship consistently documents a dual and asymmetric effect: AI adoption displaces routine and low-skill employment while generating new high-skill opportunities, with distributional consequences that disproportionately harm vulnerable workers—particularly women and informal sector employees—unless counteracted by targeted policy. The magnitude of these effects varies significantly across countries, conditioned by institutional quality, educational endowments, digital infrastructure, and sectoral composition.

The review identifies three significant gaps in the existing literature. First, rigorous firm-level and household-level empirical studies directly measuring AI adoption and its labour market consequences in emerging economy contexts remain scarce; most evidence is extrapolated from advanced economy studies or aggregate cross-country data. Second, the gender dimensions of AI's labour market impact in the Global South are underexplored, despite clear evidence that women are disproportionately concentrated in high-risk sectors. Third, the political economy of AI policy reform in emerging economies—the conditions under which governments are able and willing to implement the policies the literature recommends—is almost entirely absent from the literature.

Future research should address these gaps through longitudinal panel studies at the firm and household level, gender-disaggregated analyses of automation risk and retraining outcomes, and political economy investigations of AI governance in emerging market economies contexts. The rise of AI is not an event that emerging economies can afford to wait passively; but neither can policymakers act effectively without a more robust and context-specific evidence base than currently exists.

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