

The Political Economy of AI-Driven Productivity: Impacts on
Employment, Wages, and Inequality in Emerging Markets

Saifi walid¹

¹University of Biskra(Algeria), walid.saifi@univ-biskra.dz

Received: 16/01/2026

Accepted: 16/04/2026

Published: 30/04/2026

Abstract:

This study examines the impact of the rapid spread of Artificial Intelligence (AI) and automation on emerging markets, highlighting the paradox between enhanced productivity opportunities and the erosion of traditional labor-intensive advantages. It integrates insights from management science, development economics, and critical political economy, supported by recent empirical evidence, to analyze shifts in employment structures, wage polarization, and income inequality. The paper argues that without strong institutional frameworks, AI adoption may worsen “premature deindustrialization” and expand the digital divide. It emphasizes that the socioeconomic outcomes of AI are politically shaped rather than technologically determined, with institutional quality and labor regulation acting as key mediators. Moreover, the research identifies a “double exposure” risk for emerging economies — high automation vulnerability and weak institutional adaptability — potentially leading to a new form of “technological informality.”

Keywords:

Artificial Intelligence, Emerging Markets, Labor Economics, Income Inequality, Premature Deindustrialization, Political Economy, Institutional Theory, Skill-Biased Technological Change.

1. INTRODUCTION

The integration of Artificial Intelligence (AI) into the global economic fabric represents a structural transformation comparable in magnitude to the steam engine or electrification. This "Fourth Industrial Revolution" promises to reshape the production functions of firms and the aggregate productivity of

Corresponding author: saifi walid, e-mail:walid.saifi@univ-biskra.dz

The Political Economy of AI-Driven Productivity: Impacts on Employment, Wages, and Inequality in Emerging Markets

nations. However, the academic and policy discourse surrounding this revolution has been predominantly centered on the experiences of the Global North—focusing on how AI might displace white-collar workers in New York, optimize logistics in Rotterdam, or automate manufacturing in Stuttgart. This article seeks to shift the analytical lens toward the Global South, arguing that the stakes for emerging markets (EMs) are not merely different in degree, but in kind.

For economies that have historically relied on low-cost, abundant labor to attract foreign direct investment (FDI) and integrate into global value chains, the rise of labor-saving AI technologies poses an existential strategic challenge. The central problem this article addresses is the tension between the necessity of technological adoption for productivity growth and the imperative of social stability through mass employment. The classical development ladder, famously described by varying modernization theorists like Rostow and Lewis, relies on moving surplus labor from low-productivity agriculture to higher-productivity manufacturing. However, recent trends suggest that AI and robotics may be severing this link, leading to what Rodrik (2016) has termed "premature deindustrialization." If manufacturing becomes less labor-intensive due to AI-driven efficiency, the traditional path to middle-income status may be foreclosed.

Furthermore, the introduction of AI in EMs is not occurring in a vacuum. It interacts with pre-existing structural vulnerabilities: high levels of informal employment, fragile social safety nets, and educational systems often misaligned with future skills. This creates a scenario of "double exposure," where EMs face the external shock of automation reducing demand for their exports, and the internal shock of AI displacing domestic service and industrial jobs.

This paper aims to bridge the gap between management science—which often views AI through the lens of firm-level efficiency, competitive advantage, and innovation adoption—and political economy, which views these shifts through the lens of power dynamics, institutional friction, and

distributive justice. By doing so, we contribute to the literature by modeling how institutional voids in EMs might amplify the inequality-generating effects of AI. We ask: How does the political economy of AI differ in contexts where labor institutions are weak? And what strategic responses are available to EM governments to avoid a "race to the bottom"?

The article is structured as follows: Section 2 reviews the theoretical background, contrasting neoclassical views with institutional perspectives. Section 3 outlines the conceptual framework and methodology. Section 4 presents a detailed analysis of sectoral impacts and specific case studies from Asia and Latin America. Section 5 discusses the broader sociopolitical implications, including the gendered dimension of AI displacement. Finally, Section 6 offers policy implications and concludes.

2. Theoretical Background and Literature Review

2.1 Technological Unemployment vs. The Productivity Effect

The debate over technological unemployment is centuries old, dating back to the Luddite movement. In modern economic theory, this is often framed as a contest between two forces. On one side is the "displacement effect," where capital (AI/robots) replaces labor in performing specific tasks (Acemoglu & Restrepo, 2018). On the other is the "productivity effect" (or reinstatement effect), where the cost savings from automation lead to lower prices, higher demand, and the creation of new, more complex tasks requiring human labor. In advanced economies, historical data suggests that the reinstatement effect has generally kept pace with displacement, preventing long-term mass unemployment. However, for emerging markets, the transfer of technology is often exogenous. As technological capital is imported rather than developed indigenously, the "reinstatement effect"—the creation of new, high-value tasks such as AI system design or robot maintenance—often occurs in the technology-exporting country (e.g., the U.S., China, or Germany), while the "displacement effect" is felt acutely in the technology-importing country (e.g., Brazil, Indonesia, or Bangladesh). This asymmetry challenges the assumption that technological progress is automatically Pareto-improving for all nations.

2.2 Skill-Biased Technological Change (SBTC) in the Global South

The theory of Skill-Biased Technological Change posits that modern technology complements high-skilled workers while substituting for low-skilled ones. In the context of the Global South, the implications are profound. The "hollowing out" of the middle class seen in the West may manifest differently in EMs. Instead of hollowing out a middle, we may observe a hardening of the barrier between the informal economy and the formal, digital economy.

Baldwin (2019) introduces the concept of "globotics," arguing that while AI automates tasks, "telemigration" allows service sector jobs to be offshored to EMs via digital platforms. While this offers a potential upside—a new digital middle class in Lagos or Manila—it is likely to be concentrated among the urban, English-speaking elite. This exacerbates the rural-urban divide, a critical fault line in the political economy of developing nations.

2.3 The Institutional View and "Data Colonialism"

From a management science perspective, technology adoption is effectively a strategic choice influenced by organizational capabilities. However, institutional theory suggests that the impact of this choice is contingent on the regulatory environment (North, 1990). In many EMs, labor institutions are bifurcated: a protected formal sector and a vast, unregulated informal sector. Integrating AI into this mix could incentivize firms to automate formal jobs to avoid regulatory costs, pushing more workers into the precarious informal sector—a phenomenon this paper defines as "technological informality."

Furthermore, critical scholars like Couldry and Mejias (2019) argue that the current AI paradigm represents a form of "data colonialism." Just as colonial powers extracted natural resources from the Global South to fuel industrialization in the North, modern tech giants extract data (the raw material of AI) from users in EMs to train algorithms that are then sold back to these markets as services. This extraction of "data rents" without corresponding compensation or tax revenue represents a significant leakage of value, complicating the economic catch-up of EMs.

3. Methodology and Conceptual Framework

3.1 Conceptual Framework

This study adopts a Political Economy framework that treats "AI Adoption Intensity" as the independent variable and "Socioeconomic Equity" (comprising employment rates, wage distribution, and labor share of income) as the dependent variable. Crucially, we introduce "Institutional Capacity" as a moderating variable.

- **Independent Variable:** AI Adoption (measured by robot density, digital infrastructure investment, and AI software penetration).
- **Dependent Variable:** Socioeconomic Equity (Gini coefficient, manufacturing employment share, wage polarization ratio).
- **Moderator:** Institutional Capacity (Labor law strength, social safety net coverage, education quality, and intellectual property governance).

We posit that the relationship between AI and inequality is mediated by the political bargaining power of labor. In economies where legal frameworks and public policy favor capital accumulation over labor protection, AI acts as a wealth concentrator. Conversely, where active labor market policies exist, AI can be a wealth multiplier.

3.2 Analytical Approach

Given the nascent stage of widespread AI deployment in many EMs, long-term time-series data is scarce. Therefore, this article employs a comparative analytical approach, utilizing:

1. **Macro-level data triangulation:** Synthesizing datasets from the World Bank, the International Labour Organization (ILO), and the International Federation of Robotics (IFR) to identify trends in productivity versus employment.
2. **Sectoral Case Studies:** Examining specific industries (Business Process Outsourcing and Automotive Manufacturing) where AI adoption is most advanced to serve as leading indicators for broader economic shifts.
3. **Scenario Analysis:** Projecting potential future impacts on income inequality based on different policy intervention levels.

4. Analysis and Discussion

4.1 The Productivity-Employment Trade-off:

Evidence of Premature Deindustrialization

The empirical reality in emerging markets suggests a decoupling of productivity growth from employment generation. While aggregate GDP may rise due to AI-driven efficiencies in resource extraction, precision agriculture, or algorithmic finance, the labor intensity of growth is declining.

Table 1: Divergent Trends in Manufacturing Employment and Value Added (Select EMs, 2015–2023)

Country	Manufacturing Value Added (CAGR %)	Manufacturing Employment Growth (CAGR %)	Implied Productivity Gap	Context
Vietnam	7.2%	4.1%	+3.1%	Supply chain shifts counteract automation, yet gap persists.
Brazil	1.8%	-1.2%	+3.0%	Classic premature deindustrialization; factories automate or close.
South Africa	0.9%	-2.1%	+3.0%	High structural unemployment exacerbated by capital-intensive mining/auto.
India	5.5%	1.8%	+3.7%	"Jobless growth" in manufacturing; service sector reliance.

Source: Author's compilation based on World Bank WDI and ILOStat data (2024). Note: 2023 figures are preliminary estimates.

Table 1 illustrates this divergence. In countries like Brazil and South Africa, we observe a contraction in manufacturing employment even as value-added stabilizes or grows—a hallmark of automation's encroachment. Brazil, once a manufacturing powerhouse, has seen its industrial base erode not just due to Chinese competition, but due to the modernization of the remaining plants which require fewer, higher-skilled workers. Vietnam remains an outlier due to supply chain shifts away from China ("China Plus One" strategy), but even there, the productivity gap indicates that output is growing nearly twice as fast as jobs. This supports the hypothesis that EMs are importing "labor-saving" growth, bypassing the mass employment phase of industrialization.

4.2 Sectoral Case Studies

1. Case Study A: The BPO Crisis in the Philippines and India

The Business Process Outsourcing (BPO) sector has been a miracle engine for the middle class in India and the Philippines. However, this sector is uniquely vulnerable to Generative AI (GenAI). The "Level 1" support tasks—answering basic queries, data entry, and simple translation—are precisely what Large Language Models (LLMs) excel at. Recent industry reports suggest a freeze in hiring for entry-level BPO roles. If a chatbot can handle 80% of customer queries at near-zero marginal cost, the rationale for maintaining vast call centers diminishes. This represents a "rungs on the ladder" problem: if the entry-level jobs disappear, how do workers acquire the skills to move to high-value tasks? The "demographic dividend" of a young, English-speaking workforce risks becoming a liability if that workforce cannot underbid software.

2. Case Study B: Automotive Manufacturing in Mexico

Mexico's automotive sector is highly integrated with the US market. Under the USMCA trade agreement, there are pressures to increase wages, but simultaneously, firms are investing heavily in robotics to remain competitive. The result is "islands of high productivity"—highly automated plants that employ a small cadre of engineers and technicians—surrounded by a sea of low-productivity informal service work. The spillover effects (multiplier

effects) of these factories are diminishing because robots do not consume local goods and services in the way human workers do.

4.3 Wage Polarization and the "Smile Curve"

The impact of AI on wages is best understood through the deepening of the "Smile Curve," where value is concentrated in the pre-production (R&D, design) and post-production (marketing, services) phases, while the manufacturing/execution phase sees value compression. AI exacerbates this by commoditizing routine cognitive and manual tasks.

Hypothesized Wage Distribution Shift in Emerging Markets Post-AI Adoption.

Description : The figure would depict two frequency distribution curves.

1. **Pre-AI (The Bell Curve):** A standard normal distribution representing a healthy middle class in the formal sector.
2. **Post-AI (The Camel Curve):** A bimodal distribution. On the left, a massive spike in low-wage, low-productivity service/gig work (food delivery, care work). On the right, a smaller spike in high-wage cognitive technical work (AI specialists, data scientists). The middle—routine administration and manufacturing—is collapsed.

Analysis: This polarization risks creating a "dual economy" within EMs. The upper tier, integrated into the global AI ecosystem (e.g., software engineers in Bangalore, São Paulo, or Tallinn), sees wages converge with global OECD standards. The lower tier, competing with algorithms (e.g., call center workers facing chatbots) or restricted to non-tradable services (e.g., domestic help), faces wage suppression due to labor oversupply.

4.4 Inequality and the Capital-Labor Split

A critical metric in political economy is the labor share of national income. In mature economies, this share has been declining (Karabarbounis & Neiman, 2014). In EMs, the decline is often steeper and more consequential because capital ownership is more concentrated. When a factory automates, the income that once went to a hundred workers now flows to the owner of

the capital (often foreign) and the licensor of the software (almost always foreign).

Table 2: Projected Impact of AI on Gini Coefficients in Select Regions (Scenario Analysis)

Region	Current Gini (Avg.)	Scenario A: Low Policy Intervention	Scenario B: High Policy Intervention	Projected Shift
Latin America	0.49	0.54	0.50	Critical Regression
Southeast Asia	0.38	0.44	0.39	Moderate Risk
Sub-Saharan Africa	0.42	0.46	0.43	High Vulnerability

Source: Hypothetical projections based on elasticity models derived from IMF inequality datasets and estimated automation probabilities.

Table 2 presents a scenario analysis suggesting that without significant policy intervention—such as redistributive taxation or aggressive upskilling—inequality metrics in Latin America could regress to levels not seen since the 1990s. The "Low Policy Intervention" scenario assumes a laissez-faire approach where AI deployment is dictated solely by market forces, maximizing efficiency but ignoring equity.

5. Broader Sociopolitical Implications

5.1 The Gendered Dimension of AI Displacement

The impact of AI is not gender-neutral. In many emerging markets, women are disproportionately represented in sectors with high "routinization," such as garment manufacturing (e.g., Bangladesh, Vietnam) and BPO/clerical work (e.g., Philippines). The ILO estimates that women in SE Asia are 2.4 times more likely to hold jobs at high risk of automation than men. If these "entry-point" sectors into the formal economy close, women may be forced

back into the informal sector or unpaid domestic labor, reversing decades of progress in gender economic equality.

5.2 Algorithmic Management and Legal Voids

The economic shifts described above have profound legal consequences. The rise of the "gig economy," powered by AI algorithms (e.g., Uber, Rappi, Gojek), creates a new class of worker who is legally an entrepreneur but economically a dependent. Legally, current frameworks in many EMs are ill-equipped to handle algorithmic management. If an algorithm determines a gig worker's pay or deactivates their account based on opaque metrics, is there legal recourse? In many jurisdictions, these workers fall outside labor law protection. This creates a regulatory vacuum that facilitates the erosion of worker rights and social security contributions, weakening the fiscal state.

5.3 Political Stability and Security

Politically, high youth unemployment combined with high inequality is a historic recipe for instability. If the "demographic dividend" of countries like Nigeria, Egypt, or India turns into a "demographic burden" because AI limits low-skilled job creation, the result could be significant social unrest. This brings the discussion into the realm of security studies, suggesting that AI policy in EMs is, effectively, national security policy.

6. Conclusion and Policy Implications

This article has argued that the diffusion of AI into emerging markets is not a neutral trajectory of modernization but a politically charged process that threatens to widen the gap between capital and labor. The evidence suggests that while AI drives productivity, it creates a centrifugal force on income distribution, pushing rewards to the edges (high capital owners and high-skilled elites) and hollowing out the developmental middle.

7. Theoretical Contributions

For management science and economic theory, this study underscores the limitations of the "catch-up" growth model in the AI era. It suggests that the

"Resource-Based View" of the firm must be expanded to include "Institutional Intelligence." Firms in EMs cannot merely optimize for technological efficiency; they must account for social legitimacy to avoid regulatory backlash. Furthermore, it challenges the universality of the Kuznets Curve, suggesting that in the digital age, inequality may not naturally decrease with development without specific political intervention.

Practical and Policy Implications

To mitigate the risks of "premature deindustrialization" and inequality, EM governments must move beyond passive acceptance of technology:

1. ***Fiscal Policy Reform (The Robot Tax Debate):*** Governments must shift the tax base. Currently, labor is heavily taxed while capital and digital services are often under-taxed. Implementing "Digital Services Taxes" (DST) is essential to capture the value generated by foreign AI giants within the domestic economy. This revenue should fund social safety nets.
2. ***Adaptive Labor Law:*** Legal frameworks must evolve to recognize "digital labor." The distinction between employee and contractor is blurred by algorithmic management; laws must look at the *reality of control* rather than the contract. Extending social security to gig workers is a priority.
3. ***Sovereign AI Strategy:*** EMs cannot simply be consumers of Western AI. There is a need for industrial policies that foster "labor-augmenting" rather than "labor-replacing" AI. Governments should incentivize R&D in sectors like "AI for agriculture" or "AI for healthcare diagnostics," which complement human labor rather than replacing it.
4. ***Education Reform:*** Curricula must shift from rote memorization (which AI renders obsolete) to "human-centric skills"—critical thinking, empathy, negotiation, and complex problem-solving. Vocational training must be decoupled from specific legacy machineries and focused on adaptability.

8.Future Research Directions

Future scholarship should focus on the granular impact of Generative AI specifically, which may distinctively impact the "knowledge outsourcing" sector. Furthermore, empirical studies on the psychological contract between

The Political Economy of AI-Driven Productivity: Impacts on Employment, Wages, and Inequality in Emerging Markets

workers and firms in the age of algorithmic management in the Global South are largely missing. Longitudinal studies tracking the career trajectories of displaced manufacturing workers in EMs would also be invaluable.

In conclusion, the "political economy of productivity" demands that we look beyond the GDP numbers. If AI lifts the ceiling of an economy while lowering the floor for its workers, the resulting structure is unstable. The challenge for emerging markets is not just to acquire artificial intelligence, but to cultivate the political and institutional wisdom required to govern it equitably.

References

- Acemoglu, D., & Restrepo, P. (2018). The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. *American Economic Review*, 108(6), 1488–1542.
- Arntz, M., Gregory, T., & Zierahn, U. (2016). The Risk of Automation for Jobs in OECD Countries. *OECD Social, Employment and Migration Working Papers*, No. 189.
- Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, 29(3), 3–30.
- Baldwin, R. (2019). *The Globotics Upheaval: Globalization, Robotics, and the Future of Work*. Oxford University Press.
- Brynjolfsson, E., & McAfee, A. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W.W. Norton & Company.
- Couldry, N., & Mejias, U. A. (2019). *The Costs of Connection: How Data Is Colonizing Human Life and Appropriating It for Capitalism*. Stanford University Press.
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How

susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280.

International Labour Organization. (2024). *World Employment and Social Outlook: Trends 2024*. ILO Publishing.

International Federation of Robotics. (2023). *World Robotics 2023: Industrial Robots*. IFR Statistical Department.

Karabarbounis, L., & Neiman, B. (2014). The Global Decline of the Labor Share. *The Quarterly Journal of Economics*, 129(1), 61–103.

Korinek, A., & Stiglitz, J. E. (2019). Artificial Intelligence and Its Implications for Income Distribution and Unemployment. In Agrawal, A., Gans, J., & Goldfarb, A. (Eds.), *The Economics of Artificial Intelligence: An Agenda* (pp. 349-390). University of Chicago Press.

Lee, K. F. (2018). *AI Superpowers: China, Silicon Valley, and the New World Order*. Houghton Mifflin Harcourt.

North, D. C. (1990). *Institutions, Institutional Change and Economic Performance*. Cambridge University Press.

Rodrik, D. (2016). Premature Deindustrialization. *Journal of Economic Growth*, 21(1), 1–33.

Schlogl, L., & Sumner, A. (2020). *Disrupted Development and the Future of Inequality in the Age of Automation*. Palgrave Macmillan.

Susskind, D. (2020). *A World Without Work: Technology, Automation, and How We Should Respond*. Metropolitan Books.

World Bank. (2024). *Global Economic Prospects, January 2024*. World Bank Group.

Zuboff, S. (2019). *The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power*. PublicAffairs.