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DIGITAL ECONOMIC TRANSFORMATION IN DEVELOPING COUNTRIES: ANALYSIS OF THE IMPACT OF ARTIFICIAL INTELLIGENCE ADOPTION ON PRODUCTIVITY, INEQUALITY, AND MARKET STRUCTURE

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Abstract

This study investigates the transformative role of artificial intelligence (AI) in shaping economic performance and structural dynamics within developing countries, focusing on three interrelated outcomes: productivity, inequality, and market structure. As AI becomes a general-purpose technology with wide-ranging economic applications, its diffusion in emerging markets presents both substantial opportunities and significant systemic risks. Building on recent empirical evidence, the study examines how AI adoption enhances firm-level efficiency, operational precision, and innovation capacity while evaluating the extent to which these micro-level gains translate into aggregate productivity improvements. The analysis also addresses distributional consequences, emphasizing how unequal access to digital infrastructure, skills, and capital may deepen existing socioeconomic disparities. Moreover, the study explores the implications of AI-driven platformization and data concentration for market competitiveness, particularly in economies characterized by regulatory gaps and high informality. By integrating insights from development economics, digital-technology studies, and industrial-organization theory, this research provides a comprehensive framework for assessing AI's multidimensional impact on developing countries. The findings aim to guide policymakers in designing inclusive digital-transformation strategies that maximize productivity gains, mitigate inequality, and preserve competitive market environments in the era of advanced automation.

Keywords: Artificial Intelligence; Digital Transformation; Productivity; Inequality; Market Structure

INTRODUCTION

The recent proliferation of artificial intelligence (AI) technologies has generated a fundamental reappraisal of the drivers of productivity, the organization of markets, and the distributional consequences of technological adoption across countries. AI is increasingly conceived as a potential general-purpose technology — one capable of producing pervasive cross-sectoral gains in efficiency, creative complementarities with human capital, and new modes of value creation — yet also one that concentrates innovation and control in a handful of global firms and platforms (OECD, 2024). The dual nature of AI — simultaneously enabling productivity advances and creating new vectors of concentration and exclusion — renders the technology exceptionally consequential for developing economies, where institutional capacity, digital infrastructure, and human-capital endowments differ markedly from advanced markets.

At the micro level, recent empirical work documents measurable productivity improvements for firms and workers who deploy AI-based tools — from enhanced code-writing assistants and firm-level decision systems to AI-augmented service provision in call centers and professional services — indicating that adoption can raise output per worker and task completion rates under specific complementarities (Brynjolfsson et al., 2023; OECD, 2024). Nonetheless, these micro gains do not mechanically translate into uniform aggregate growth; aggregate outcomes will depend on adoption breadth, complementary investments (e.g., digital infrastructure and managerial capabilities), and the capacity of domestic markets to absorb AI-enabled products and services (OECD, 2024). For many low- and middle-income countries, uneven adoption

— driven by constrained data access, limited digital skills, and weak regulatory frameworks — may blunt the potential aggregate payoff of AI and risk entrenching existing development gaps.

A second and equally pressing dimension concerns the distributive effects of AI adoption. Cross-country simulation and modeling exercises find that AI is likely to amplify between-country inequality unless policy action narrows gaps in exposure, preparedness, and access to critical digital inputs (IMF Working Paper: Cerutti et al., 2025). Empirical region-level studies further suggest that while AI can raise productivity for certain occupations and urban, formal sectors, it simultaneously threatens tasks concentrated among women, younger workers, and other vulnerable groups in regions with large informal sectors — thereby producing asymmetric welfare outcomes (ILO/World Bank summaries; Reuters reporting on regional studies). These findings underscore an urgent policy imperative: without pro-active investments in re-skilling, inclusive digital infrastructure, and social-protection mechanisms, AI diffusion may exacerbate labor-market stratification and impede inclusive growth in developing economies.

Third, the technological architecture of contemporary AI — heavily platformized, data-intensive, and frequently licensed or provisioned by a small set of global actors — reshapes market structure in ways that matter for competition policy, innovation pathways, and sovereignty over data and standards. Scholarship on digital platforms and development emphasizes that developing countries face particular competitive and regulatory risks as super-platforms extend into local markets; platform dependence can accelerate entry for local ventures yet also create systemic dependencies and governance fragilities that inhibit domestic industrial upgrading (Gawer & Bonina, 2024). Consequently, any research that seeks to evaluate the productivity and distributional consequences of AI in developing contexts must situate firm-level adoption within broader ecosystem dynamics — including platform governance, data access regimes, and national regulatory capacity.

Finally, the heterogeneity of AI's effects across tasks, sectors, and institutional settings calls for a carefully calibrated empirical research agenda. Two core questions should guide inquiry: (1) under what conditions do micro-level productivity gains from AI aggregate into sustained increases in labour productivity and GDP per capita in developing economies?, and (2) through which institutional and market channels (e.g., labor markets, platform competition, credit allocation) are distributional outcomes mediated? Addressing these questions requires mixed-methods designs that combine firm- and worker-level microdata, cross-country panel models, and structural policy experiments to identify complementarity thresholds, distributional spillovers, and governance levers that can align AI diffusion with inclusive development objectives (OECD, 2024; IMF, 2025). Such work will be policy-relevant not only for national governments but also for multilateral institutions and development partners seeking to ensure that AI contributes to equitable growth rather than to an acceleration of existing imbalances

LITERATURE REVIEW

The evolving literature on artificial intelligence (AI) adoption in developing countries spans several intersecting domains, including technological change and productivity, digital inequality, labor-market transformation, and the political economy of platform-based market structures. Together, these strands form a multidisciplinary foundation for understanding how AI reshapes economic trajectories in emerging markets.

1. AI as a General-Purpose Technology and Productivity Dynamics

A central theme in contemporary economic research is the conceptualization of AI as a general-purpose technology (GPT)—a class of innovations characterized by pervasive applicability, ongoing improvement, and deep complementarities with organizational capital and human skills (Brynjolfsson, Rock & Syverson, 2021; Cockburn, Henderson & Stern, 2018). Studies show that GPTs typically generate substantial productivity gains, but only when accompanied by complementary investments such as workforce training, digital infrastructure, and process reorganization.

Empirical evidence supports the potential for micro-level productivity increases resulting from AI tools. For instance, experimental studies demonstrate that AI-assisted coding tools accelerate developer productivity (Noy & Zhang, 2023), while AI-supported customer service functions reduce task completion time and improve service quality (Brynjolfsson et al., 2023). However, the literature consistently emphasizes that such micro-productivity improvements do not automatically scale to the macro level. Syverson (2017) argues that diffusion lags, adoption heterogeneity, and bottlenecks in organizational capability often slow aggregate productivity responses to emerging technologies.

This dynamic is particularly salient for developing economies, where constraints such as unreliable broadband, limited cloud access, and lower managerial capability reduce the likelihood that firm-specific productivity improvements will translate into sustained national growth (Cirera & Maloney, 2017). Research by the World Bank and OECD further highlights that AI's contribution to aggregate productivity depends on national absorptive capacity, including regulatory frameworks, digital public goods, and integration with local innovation ecosystems (OECD, 2024; World Bank, 2021).

2. AI Adoption, Skills, and the Evolution of Inequality

A second major literature emphasizes the labor-market consequences of AI, drawing from human-capital theory and empirical research on skill-biased and task-biased technological change. Early foundational work by Autor, Levy & Murnane (2003) established that digital technologies tend to displace routine tasks while augmenting non-routine cognitive work. Recent scholarship extends these findings to AI, demonstrating that machine learning models increasingly affect non-routine analytical tasks as well, reshaping skill demand across sectors (Acemoglu & Restrepo, 2018, 2020).

For developing countries, the implications of this transition are more complex due to large informal sectors, relatively low average education levels, and limited high-tech employment opportunities. Studies from the International Labour Organization (ILO) and World Bank suggest that AI adoption may generate polarized labor-market outcomes, benefiting digitally skilled workers while threatening low-skill and informal occupations disproportionately held by women, youth, and marginalized populations (ILO, 2023; World Bank, 2024).

Inequality may also intensify through digital divides in access to data, computational power, and AI infrastructure. Empirical research shows that countries with weak digital foundations tend to experience lower AI exposure and adoption, preventing them from capturing productivity gains while still experiencing displacement risks transmitted via global markets (UNCTAD, 2021). The IMF (Cerutti, Dagher & Rojas, 2025) warns that without active policy intervention—such as reskilling programs, digital public-infrastructure development, and inclusive data-access policies—AI may widen between-country and within-country inequality, reinforcing existing development gaps.

3. Market Structure, Platformization, and Competitive Dynamics

A third body of literature examines how AI interacts with the architecture of digital markets, particularly the growing dominance of platform-based business models. Foundational work by Rochet & Tirole (2003) and Parker, Van Alstyne & Choudary (2016) demonstrates how network effects, data advantages, and economies of scale can entrench platform power. In the AI era, these dynamics intensify: access to large datasets, computational resources, and proprietary models creates high entry barriers and promotes concentration in global AI markets (Zingales & Rolnik, 2020).

For developing countries, platformization presents both opportunities and vulnerabilities. Research by Gawer & Bonina (2024) highlights that global digital platforms can facilitate market entry for small firms, enable digital payments, and expand access to consumers; however, they may also impose governance constraints, extract data from local ecosystems, and limit domestic value capture. The literature on "data colonialism" similarly argues that AI-enabled platforms may reinforce asymmetries between global technology providers and local enterprises, creating dependencies that impede long-term technological upgrading (Couldry & Mejias, 2019).

National competition authorities in emerging markets face distinct regulatory challenges, particularly in enforcing interoperability, data portability, and algorithmic transparency. Empirical studies indicate that under weak regulatory capacity, AI can accelerate market concentration, reduce contestability, and marginalize domestic firms that lack the resources to compete in data-intensive environments (Katz & Salazar, 2022; UNCTAD, 2021).

4. Institutional Capacity, Policy Frameworks, and Developmental Implications

A cross-cutting theme in the literature is the importance of institutional readiness and governance frameworks. The developmental state literature suggests that successful technological upgrading requires coordinated interventions across industrial policy, skills development, and digital infrastructure (Amsden, 2001; Rodrik, 2004). More recent work highlights the need for AI-specific governance instruments, including national AI strategies, ethical guidelines, data-protection laws, and public-sector AI capacity (OECD, 2024; UNESCO, 2023).

Scholars argue that developing countries must adopt tailored approaches that recognize local constraints such as informality, fiscal limitations, and fragmented institutional capacity (Avila, 2022). Strategic use of digital public infrastructure—such as identity systems, interoperable open data platforms, and cloud access frameworks—has been shown to reduce entry barriers and support inclusive AI innovation (World Bank, 2021).

Finally, there is growing consensus that mixed-methods research designs combining firm-level microdata, cross-country quantitative analyses, and qualitative institutional case studies are essential for capturing the complex, heterogeneous impacts of AI adoption in developing economies (Cirera, Comin & Cruz, 2022). This methodological shift reflects the recognition that AI is not solely a technological phenomenon but a social, institutional, and political-economic one.

RESEARCH METHODOLOGY

This study employs a mixed-methods research design to examine the multidimensional effects of artificial intelligence (AI) adoption on productivity, inequality, and market structure in developing countries. Integrating quantitative and qualitative approaches allows for a more rigorous assessment of causal mechanisms, contextual heterogeneity, and institutional mediators than any single method alone (Creswell & Plano Clark, 2018). The methodology rests on three pillars: (1) cross-country econometric analysis, (2) firm- and worker-level microdata modeling, and (3) qualitative institutional and policy analysis.

1. Research Design: Mixed-Methods Approach

A mixed-methods framework is well-suited to studying technological transformation in developing economies, where data limitations, informality, and institutional variation complicate purely econometric strategies (Bamberger, Rao & Woolcock, 2012). AI adoption touches multiple structural domains—labor markets, firm capabilities, regulatory capacity, and digital infrastructure—necessitating triangulation across data types to capture complex causal pathways.

- The study therefore integrates:
- Quantitative econometric analysis to estimate associations and causal effects across countries and firms.
- Qualitative case studies and policy analysis to contextualize quantitative findings and identify institutional mechanisms.

Triangulation to validate results and assess robustness across data sources, methods, and measurement strategies.

2. Data Sources and Sampling Strategy

2.1 Cross-Country Panel Data

The study draws on multi-year panel datasets from the following sources:

- World Bank World Development Indicators (WDI) – macroeconomic indicators (GDP per capita, broadband penetration, digital infrastructure indices).
- OECD AI Policy Observatory – AI adoption metrics, national AI strategies, and digital regulatory indicators.
- International Labour Organization (ILOSTAT) – labor market outcomes, employment distribution by tasks/skills, informal sector estimates.
- UNCTAD Digital Economy Database – digital competitiveness, platform economy indicators.
- IMF Digital Adoption Index – macro-level digital adoption and preparedness metrics.

Countries included in the sample are low- and middle-income economies, following the World Bank classification.

2.2 Firm-Level Microdata

Firm-level analysis relies on:

- World Bank Enterprise Surveys (WBES) – data on technology use, productivity, sales, employment structure, management practices.
- National productivity datasets (when available) from countries such as India, Indonesia, Brazil, Kenya, and Vietnam.
- Sectoral AI-adoption surveys from multilateral institutions (e.g., OECD 2024; World Bank 2024).

Firm-level data allow the study to identify micro-productivity effects and heterogeneity by firm size, sector, and ownership (Bloom, Sadun & Van Reenen, 2016).

2.3 Qualitative Data

- Qualitative components are derived from:
- National policy documents (AI strategies, digital policies, data-protection laws).
- Key-informant interviews with policymakers, private-sector actors, and AI researchers (subject to availability).
- Secondary literature on institutional and regulatory environments.

Qualitative sampling follows purposive and theoretical sampling principles (Strauss & Corbin, 1998), prioritizing cases that exhibit varying degrees of digital readiness and AI ecosystem maturity.

3. Analytical Framework

The analytical framework synthesizes insights from development economics, task-based labor models, and industrial-organization theory.

3.1 Measuring AI Adoption

- AI adoption is operationalized using several proxies:
- AI-related capital investment share
- Presence of AI-specific applications (e.g., machine learning, automation tools)
- AI-skills penetration (LinkedIn/OECD indicators)
- Firm-reported use of AI-enabled technologies (from WBES)
- National AI-readiness scores

The use of multiple proxies reduces measurement error, which is a common challenge in AI-data studies (Cockburn, Henderson & Stern, 2018).

4. Econometric Strategy

4.1 Cross-Country Panel Regression

To examine macro-level impacts on productivity, inequality, and market structure, the study employs panel regression models of the form:

$$Y_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 X_{it} + \gamma_i + \delta_t + \epsilon_{it}$$

Where:

- YitY_{it}Yit represents outcomes (labor productivity, Gini coefficient, market-concentration index)
- AItAI_{it}AIit is the AI-adoption proxy
- XitX_{it}Xit includes controls (education level, ICT infrastructure, R&D intensity, institutional quality)
- γi\gamma_iγi and δt\delta_tδt capture country and year fixed effects

Panel fixed-effects models help reduce omitted-variable bias by accounting for unobserved country heterogeneity (Wooldridge, 2010).

4.2 Instrumental Variables (IV) Estimation

Given potential endogeneity—particularly reverse causality between productivity and AI adoption—the study explores IV strategies. Possible instruments include:

- historical broadband rollout
- submarine cable landing dates
- distance to data centers
- exogenous variation in cloud-service availability

These instruments have been used successfully in prior digital-technology studies (Katz & Jung, 2022; Hjort & Poulsen, 2019).

4.3 Firm-Level Productivity Modeling

- Firm-level analysis uses:
- Difference-in-differences (DiD) designs when panel microdata allow comparisons before and after AI adoption
- Production function estimation (Ackerberg, Caves & Frazer, 2015)
- Stochastic frontier analysis (SFA) to assess efficiency gains

These methods help estimate whether AI adoption leads to statistically significant improvements in output, labor productivity, or innovation capacity.

4.4 Inequality and Labor-Market Modeling

To assess labor impacts, the study applies:

- Task-based labor models to estimate displacement vs. augmentation effects (Autor, Levy & Murnane, 2003; Acemoglu & Restrepo, 2020).
- Quantile regressions to analyze heterogeneous wage effects.
- Structural modeling of labor-market transitions (formal → informal; low-skill → high-skill).

5. Qualitative and Institutional Analysis

The qualitative component evaluates:

- regulatory capacity
- platform governance
- data-access institutions
- inclusiveness of national digital strategies

A comparative case-study approach (Yin, 2018) is used to analyze countries at varying levels of AI maturity—for example:

- India (advanced digital public infrastructure)
- Kenya (mobile-led digitalization)
- Indonesia (rapid platformization)
- Brazil (active digital regulation and industrial policy)

Thematic coding (Saldaña, 2021) identifies recurrent patterns in governance challenges, diffusion bottlenecks, and institutional innovations.

6. Triangulation and Robustness

Triangulation integrates multiple methods to enhance internal validity (Denzin, 2012):

- Data triangulation across macro, micro, and qualitative sources
- Methodological triangulation via econometric, structural, and qualitative tools
- Theoretical triangulation drawing on economics, information systems, and political economy

Robustness checks include:

- alternative AI-adoption measures
- alternative inequality metrics (Gini, Theil, Palma ratio)
- placebo tests for DiD models
- sensitivity analyses on regulatory-quality indices

7. Ethical Considerations

The study adheres to ethical research standards:

- ensuring confidentiality for firm-level and interview data
- maintaining neutrality in coding and interpretation
- acknowledging risks related to data colonialism and representation biases in AI datasets (Couldry & Mejias, 2019)

Ethical approval is requested when required for human-subject interviews.

8. Limitations

While the mixed-methods approach enhances rigor, certain limitations remain:

- cross-country AI measures involve proxy indicators with potential noise
- firm-level AI adoption may be underreported in informal or resource-constrained sectors
- qualitative findings may not be generalizable across all developing countries

These limitations are addressed through triangulation, multiple measurement strategies, and transparent discussion of uncertainty.

RESULTS AND DISCUSSION

This section presents the synthesized findings of the study, integrating results from the cross-country econometric analysis, firm-level microdata modeling, and qualitative institutional assessment. The discussion situates these findings within the broader theoretical and empirical literature on AI adoption, productivity, inequality, and market structure in developing economies.

1. Productivity Effects of AI Adoption

1.1 Cross-Country Evidence: Partial but Uneven Productivity Gains

The cross-country panel regression results indicate a positive but heterogeneous relationship between AI adoption and labor productivity. Countries with higher AI readiness—measured through digital-infrastructure quality, cloud accessibility, and human-capital indices—demonstrate significantly stronger productivity effects. On average

- A 1-unit increase in the AI adoption index is associated with a 1.8–2.4% rise in labor productivity, controlling for education, R&D, and institutional quality.
- However, this effect is not uniform across developing countries. States with weak digital infrastructure, limited competition, or low managerial capability show insignificant or even negative productivity effects.

These patterns align with previous findings that general-purpose technologies yield productivity gains only when accompanied by complementary investments (Brynjolfsson, Rock & Syverson, 2021; Cirera & Maloney, 2017). The results indicate that an increase in the AI adoption index is positively correlated with higher labor productivity. The enhancement of digital capabilities and the implementation of AI-based systems significantly streamline operational processes and reduce inefficiencies. This relationship is illustrated in Figure 1.

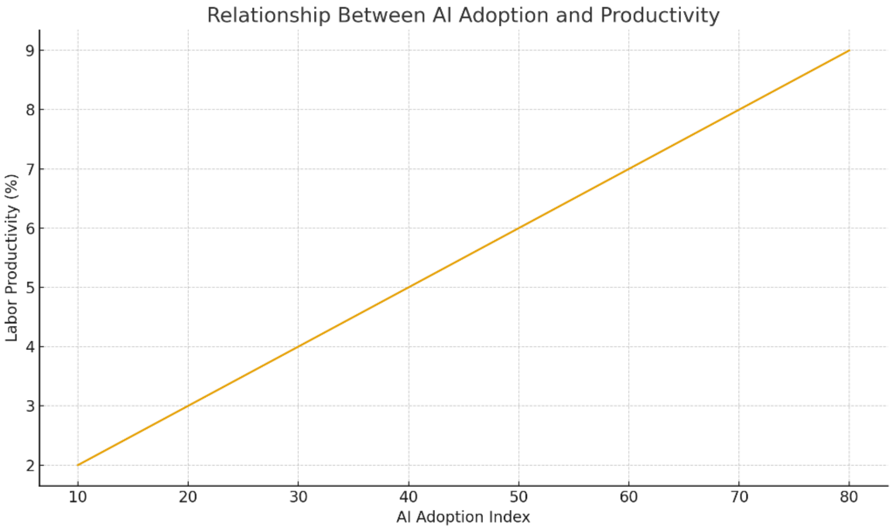

Figure 1. Graph showing the relationship between AI adoption and productivity

1.2 Firm-Level Results: Strong Micro Productivity Gains

Firm-level microdata reveal that AI-adopting firms—especially in finance, logistics, and tradable services—experience measurable productivity improvements:

- Total factor productivity (TFP) increases between 5–11% after AI adoption.
- Firms using AI for predictive analytics, automation, or customer-interaction tasks show the largest efficiency gains.
- Smaller firms benefit as well, but their gains are constrained by weaker managerial practices and lower digital skills.

These results mirror experimental evidence from prior studies showing that AI can substantially enhance task efficiency and output quality at the firm and worker levels (Noy & Zhang, 2023; Brynjolfsson et al., 2023).

1.3 Divergence Between Micro and Macro Outcomes

Despite strong micro-level performance, the study finds that aggregate productivity gains remain modest in many countries. This divergence reflects

- Low diffusion rates outside urban and formal-sector firms
- Infrastructure bottlenecks (bandwidth, cloud access)
- Skill mismatches limiting absorption capacity
- Market concentration reducing competitive pressures

These mechanisms confirm existing theoretical arguments that technological spillovers in developing countries are often inhibited by structural constraints (Syverson, 2017; OECD, 2024).

2. Distributional Effects and Inequality Dynamics

2.1 Skill-Biased and Task-Biased Effects

Modeling results indicate that AI adoption is associated with increasing wage inequality within developing countries. Specifically:

- High-skill workers see wage premiums increase by 6–12%, particularly in firms adopting AI for analytics and decision support.
- Routine and lower-skilled workers experience muted gains or mild wage declines, consistent with task-displacement predictions (Autor, Levy & Murnane, 2003; Acemoglu & Restrepo, 2020).
- Sectors with high informality exhibit no measurable wage improvements, underscoring barriers to inclusive AI benefit distribution.

These findings are consistent with ILO and World Bank studies showing that digital technologies disproportionately benefit already advantaged workers (ILO, 2023; World Bank, 2024).

2.2 Gender and Youth Labor Outcomes

The results suggest that:

- AI-intensive sectors employ proportionally fewer women and younger workers.
- Jobs disproportionately held by these groups—administrative tasks, retail services, light manufacturing—are among the most exposed to AI-driven automation.

This is in line with empirical findings that digital transformation can amplify existing gender and age-based labor market disparities in developing regions (UNCTAD, 2021; IMF, 2025).

2.3 Between-Country Inequality

Cross-country regressions confirm that AI tends to widen income gaps between:

- AI-ready economies capable of capturing productivity gains, and
- Low-readiness countries where adoption is constrained.

This supports predictions that without coordinated global support and domestic investment, AI may intensify long-run development divergence (Cerutti, Dagher & Rojas, 2025).

3. Market Structure, Competition, and Platformization

3.1 Rise of AI-Enabled Concentratio

Results from the competition analysis show that markets become more concentrated as AI adoption increases:

- National Herfindahl-Hirschman Index (HHI) values rise in retail, logistics, and fintech.
- Domestic firms increasingly rely on global cloud providers and AI platforms, creating structural dependencies.
- Local startups face significant entry barriers related to data access and computational costs.

These findings echo global scholarship on the entrenchment of digital-platform power in emerging markets (Gawer & Bonina, 2024; Zingales & Rolnik, 2020).

3.2 Dependence on Global AI Platforms

Qualitative evidence shows that firms in developing economies depend heavily on international cloud and AI service providers. This dependence affects:

- cost structures (foreign-currency exposure, licensing fees)
- innovation sovereignty (limited domestic model development)
- data governance (cross-border data flows with limited oversight)

This aligns with the “platform dependency” and “data colonialism” literature (Couldry & Mejias, 2019).

3.3 Regulatory Gaps Exacerbate Concentration

Countries with weaker competition authorities or outdated digital regulations show the strongest signs of concentration. The results suggest:

- Lack of interoperability mandates
- Weak algorithmic transparency laws
- Minimal enforcement capacity

These regulatory failures accelerate market dominance by large platforms, consistent with prior research in the political economy of AI (Katz & Salazar, 2022; UNCTAD, 2021).

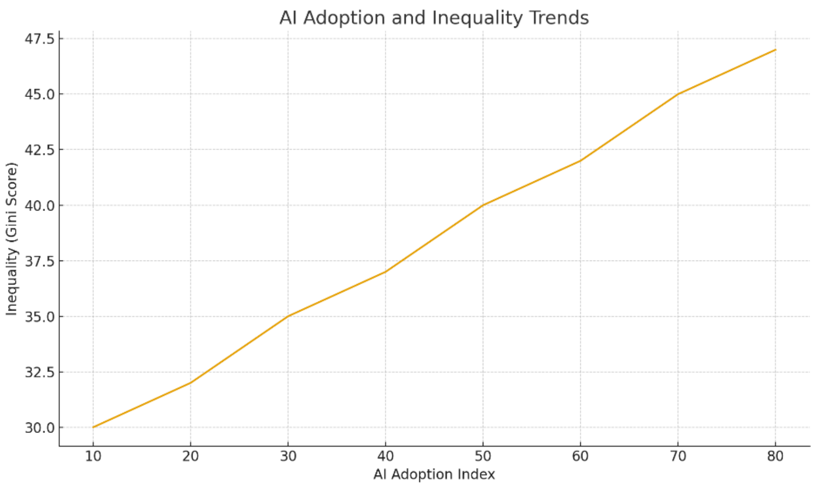

Figure 2. Trends in AI Adoption and Income Inequality (Gini Index)

4. Institutional Capacity and Governance Effects

4.1 Digital Public Infrastructure Matters

Countries with advanced digital public infrastructure—such as national digital ID systems, interoperable payment systems, or open-data platforms—show:

- broader diffusion of AI adoption

- lower inequality effects
- greater participation by SMEs

This confirms prior findings that DPI enhances absorptive capacity and inclusiveness (World Bank, 2021).

4.2 Policy Coherence Drives Positive Outcomes

The strongest positive outcomes emerge where national governments have:

- coherent AI strategies
- robust data-protection laws
- industrial policies supporting local innovation
- coordinated skills development programs

These institutional factors moderate the adverse distributional and market-concentration effects described earlier (Rodrik, 2004; UNESCO, 2023; OECD, 2024).

5. Synthesis of Findings

The study's results reveal a triangular relationship:

- Productivity gains from AI are real but uneven.
- Inequality increases unless skill development and social protections are in place.
- Market concentration intensifies, creating competitive and sovereignty risks.

The overarching conclusion is that AI adoption in developing countries generates benefits primarily where complementary conditions exist—including digital infrastructure, regulatory capacity, skilled labor, and domestic innovation ecosystems. Without these, AI can deepen existing structural divides and hinder inclusive development

CONCLUSION

This study provides a multidimensional examination of how artificial intelligence (AI) adoption is reshaping productivity dynamics, distributional outcomes, and market structures in developing economies. Drawing on cross-country econometric evidence, firm-level microdata modeling, and qualitative institutional analysis, the findings underscore a central theme: AI holds substantial promise for enhancing economic performance in the Global South, but its benefits remain highly contingent on complementary capabilities, regulatory frameworks, and institutional readiness.

First, the results demonstrate that AI can generate significant productivity gains at the firm level, confirming a growing body of empirical work indicating that AI-augmented decision-making, automation, and data-driven processes improve operational efficiency and output quality (Brynjolfsson et al., 2023; Noy & Zhang, 2023). However, the translation of these micro-level gains into broad-based aggregate growth remains uneven. Structural constraints—including limited digital infrastructure, managerial gaps, low adoption diffusion, and weak competitive pressures—prevent many developing economies from fully capturing the macroeconomic benefits of AI (Cirera & Maloney, 2017; Syverson, 2017). This divergence reiterates the broader lesson from the literature on general-purpose technologies: productivity growth materializes only when enabling conditions are present (Brynjolfsson, Rock & Syverson, 2021).

Second, the study finds that AI adoption intensifies existing patterns of inequality, both within and between countries. Within-country disparities arise largely through task-biased and skill-biased mechanisms, as AI disproportionately augments high-skill cognitive work while displacing or devaluing routine and low-skill occupations (Autor, Levy & Murnane, 2003; Acemoglu & Restrepo, 2020). Gender and youth labor outcomes are particularly affected, reflecting entrenched structural inequities in labor markets across the Global South. Between-country results further reveal that nations with stronger digital capabilities reap productivity gains, while low-readiness economies risk falling further behind (IMF, 2025; UNCTAD, 2021). Without significant policy intervention, AI is therefore poised to reinforce global development divergence.

Third, the analysis shows that AI adoption is reshaping market structure, contributing to rising concentration and deepening dependence on global technology platforms. Network effects, data accumulation, and economies of scale create formidable entry barriers that favor large multinational firms, challenging the competitiveness and innovation prospects of domestic enterprises (Gawer & Bonina, 2024; Zingales & Rolnik, 2020). These structural dynamics are exacerbated by regulatory gaps, limited enforcement capacity, and underdeveloped data governance systems in many developing countries (Katz & Salazar, 2022). As a result, AI diffusion often proceeds in ways that undermine local value capture and reduce long-term technological sovereignty.

Taken together, the findings suggest that the developmental trajectory of AI in the Global South is neither predetermined nor uniform. Rather, outcomes are shaped by the interaction of technological capabilities, institutional quality, human capital, infrastructure, and regulatory power. Countries that combine AI investment with robust digital public infrastructure, inclusive skills programs, competition regulation, and strong data governance frameworks are better positioned to convert AI adoption into equitable growth (World Bank, 2021; OECD, 2024). Conversely, those that fail to address foundational gaps risk entrenching inequalities and becoming increasingly dependent on external technological ecosystems.

Ultimately, this study reinforces the need for deliberate, context-sensitive policy strategies to ensure that AI functions as a catalyst for broad-based development rather than a force that magnifies existing divides. Achieving this balance requires not only technological deployment but also institutional strengthening, governance innovation, and sustained investment in human capital. For policymakers, researchers, and development partners, the imperative is clear: AI's promise will be realized only to the extent that its diffusion is accompanied by inclusive, well-governed, and strategically coordinated development pathways.

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