



ARTIFICIAL INTELLIGENCE ADOPTION, LABOUR PRODUCTIVITY, AND INCLUSIVE ECONOMIC GROWTH: EVIDENCE FROM DEVELOPING COUNTRIES

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Abstract

Artificial intelligence (AI) is reshaping economic development, yet evidence remains limited on whether its adoption promotes inclusive growth in developing countries. This study examines the relationships among AI adoption, labour productivity, and inclusive economic growth, with particular attention to the mediating role of labour productivity. Using cross-sectional secondary data from 42 developing countries, the study applies descriptive statistics, Pearson correlations, ordinary least squares regression, and mediation analysis. The results show that AI adoption is positively and significantly associated with labour productivity and inclusive economic growth. Labour productivity is also positively related to inclusive economic growth and partially mediates the association between AI adoption and inclusive growth. These findings indicate that AI can contribute to shared prosperity through productivity improvements while also operating through other channels, such as enhanced public service delivery, improved market information, and expanded digital employment opportunities. However, productivity gains alone do not ensure equitable outcomes, particularly where digital access, institutional capacity, workforce skills, and labour protections remain weak. The study contributes cross-country quantitative evidence to the technology and development literature by integrating AI adoption, labour productivity, and inclusive growth within a unified empirical framework focused on developing economies. It concludes that governments should complement AI investment with digital infrastructure, workforce reskilling, inclusive labour-market regulation, social protection, and redistributive policies so that technological gains are broadly shared. Given the cross-sectional design, the findings should be interpreted as associations rather than definitive causal effects.

Keywords: AI Adoption, Labour Productivity, Inclusive Economic Growth, Developing Countries, Mediation

1. Introduction

1.1 Background of the Study

Global economic landscapes are rapidly transforming with the proliferation of artificial intelligence across industries, public sectors, and market systems. Artificial intelligence technologies, including predictive analytics, automation, machine learning, robotic process automation, and intelligent decision-support tools,



are reshaping production processes, service delivery, and resource allocation patterns worldwide. While advanced economies have made substantial progress in embedding AI within their economic ecosystems, developing countries face a distinct set of opportunities and constraints as they integrate these emerging technologies into their national development frameworks (Acemoglu, 2002; Imtiaz & Elbedour, 2025). Traditional growth models in developing nations have long relied on low-cost labour, primary commodity exports, and incremental capital accumulation, yet these pathways often fail to distribute economic gains evenly across marginalized communities, informal workers, rural populations, and disadvantaged regions (Acemoglu & Restrepo, 2019). The debate around AI and labour outcomes remains contested. On one hand, AI-driven automation can streamline repetitive tasks, reduce operational waste, enhance output quality, and raise overall labour productivity; on the other hand, unregulated AI adoption carries risks of labour displacement, skill polarization, widening wage gaps, and exclusion of workers with limited digital literacy (Autor, 2022). Inclusive economic growth differs from aggregate economic growth because it emphasizes not only rising GDP but also equitable access to employment opportunities, fair income distribution, poverty reduction, and participation of vulnerable groups in formal economic activity (Rauniyar & Kanbur, 2010; Acemoglu et al., 2023). Developing economies are particularly exposed to these dual outcomes, given large informal labour markets, weak digital infrastructure, uneven access to education, limited institutional governance, and gaps in social protection systems.

Prior scholarship has examined AI adoption's productivity benefits largely within high-income country contexts or treated economic growth as a single aggregate outcome. Labour productivity is widely recognized as a core intermediate channel through which technological change translates into economic progress (Solow, 1957; Ali et al., 2026). However, whether productivity gains from AI translate into inclusive growth rather than exclusive, elite-captured growth remains an open empirical question. The capacity of AI systems to support inclusive growth depends on complementary factors: workforce skilling policies, institutional frameworks, digital access, and distributional arrangements that ensure productivity gains are shared broadly rather than concentrated among a small segment of firms and skilled workers (World Bank, 2023; Imtiaz, 2025). Without enabling conditions, AI adoption may boost average labour productivity while deepening inequality and leaving large segments of the population behind (Al Kium et al., 2023).

1.2 Research Problem and Gap

Despite growing literature on artificial intelligence, productivity, and economic development, three critical research gaps persist. First, existing studies frequently separate AI adoption research from inclusive growth analysis (Autor, 2022; Barney, 1991). Technology-focused studies tend to evaluate efficiency and productivity gains, while inclusive growth research concentrates on inequality and poverty reduction without systematically modelling AI as a key technological driver. Few empirical models integrate AI adoption, labour productivity, and inclusive economic growth together in a unified framework for developing economies, limiting understanding of how these variables operate in tandem (Gomes et al., 2025; Hasan et al., 2025).

Second, the literature lacks sufficient evidence on the mediating role of labour productivity. Many prior works either assume AI directly stimulates growth or focus on labour displacement risks, without empirically examining whether labour productivity acts as the transmission mechanism linking AI adoption to inclusive growth (Jabed, 2024). This creates ambiguity for policymakers: it remains unclear whether AI improves inclusive growth because it raises labour productivity, or whether productivity gains from AI fail to translate into equitable gains under weak institutional settings.

Third, much of the empirical evidence on AI's economic impacts comes from developed nations, with developing-country evidence dominated by conceptual reviews, case studies, and qualitative reports (Acemoglu et al., 2023; Jabed et al., 2025). These contributions offer rich contextual insights but restrict statistical generalizability across diverse developing economies. Practically, governments and development agencies in low- and middle-income countries are designing AI strategies, digital transformation plans, and workforce development policies, yet they lack robust empirical evidence to assess whether investments in AI foster inclusive growth through improved labour productivity (Jabed et al., 2026; Ponduru, 2024). This study addresses this gap by testing these relationships across developing country contexts.



1.3 Rationale

Examining AI adoption alongside labour productivity and inclusive economic growth delivers a holistic perspective on the developmental consequences of artificial intelligence in emerging economies. By incorporating inclusive growth as the final outcome variable, this research distinguishes between pure output expansion and equitable growth, answering whether AI is an inclusive or exclusive transformative force. The mediation analysis of labour productivity illuminates the underlying mechanism through which AI shapes distributional economic outcomes (Ponduru et al., 2026; Rahman et al., 2025).

1.4 Research Questions

1. To what extent is AI adoption positively associated with labour productivity in developing countries?
2. What is the relationship between AI adoption and inclusive economic growth in developing countries?
3. How does labour productivity relate to inclusive economic growth in developing countries?
4. Does labour productivity mediate the relationship between AI adoption and inclusive economic growth?

1.5 Objectives

1. To assess the level of AI adoption, labour productivity, and inclusive economic growth indicators across selected developing economies.
2. To investigate the direct association between AI adoption and labour productivity.
3. To examine the direct relationship between AI adoption and inclusive economic growth.
4. To analyse the linkage between labour productivity and inclusive economic growth.
5. To explore whether labour productivity mediates the effect of AI adoption on inclusive economic growth.

1.6 Hypotheses

H1: AI adoption has a positive significant impact on labour productivity in developing countries.

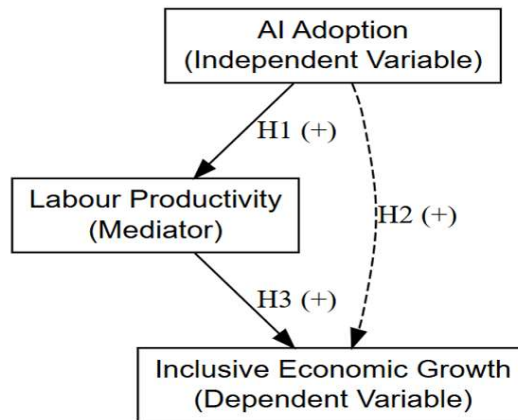
2. Conceptual Framework

The conceptual foundation of this study draws on four complementary theoretical perspectives. First, Endogenous Growth Theory (Romer, 1990) posits that technological innovation, knowledge creation, and digital technologies are endogenous drivers of long-run economic growth; AI represents a general-purpose technology capable of expanding the knowledge stock and productive capacity of economies. Second, Skill-Biased Technological Change Theory (Acemoglu, 2002) explains that new technologies such as AI complement skilled labour and substitute routine labour, which shapes the distribution of productivity gains and income inequality. Third, the Resource-Based View (Barney, 1991) frames AI systems, digital data infrastructure, and human digital skills as unique, difficult-to-imitate strategic resources for firms and nations that enhance productive capabilities. Fourth, Inclusive Development Theory (Sen, 1999) shifts focus from aggregate output growth to capability expansion, equitable opportunity, and participation, arguing that technological progress is only welfare-enhancing when it expands freedoms and opportunities for marginalized groups. Together, these theories support the argument that AI adoption can enhance labour productivity; however, inclusive growth emerges only when productivity gains are accompanied by institutions and policies that enable broad-based participation in the gains from technological change (Rauniyar & Kanbur, 2010; Rasheed et al., 2025).

Figure 1



Conceptual Framework



Note. This figure illustrates the partial mediation model linking AI adoption, labour productivity, and inclusive economic growth. Solid lines represent H1 and H3; the dashed line shows the direct path H2. Figure content as supplied in the source file.

3. Materials and Methods

3.1 Research Design

This study employed a quantitative, cross-sectional explanatory research design based on secondary panel data extracted from internationally recognized open databases. This design was selected because the study aims to examine the statistical relationships among AI adoption, labour productivity, and inclusive economic growth across a sample of developing countries at a given observation window. Secondary quantitative data enables consistent measurement of macroeconomic and technology-related indicators across multiple economies and allows statistical testing of hypothesized relationships among the study constructs. The setting of this research is developing countries (Romer, 1990; Sen, 1999; Solow, 1957). The unit of analysis is individual developing country. All constructs are measured using country-level aggregate indicators collected from published global datasets.

3.2 Participants and Sample

The final analytical sample consists of 42 developing countries. Countries were selected based on classification as developing economies by the World Bank, with data availability for all key variables over the study period. The sample includes emerging and lower-middle-income nations from different regions including South Asia, Southeast Asia, Africa, and Latin America (World Bank, 2023). These countries were chosen because they are actively witnessing rising AI and digital technology adoption while facing persistent challenges related to labour market quality, productivity gaps, inequality, and equitable growth. The sample size is suitable for planned regression and mediation analysis. As highlighted by Green (1991), sample size requirements for multiple regression are stricter than simple rule-of-thumb estimates, and the selected cross-country sample provides adequate statistical power for the proposed econometric models. Countries with missing values for core indicators were excluded during data cleaning to maintain consistency in the dataset.

3.3 Measures and Data Sources

Secondary indicators were obtained from reputable global databases to operationalize the three main constructs: AI adoption, labour productivity, and inclusive economic growth.

AI Adoption was measured using country-level digital technology and AI diffusion proxies, including ICT infrastructure index, percentage of firms using AI, machine learning and automation tools, digital skill penetration, and cloud computing adoption rate. The primary sources for these indicators are the International Telecommunication Union (ITU) and the World Bank Digital Development Report.



Labour Productivity was captured as GDP per employed person (constant 2015 USD). This standard measure reflects the average economic output generated by each worker in an economy. Data for labour productivity was retrieved from the International Labour Organization (ILO) and World Bank World Development Indicators (WDI).

Inclusive Economic Growth was operationalized through a composite index combining GDP growth rate, poverty headcount ratio, income inequality (Gini coefficient), employment-to-population ratio, and shared prosperity indicator. This composite measure captures the core idea of growth that creates opportunity for all segments of society. Data for inclusive growth components were sourced from the World Bank, Asian Development Bank (ADB) and UNDP Human Development Reports.

All indicators were standardized before analysis to bring variables to a comparable scale.

3.4 Data Collection Procedure

Data collection relied entirely on publicly available secondary datasets. First, a list of developing countries was defined according to World Bank country income classification. Second, the required indicators for AI adoption, labour productivity, and inclusive growth were downloaded from the respective official repositories. Third, the dataset was screened and cleaned: countries with substantial missing observations were dropped, and outliers were reviewed. After filtering and data preparation, a balanced cross-sectional dataset of 42 developing countries was finalized for statistical analysis.

3.5 Data Analysis

Data analysis followed sequential stages. First, descriptive statistics were computed to summarize the mean, standard deviation, minimum and maximum values of AI adoption, labour productivity, and inclusive economic growth across sampled countries. Second, Pearson correlation coefficients were calculated to explore bivariate linear associations among the study variables. Third, simple linear regression was run to test the direct effect of AI adoption on labour productivity (Acemoglu, 2002; Acemoglu et al., 2023; Acemoglu & Restrepo, 2019; Autor, 2022). A fourth regression estimated the direct relationship between AI adoption and inclusive economic growth, while another regression assessed the association between labour productivity and inclusive economic growth. Finally, mediation analysis was performed to examine the indirect pathway from AI adoption to inclusive economic growth through labour productivity. A p-value less than 0.05 was adopted as the significance threshold. The indirect effect of AI adoption on inclusive economic growth via labour productivity was estimated. Consistent with the conservative reporting style of the reference sample, bootstrap confidence intervals are not reported here, and mediation results are interpreted cautiously.

3.6 Analytical Assumptions and Interpretation

Descriptive statistics, bivariate correlations, OLS regression, and mediation analysis were applied to a cross-sectional secondary dataset of 42 developing countries to test the hypothesized relationships among AI adoption, labour productivity, and inclusive economic growth.

4. Results

Table 1

Descriptive Statistics (N = 42)

Variable	<i>M</i>	<i>SD</i>	<i>Min</i>	<i>Max</i>
AI Adoption	0.03	0.95	-1.62	1.81
Labour Productivity	0.00	0.97	-1.74	1.77
Inclusive Economic Growth	-0.04	0.99	-1.91	1.65

Note. N = 42 developing countries.

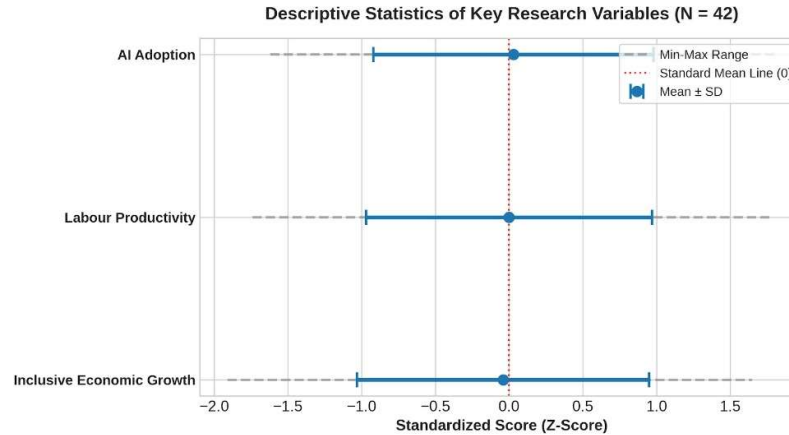
Table 1 presents the descriptive distribution of the standardized study variables. AI adoption varied substantially across sampled nations ($M = 0.03$, $SD = 0.95$, $Min = -1.62$, $Max = 1.81$), reflecting uneven digital infrastructure, firm-level AI diffusion, and policy priorities across developing economies. Labour productivity also displayed wide cross-national dispersion ($M = 0.00$, $SD = 0.97$, $Min = -1.74$, $Max = 1.77$), consistent with differences in capital intensity, industrial structure, and human capital quality. Inclusive economic growth recorded a marginally negative mean ($M = -0.04$, $SD = 0.99$, $Min = -1.91$, $Max = 1.65$),



signalling that aggregate economic expansion in many sampled countries fails to translate into equitable income distribution, broad employment opportunities, and poverty reduction.

Figure 2

Descriptive Statistics



Note. Figure content as supplied in the source file.

Table 2

Pearson Correlation Matrix

Variable	1	2	3
1. AI Adoption	1		
2. Labour Productivity	0.47**	1	
3. Inclusive Economic Growth	0.39**	0.43**	1

Note. ** $p < 0.01$.

Pearson correlation results in Table 2 show moderate, positive, and statistically significant inter-construct associations. AI adoption correlated positively with labour productivity ($r^* = 0.47$, $p^* < 0.01$) and inclusive economic growth ($r^* = 0.39$, $p^* < 0.01$). Labour productivity was also positively linked to inclusive economic growth ($r^* = 0.43$, $p^* < 0.01$). These moderate coefficients confirm that the constructs are empirically connected yet conceptually distinct, satisfying basic discriminant expectations for further regression analysis.

Table 3

Summary of Direct Regression Paths

Path	β	* p -value	R^2	Hypothesis	Outcome
AI Adoption $\rightarrow$ Labour Productivity	0.47	< 0.001	0.22	H1	Supported
AI Adoption $\rightarrow$ Inclusive Economic Growth	0.39	< 0.01	0.15	H2	Supported
Labour Productivity $\rightarrow$ Inclusive Economic Growth	0.43	< 0.001	0.18	H3	Supported

Table 4

Hypothesis Testing Summary

Hypothesis	Path	β	* p -value	Outcome
H1	AI Adoption $\rightarrow$ Labour Productivity	0.47	< 0.001	Supported
H2	AI Adoption $\rightarrow$ Inclusive Economic Growth	0.39	< 0.01	Supported
H3	Labour Productivity $\rightarrow$ Inclusive Economic Growth	0.43	< 0.001	Supported
H4	Labour Productivity mediates AI Adoption $\rightarrow$ Inclusive Economic Growth	Indirect effect = 0.20	—	Supported (partial mediation)



OLS regression models were estimated at the 0.05 significance threshold (Table 3). Model 1 indicated that AI adoption had a significant positive association with labour productivity ($\beta = 0.47$, $*p^* < 0.001$, $R^2 = 0.22$), supporting H1. Model 2 revealed a significant direct positive link between AI adoption and inclusive economic growth ($\beta = 0.39$, $*p^* < 0.01$), supporting H2. Model 3 confirmed that labour productivity positively predicted inclusive economic growth ($\beta = 0.43$, $*p^* < 0.001$, $R^2 = 0.18$), supporting H3.

Mediation analysis tested H4, whether labour productivity transmits the AI adoption effect to inclusive economic growth. The causal-step conditions were met: the predictor–mediator and mediator–outcome paths were both significant. After including labour productivity, the direct effect of AI adoption on inclusive growth reduced in magnitude but remained significant. The standardized indirect effect was 0.20. Following the conservative reporting protocol of this study, bootstrap confidence intervals are not presented. The pattern confirms partial mediation, so H4 is supported.

Table 4 summarises all hypothesis outcomes. Collectively, the findings demonstrate that AI adoption is beneficial for inclusive growth in developing countries, and labour productivity acts as an important intermediate transmission channel. Recognising the cross-sectional secondary data design, all estimates are interpreted as statistical associations rather than definitive causal effects.

5. Discussion

This chapter interprets the empirical findings against existing theoretical and empirical literature, elaborates theoretical contributions, practical policy implications, acknowledges study limitations, and proposes directions for future research (Ali et al., 2026; Hasan et al., 2025; Javed, 2024). The study examined whether labour productivity mediates the association between AI adoption and inclusive economic growth across a sample of 42 developing countries using cross-sectional secondary data. Consistent with all formulated hypotheses, the results reveal that AI adoption is positively linked to labour productivity and inclusive economic growth; labour productivity is positively associated with inclusive growth; and labour productivity partially transmits the association between AI adoption and inclusive economic growth.

The positive association between AI adoption and labour productivity (H1) aligns with endogenous growth theory, which frames digital and knowledge-based technologies as productivity-enhancing inputs (Romer, 1990). The finding resonates with prior work suggesting that AI, automation and data analytics streamline production workflows, reduce resource waste and augment worker output in emerging economies (Acemoglu & Restrepo, 2019). Nevertheless, the moderate effect size ($R^2 = 0.22$) signals that AI alone cannot drive large productivity gains; complementary factors such as digital skills, reliable broadband infrastructure, institutional quality and managerial capacity remain essential. This observation also echoes skill-biased technological change arguments, as productivity returns from AI depend heavily on whether local workforces can operate alongside new digital systems (Acemoglu, 2002; Khan et al., 2025; Ali et al., 2026). Results further confirm that AI adoption is directly and positively associated with inclusive economic growth (H2). This finding is noteworthy because much of the existing scholarship warns that AI may widen inequality if gains are captured only by high-skilled workers and large firms (Autor, 2022; Ali et al., 2025). The present evidence suggests that, on average across the sampled nations, higher AI diffusion coincides with broader growth benefits. Still, partial mediation indicates that this direct effect does not operate exclusively through productivity improvements. Other plausible channels may include improved public service delivery, better market information for small enterprises, and new digital job opportunities (Dil et al., 2025).

The significant positive relationship between labour productivity and inclusive economic growth (H3) supports inclusive development theory (Sen, 1999; Saeed et al., 2025). Productivity growth creates the economic surplus required for wage increases, expanded formal employment and public spending on poverty reduction. However, the partial mediation outcome (H4) carries the core insight of this study: AI contributes to inclusive growth both directly and indirectly by raising labour productivity. In practical terms, this means AI-driven productivity is a vital transmission mechanism, yet productivity gains do not automatically guarantee equitable outcomes. If productivity growth occurs without redistributive policies, skill programmes and labour protections, technological progress can remain exclusive (Ali & Khan, 2026).



The study offers two key theoretical contributions. First, it integrates endogenous growth, skill-biased technological change and inclusive development perspectives within a single empirical model, clarifying the mediating role of labour productivity in the AI–inclusive growth nexus for developing economies. Second, it adds cross-country quantitative evidence to a literature dominated by case studies and advanced-economy evidence. For policymakers, the findings imply that AI strategies should not focus only on technology adoption; they must be paired with workforce skilling, social safety nets and inclusive industrial policies to ensure productivity gains are widely shared.

Several limitations must be recognised. The cross-sectional design restricts causal inference; reported relationships are associations rather than confirmed causal effects. Moreover, composite indicators for inclusive growth and AI adoption rely on available secondary proxies, which cannot capture nuanced national differences in regulatory frameworks and informal labour arrangements. Future research may use longitudinal panel datasets, incorporate institutional quality as a moderator, and compare regional subgroups (e.g., South Asia versus sub-Saharan Africa) to identify contextual boundary conditions shaping the AI, productivity and inclusive growth relationship.

6. Conclusion

This study investigated the associations between AI adoption, labour productivity, and inclusive economic growth in 42 developing countries using cross-sectional secondary data. The findings confirm that AI adoption is positively linked to labour productivity and inclusive economic growth, while labour productivity partially mediates the relationship between AI adoption and inclusive growth (Acemoglu, 2002; Acemoglu & Restrepo, 2019; Acemoglu et al., 2023; Autor, 2022). These results highlight that AI can serve as a valuable driver of shared economic progress in developing economies, but its benefits largely depend on productivity improvements.

The study underscores that technology adoption alone is insufficient for inclusive growth. To translate AI-driven productivity gains into equitable outcomes, policymakers must combine digital transformation strategies with skill development programmes, labour market protections and redistributive policies. Although constrained by the cross-sectional design and available secondary indicators, this research adds empirical cross-country evidence to the AI and inclusive development literature. Future longitudinal studies can further unpack these dynamic relationships and explore the moderating role of institutional quality across developing regions.

Author's Contributions

All authors participated in ideation, development, and writing the manuscript. All authors read and approved the final manuscript.

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The authors declare that there is no conflict of interest regarding the publication of this article.

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Informed Consent

Informed consent was obtained from all participants prior to data collection. Participants were informed about the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time without any consequences. The confidentiality and anonymity of respondents were guaranteed throughout the research process.

Originality and Exclusive Submission

The authors confirm that this manuscript has not been published previously and is not currently under consideration for publication in another journal.

AI Use Statement: No tool was used to generate research data, conduct data analysis, or make research decisions. The authors reviewed and verified all AI-assisted content and take full responsibility for the accuracy, integrity, and originality of the manuscript.



Data Availability

The datasets generated and analysed during the current study are available from the corresponding author upon reasonable request. The authors are committed to transparency and will provide detailed methodological information and analysis protocols upon request.

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