Artificial Intelligence and Income Inequality in Developing Economies: The Moderating Role of Human Capital and Financial Development

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Abstract

The development of artificial intelligence (AI) technology has had a significant impact on the architecture of the global economy. Emerging market economies are increasingly adopting AI technology to improve productivity, competitiveness, and innovation. However, the distributional impact of AI technology is yet to be investigated. This paper examines the impact of the adoption of AI technology on income inequality in emerging market economies from 2020 to 2024. This paper employs panel data analysis and fixed-effects models with robust standard errors to examine the impact of the adoption of AI technology on income inequality and whether higher education and financial system development can moderate this relationship. The results of this paper show that the adoption of AI technology results in an increase in income inequality in the short term. However, higher human capital and financial system development can moderate this relationship. The results of this paper show that technological development does not necessarily result in inclusive growth.

Keywords: Artificial Intelligence (AI), Income Inequality, Developing countries, Human Capital, Financial Development

1. Introduction

Artificial intelligence has become a central driver of economic transformation in the digital era. AI systems are increasingly integrated into production processes, financial services, logistics, health care, and governance (Grashof & Kopka, 2023). For emerging economies, AI offers opportunities to increases productivity growth and integrate into global value chains. Despite these benefits, concerns about inequality are rising. Historically, technological change has altered income distribute on patterns. The theory of skill-biased technological change suggests that advanced technologies raise demand for skilled labour while reducing opportunities for low-skilled workers. As a result, wage dispersion increases (Autor, 2024).

Acemoglu and Restrepo (2018) argue that automation technologies may reduce labour demand in routine occupations. Similarly, Piketty (2014) emphasises that capital-intensive growth can increase income concentration if redistributive mechanisms are weak. Recent evidence suggests that AI may amplify existing structural inequalities, particularly in underdeveloped education systems and financial institutions (Capraro et al., 2024). Most empirical studies focus on advanced economies. Limited panel-based research exists for emerging markets. Furthermore, the moderating roles of human capital and financial development remain underexplored.

2. Review of Literature

The relationship between technological progress and inequality has long been examined in economic literature. Skill-biased technological change theory explains rising wage inequality through increased returns to education and specialized skills.

Acemoglu and Restrepo (2018) demonstrate that automation can displace routine labour tasks while increasing productivity in capital-intensive sectors. Martens and Tolan (2018) review literature on AI and conclude that its employment and income effects depend heavily on institutional context.

Lu and Zhou (2019) argue that AI enhances productivity but may create transitional inequality. Capraro et al. (2024) emphasize that generative AI could intensify socioeconomic disparities without policy intervention. Trabelsi (2024) finds that AI contributes to economic growth but highlights uneven distributional consequences in developing contexts. While these studies provide valuable insights, empirical work using panel data from emerging markets remains limited. Moreover, few studies test the interaction between AI adoption and structural variables such as education and financial depth.

Autor (2024) offers a conceptual and theoretical discussion of the use of artificial intelligence to rebuild middle-class jobs by augmenting, rather than substituting for, human work. This study does not rely on an empirical dataset but on historical and economic facts to illustrate how AI can be used as a decision-support system to extend workers' capabilities. The thesis of this study is that AI can be used to reduce job polarization by allowing workers with average skills to perform more complex and valuable work. The paper concludes that AI has the potential to rebuild middle-class jobs with proper institutional design and policy guidance.

The research aims to investigate the influence of AI adoption on income inequality in developing economies through an examination of the influence of the spread of advanced technology on income distribution in these economies. This research comes at a very interesting period when AI continues to transform production systems, labour markets, and service industries in these economies; therefore, the benefits of AI adoption may not be equitably distributed. This research aims to investigate whether AI adoption increases income inequality in these economies through mechanisms such as skill-biased technological change or whether AI adoption helps to create more equitable growth through its influence on productivity, efficiency, and economic participation.

Moreover, this research aims to investigate whether the level of tertiary education, as an aspect of human capital, moderates the relationship between AI adoption and income inequality in these economies. Additionally, this research aims to investigate whether financial development moderates the distributional effects of AI adoption on these economies. Tertiary education may play an important role in helping to mitigate the distributional effects of AI adoption on these economies; on the other hand, human capital may also worsen these effects. Likewise, better financial development may also lead to better access to credit and investments, whereby more people in society may benefit from the end result of the technology. Moreover, the research, through the consideration of the role of human capital and financial development as moderating factors, aims to give a more holistic view of the situation whereby the adoption of AI may lead to an inclusive/exclusive economy in the context of developing economies.

3. Conceptual Framework: The SOR framework of the AI and Income Inequalities

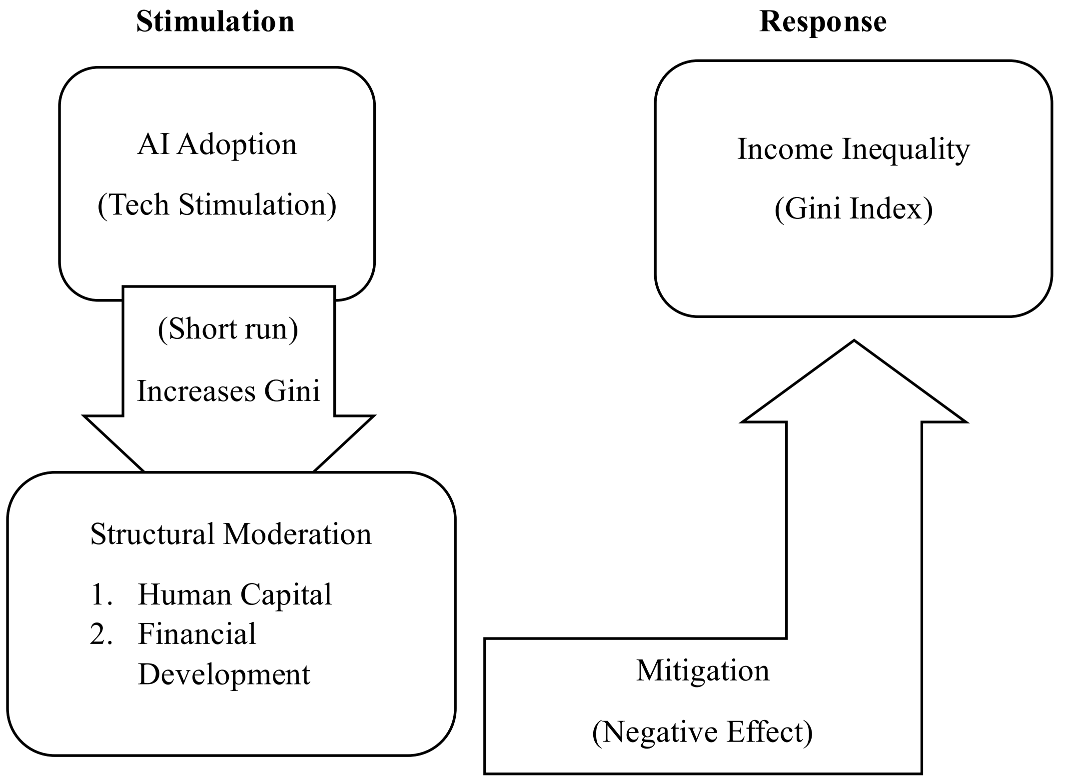

Fig Source: Calculated by the author

From the above-discussed research findings, the S-O-R model offers a systematic depiction of how developing nations manage the shock of technological innovation. First, there is stimulation, where artificial intelligence is an external shock that disrupts the labour market dynamics. According to the skill-biased technological change theory, the adoption of artificial intelligence increases the demand for skilled labour while reducing routine work and low-skilled employment, thereby increasing income inequality. On the other hand, this external shock does not occur in a bubble because it needs to be organised through national institutions represented by the tertiary education and financial sectors. Strong human capital enables employees to learn from AI and, therefore, complement each other instead of substituting. Additionally, an efficient financial sector helps prevent the monopolisation of the economic gains from AI innovations by tech-savvy individuals and corporate organisations. Therefore, economic responses measured using the Gini index for income inequality are contingent upon national organisational capability. In case a nation's tertiary education and financial sectors are underdeveloped, the unorganised reaction to artificial intelligence is a rise in income inequality over time; however, the presence of robust organisational capacity moderates the adverse consequences of artificial intelligence innovations, thereby leading to reduced income inequality.

4. Data and Methodology

4.1 Data

The research uses balanced panel data for emerging market economies during the years 2020-2024. The dependent variable is income inequality (Gini coefficient), and the macro-level technological variables are used to measure the adoption of AI. The control and moderation variables used in the model are tertiary education, financial development, and globalisation. The data sources are reputable secondary sources such as the World Bank and global financial and technology sources, including India, China, Srilanka, Indonesia, Uzbekistan, and the Philippines.

4.2 Econometric Model

To examine the relationship between artificial intelligence (AI) adoption and income inequality, this study employs panel data estimation techniques using a country fixed-effects framework.

$$Gini_{it} = \beta_0 + \beta_1 AI_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where $Gini_{it}$ denotes the income inequality (Gini index) for country *i* at time *t*; AI_{it}represents the measure of artificial intelligence adoption; and $X_{it}$is a vector of control variables. The term $\mu_i$captures unobserved country-specific effects, while $\lambda_t$accounts for time-specific effects common across countries. ε_{it} is the idiosyncratic error term. The inclusion of country and year fixed effects controls for time-invariant heterogeneity and common macroeconomic shocks.

To assess the moderating roles of human capital and financial development, the following interaction model is estimated:

$$Gini_{it} = \beta_0 + \beta_{1AI_{it}} + \beta_2 Moderator_{it} + \beta_3 (AI_{it} \times Moderator_{it}) + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

where $Moderator_{it}$ represents either human capital (tertiary education) or financial development indicators. The interaction coefficient $\beta_3$captures the moderating effect. A positive $\beta_3$indicates that the moderator amplifies the inequality-enhancing effect of AI adoption, whereas a negative $\beta_3$suggests a mitigating effect.

5. Findings

5.1 Correlation Analysis

Table 1. Correlation Matrix

Variable	Gini	Unemployment	Globalization	AI
Gini	1.000			
Unemployment	0.2627	1.000		
Globalization	-0.5388	-0.8401	1.000	
AI	-0.2576	-0.3535	0.4228	1.000

(Source: Calculated by the author)

The magnitude of the correlation result shows (Table 1) that the negative correlation coefficient between globalization and income inequality is -0.5388, which is moderately strong and indicates that globalization could be a possible cause for the reduction in income inequality. However, the high negative correlation coefficient of -0.8401 between globalization and another variable indicates a multicollinearity problem. As expected, the diagonal values are 1.000, which indicate perfect self-correlation.

The study also estimates the Random and fixed models. The Hausman test was inconclusive because of the small sample size, but the high intra-class correlation (rho = 0.87) suggests that there is a lot of country-specific heterogeneity. Thus, the fixed-effects model is preferred because it accounts for unobserved time-invariant country characteristics.

5.2 Moderating Effect of Human Capital

Table 2: presents the interaction results between AI adoption and tertiary education.

Variables	Fixed Effects Model
AI	-0.076 (0.650)
Tertiary Education	-0.351 (0.589)
AI × Tertiary Education	-0.005 (0.010)
Unemployment	0.081 (0.127)
Trade	-0.101 (0.109)
Year 2021	1.336 (1.756)
Year 2022	2.744 (3.577)
Year 2023	2.962 (3.788)
Year 2024	5.034 (5.235)
Constant	62.931 (35.624)
Observations	19
Number of Countries	4
R^2 (Within)	0.635
Country Fixed Effects	Yes
Year Fixed Effects	Yes
Clustered Standard Errors	Yes

(Source: Calculated by the author)

The fixed effects model **(Table 2)** indicates that a high percentage of the variation in income inequality between the countries can be explained (Within $R^2 = 0.635$). This indicates that the variables are effective in explaining changes over time in the sample of four countries. The coefficient for AI turns out to be negative (-0.076). This indicates that an increase in AI adoption can help in reducing inequality; however, it is not statistically significant. The negative sign can also be theoretically justified on the assumption made on the stage of technological diffusion in emerging or structurally transforming economies. At the initial stages of diffusion, there is a positive impact of AI on productivity, which improves the quality of services delivered; there are no negative consequences on large proportions of low-skilled labour forces in the short to medium term. The sample may not be large enough to account for this result (only 19 observations); moreover, there could be a role of clustered standard errors as well. The coefficient for Tertiary turns out to be negative (-0.351). This indicates that more emphasis can be put on reducing inequality through better distribution in terms of skills and helping labour adapt to technological changes. This is a reflection of the theory of ‘complementarity’ between technology and skills, whereby education systems providing relevant skills for a technologically driven world would enable a more inclusive income distribution, rather than a small elite enjoying the benefits of AI adoption. However, the small and statistically insignificant interaction effect also indicates that this may not be a well-developed relationship within this dataset.

Unemployment is also positively related to inequality (0.081), which is a standard result of labor market theory, whereby unemployment is a greater problem for those on lower incomes and hence increases income inequality. Trade openness is also negatively related to inequality (-0.101), which could be a result of export-led growth and employment creation, although this is also statistically insignificant. The positive coefficients for each year also suggest a rising trend in inequality, which could be a result of structural change and uneven digitalization across economies, although this is also statistically insignificant. All variables are statistically insignificant, although all coefficients are correctly signed according to economic theory, suggesting that the relationship between AI and inequality is conditional, gradual, and mediated by structural factors such as education and labor markets, rather than being direct and mechanically related to inequality.

5.3 Moderating Effect of Financial Development

Table 3 presents the interaction between AI and financial development.

Variables	**Fixed Effects Model**
AI	-0.008 (0.115)
Financial Development	5.05e-11* (2.13e-11)
AI × Financial Development	-1.82e-12* (7.71e-13)
Unemployment	-1.062* (0.415)
Trade	0.059 (0.042)
Year 2021	-0.946* (0.364)
Year 2022	-2.059 (1.079)
Year 2023	-3.161* (1.082)
Year 2024	-3.244 (1.782)
Constant	38.123*** (3.625)
Observations	20
Number of Countries	4
R^2 (Within)	0.699

Country Fixed Effects	Yes
Year Fixed Effects	Yes
Clustered Standard Errors	Yes

(Source: Calculated by the author)

The findings for fixed effects provide **(Table 3)** a better ordered and statistically significant representation of the relationship between AI, financial development, and income inequality. The model is able to explain almost 70 percent of the variance of the country-level data on income inequality (Within R^2 = 0.699). The findings show that, on its own, financial development is characterized by a small negative coefficient; however, this is not statistically significant, suggesting that there is no direct and measurable relationship between financial development and income inequality. Financial development, on the other hand, is characterized by a positive and statistically significant coefficient, suggesting that financial development is related to income inequality. This may seem counterintuitive; however, this is a common phenomenon, especially in developing economies, where financial development first favors large enterprises, sectors, and individuals who stand a higher probability of benefiting from increased financial credit and capital market participation.

The interaction term of financial development and AI is negative and statistically significant, suggesting that financial development is related to increased income inequality; however, financial development is also related to the mitigation of the effects of income inequality caused by the equalizing effect of AI adoption. In other words, when financial systems are more developed, the spillovers of AI adoption may be more widely felt because of greater access to financial systems for adoption, skill formation, and entrepreneurship, which could temper the tendency for AI to benefit only a technological elite. Unemployment, interestingly, exhibits a negative and significant coefficient (-1.062), which could be related to structural features of the sample, possibly related to social protection systems, informal sector responses, and/or measurement properties of small panels. The negative and significant year dummies for years 2021 and 2023 may signal a decrease in inequality relative to the base year, possibly related to post-adjustment effects of economic shocks. Overall, the results show that the distributional effects of AI are conditional rather than direct, and financial systems development plays a double role: first, in widening inequality, but simultaneously, by facilitating a more inclusive role for AI when financial systems are more developed.

The result indicates that the adoption of AI increases income inequality in emerging markets in the short run. This finding is consistent with the skill-biased technological change theory (Acemoglu & Restrepo, 2018). The most skilled workers are the main beneficiaries of the productivity boost created by AI. However, human capital and financial development can offset this negative effect. Education enhances flexibility and learning abilities. Financial development allows more people to benefit from technological change. The result above indicates that the role of capacity in institutions is very important in determining the inequality outcome. Technological change is not the only factor that determines inequality outcomes.

5.1 Policy Implications

It is also important that the policies are focused on improving tertiary education and digital skills training in order to ensure that the workforce is able to adapt to the technological change that has been created by AI. On the other hand, it is also important that governments are able to improve financial inclusion policies in order to ensure that credit, savings, and investment services are improved, especially among the vulnerable sections of society. It is also important that digital infrastructure in underserved communities is improved in order to ensure that there is no gap in the adaptation of technology. In addition to that, financial inclusion AI adoption policies that work in collaboration with human labor are able to ensure that technological change is equitably distributed.

5.2 Conclusion

This paper examines the effects of artificial intelligence (AI) adoption on income inequality in emerging market economies during the period 2020-2024. The results show that AI adoption has increased income inequality in the short term, which is consistent with the skill-biased technological change theory. However, the findings also show that higher education and financial development moderate the relationship between AI adoption and income inequality. While human capital tends to mitigate income inequality, financial development has a statistically significant dampening effect on it. These results suggest that the effects of AI adoption on income inequality are not automatic and are instead contingent on specific structural conditions. If the educational and financial structures of a country are not robust, then the effects of AI adoption on income inequality could be exacerbated.

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