Research Article

Artificial Intelligence And Poverty Reduction: Emerging Economies

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Abstract

The recent proliferation of artificial intelligence (AI) into the economic domain has provoked a scholarly movement of rethinking the ability of technological change to act as a policy lever in alleviating poverty, especially regarding the United Nations Sustainable Development Goal 1 (SDG 1: No Poverty). The paper investigates the link between AI adoption and poverty reduction among 48 emerging and developing economies during the period 20102025, using a rigorous panel model of the economy. The study uses the Oxford Insights AI Readiness Index, AI investment as a proportion of GDP, Digital Adoption Index, internet penetration and ICT infrastructure as the primary AI-related regressors and Poverty Headcount Ratio as the dependent variable to perform the following: the Panel Fixed Effects, Random Effects, System Generalised Method of Moments (GMM), and mediation analysis. The Hausman test supports the superiority of Fixed Effects specification. Findings show that AI readiness, AI investment, and digital adoption have statistically significant negative outcomes on poverty headcount ratios, and AI investment has the most significant standardized effect size. Mediation analysis shows that economic growth, and financial inclusion convey about 17.4 and 24.3 percent of the overall poverty-reducing impact of AI, respectively. Human capital is also found to directly mediate AI-poverty, and this implies that every investment in education enhances the pro-poor benefits of AI. These results build on the theoretical explanations of endogenous growth and technology diffusion and provide practical advice to policy makers in the emerging economies. The paper closes with specific recommendations to AI-driven social protection systems, inclusive digital infrastructure, and development strategies based on skills.

Key words: artificial intelligence; alleviating poverty; digital access; developing economies; panel data, financial inclusion.

1. INTRODUCTION

1.1 Background: AI as a Development catalyst.

Artificial intelligence/development economics is one of the most debatable new intellectual boundaries of the first half of the twenty-first century. With the rise of machine learning, natural language processing, and predictive analytics to transform how advanced economies reorganize production, service delivery, and governance, whether the emerging and developing economies can similarly put technologies to work to gain traction in reducing poverty has become a crucial policy issue of urgency (Acemoglu, 2021; Vinuesa et al., 2020). In their 2024 World Development Report, the World Bank indicated that AI can potentially shorten the development path of low- and middle-income countries, although the reaction must be supported by the existing enabling conditions, such as infrastructure, human capital, and governance (World Bank, 2024).

Nevertheless, global poverty, despite decades of development, is a characteristic issue (Kamrul et al., 2024). The World Bank (2023) estimates that there are about 648 million individuals who still live below USD 2.15 per day, most of whom are found in Sub-Saharan Africa and South Asia. In 2020, the COVID-19 pandemic negated decades of accumulation of development, and it is estimated that SDG 1 will have to be met by 2030 with an unparalleled speed in the rates of poverty reduction (United Nations, 2023). It is against this background that AI technologies, including precision agriculture and algorithmic credit rating, and AI delivery of public services, can present opportunities in reducing poverty (Chou et al., 2022; ITU, 2023).

1.2 Global Poverty Problems and the Technology Imperative.

Structural factors related to the prevention of developing countries and economies in persistent poverty are multidimensional and include such factors as limited access to financial services, insufficient educational infrastructure, poor labor market institutions, and poor investment of public in health and social protection (Alkire et al., 2021; UNDP, 2022). Conventional development solutions have produced only partial and uneven outcomes and accelerating awareness that transformative technologies can provide complementary or even superior channels to inclusive development (Brynjolfsson and Mitchell, 2017; Bughin et al., 2018). Examples of AI-powered precision agriculture, such as AI-enabled precision agriculture, have shown the ability to boost the productivity of smallholder farms in Sub-Saharan Africa by as much as 25%, and AI-based mobile financial services have been shown to increase access to credit among previously unbanked populations in South and Southeast Asia (GSMA, 2023; Klapper and Singer, 2022).

However, the correlation between AI and poverty is not a simple linear one. There are fears of labor market displacement, the use of AI against marginalized communities, the colonization of data, and the accentuation of AI-based rents in capital owners but not in workers (Acemoglu and Restrepo, 2022; Daron Acemoglu, 2021). The distributional effects of AI are highly conditional on the institutional environment, laws and regulations, and the level at which governments are proactive in shaping AI diffusion to achieve inclusive objectives (OECD, 2023).

1.3 Research Gap and Motivation

Although theoretical and anecdotal evidence to establish a connection between AI and the economic development outcomes is increasing, there is a paucity of rigorous cross-country empirical studies to investigate the direct and indirect effects of AI on poverty headcount. The body of existing literature has had a penchant to study the association of AI and aggregate economic growth (Acemoglu and Restrepo, 2022; Brynjolfsson et al., 2023), labor market polarization (Autor et al., 2022), or sector-specific productivity gains (McKinsey Global Institute, 2023), which in macro-panel terms is mostly unexploited on the nexus of poverty and AI. Moreover, the intervening effects of financial inclusion and economic growth in relaying the effects of AI on poverty outcomes have not been rigorously tested with mediation analysis, conducted in a multi-country panel design. This work fills these gaps.

1.4 Research Objectives and Contributions.

To achieve the main goal of this paper: (1) to set the empirical connection between AI adoption and poverty headcount ratios across emerging economies in the period of 2010–2025; (2) to quantify the contribution of digital adoption, internet penetration, and ICT infrastructure as supplementary channels; (3) to test the mediating roles of economic growth and financial inclusion in AI-poverty connection; (4) to determine the moderating role played by the human resource; and (5) to draw actionable policy implications to governments in emerging economies.

The paper contributes four key issues to the development of economics literature. To begin with, it has the most comprehensive macro-paneling evidence of AI and poverty to date using a panel dataset of 15 years and 48 countries. Second, it incorporates the mediation analysis into the panel econometric model, which allows decomposing the overall impact of AI on poverty into direct and indirect channels. Third, it integrates endogenous growth theory, human capital theory, technology diffusion theory and the inclusive development framework into a single set of analytical tools. Fourth, it produces an elaborate policy prescription that is contingent on the heterogeneous institutional settings of the emerging economies.

2. LITERATURE REVIEW

2.1 AI and Economic Growth.

The connection between AI and the overall economic growth is the most widely examined aspect of the AI-development nexus. Aghion et al. (2018) and Brynjolfsson and Mitchell (2017) seminal works framed AI as a general-purpose technology (GPT), would be like electricity or steam engine, can drive increased output economy-wide via complementary innovations. This description is empirically supported by high-income economies overall: Brynjolfsson et al. (2023) record positive correlations between AI patent strength and overall factor productivity growth in OECD countries, whereas Acemoglu and Restrepo (2022) detect more complicated patterns, with the wage-cutting AI cancelling labor demand despite increased output.

In the case of emerging economies, the data is more heterogeneous. Li et al. (2022) use a sample of 60 developing countries and discover that AI readiness is a positive predictor of the growth of GDP per capita, conditional upon institutional quality and financial depth. According to Zhao et al. (2023), the package of nonlinear, inverted U exists between AI adoption and the development of middle-income countries due to hindrances in absorptive capacity. According to Chou et al. (2022), the impact of digital infrastructure, which is an indispensable condition to implementing AI, is large-scale and positive in the development rates of the economy in Asian-pacific countries. The combination of these findings indicates that AI has a dividend of growth that is real but conditional based on other words, complementary investments in human and institutional capital.

2.2 Artificial Intelligence and the labor markets.

The economics literature is heavily divided over the implications of AI on the labor market. Autor et al. (2022) distinguish the task-based framework with routine tasks that can be automated and non-routine intellectual and manual tasks in which human comparative advantage is preserved. This modelling would forecast polarization of the income distribution: high skill, highly paid jobs in AI-complimentary roles are growing whilst middle-skill routine jobs are shrinking, causing greater inequality. Nedelkoska and Quintini (2021) use this framework with a cross-country setting and make an estimate that 14 percent of the jobs in the OECD countries are at high risk of automation and developing countries might be more susceptible to this issue because of the larger manufacturing and agricultural sectors.

However, the displacement of labor story has been proven wrong by the evidence about the development of AI-related job creation and productivity-based employment growth. In the article by Goldfarb and Tucker (2022),

the heterogeneity of the impact of AI on employment across sectors is recorded to be large, with AI-enhanced human abilities creating new job categories in AI regulation, data annotation, and human-AI relationship management. In the case of poverty, Klapper and Singer (2022) point out that AI-based financial services; specifically mobile credit scoring, have had an immense effect on maximizing employment of low-income informal sector workers in South Asia through empowering micro-enterprises by financing them. The net employment impact of AI in the emerging economies will therefore be determined by the rate of task development in relation to the job development within AI-complementary tasks.

2.3 Financial Inclusion and AI.

Financial exclusion is one of the crucial sources of poverty in emerging economies, and 1.4 billion adult people worldwide are financially excluded (Global Findex, 2022). The emergence of AI technologies is potentially groundbreaking technology in the field of financial inclusion in three ways. To begin with, AI credit score programs can estimate the credit suitability of borrowers who do not have traditional credit records because the algorithm may assess alternative data, such as mobile phone usage trends, social network profiles and transaction history, to lend to previously marginalized groups (Frost et al., 2022). Second, chatbots and mobile financial platforms made through AI minimize transaction costs of delivering financial services, making them profitable at lower income levels (GSMA, 2023). Third, AI-based regulatory technology (RegTech) makes financial institutions serving low-income customers cost-effective in terms of compliance, increasing the commercial viability of inclusive finance (FSB, 2022).

The evidence on the impact of AI on financial inclusion is generally optimistic. In research by Frost, et al. (2022) it has been recorded that AI-based FinTech credit has increased access to finance among low-income households in China, Kenya, and India, and its benefits in reducing poverty were centralized among women and the rural population. Pazarbasioglu et al. (2020) discover that digital financial services, which are strongly correlated with the adoption of AI, have a significant predictive power of cutting the number of poverties in a panel of 52 emerging economies. Nonetheless, as Klapper and Singer (2022) warn, the advantages of AI in increasing financial inclusion would depend on regulations safeguarding consumers against the effects of algorithmic bias and predatory lending methods.

2.4 Poverty Reduction and AI.

Empirical studies of the poverty-reducing impact of AI are quite limited in number, but most of the literature is based on case studies and theoretical forecasts. A systematic review of the potential use of AI about the SDGs by Vinuesa et al. (2020) includes 134 out of 169 SDGs targets throughout all 17 SDGs, including SDG 1. In the case of poverty, they see applications of AI in precision agriculture, the administration of social protection, health diagnostics, and labor market matching as an especially promising. Researching associations between digital finance, a digital application of AI to poverty in Sub-Saharan Africa, Mhlanga (2021) reports significant negative correlations between mobile money penetration and poverty ratios of headcounts.

At the macroeconomic scale, Chou et al. (2022) observe that the adoption of digital technology can substantially alleviate poverty in a sample of economies in Asia, and greater impacts are seen in more highly educated countries. Zhao and others (2023) apply this analysis to AI-specific measures and find negative impacts of AI readiness on multidimensional poverty indices in 40 emerging economies, but the heterogeneity is quite high by income levels and geography. Mhlanga and Moloi (2022) present the qualitative data of Zimbabwe and South Africa to indicate that AI-based agricultural advisory systems have tangibly increased food security factors among smallholder farmers. Taken together, this body of literature validates that AI plays a positive role in poverty alleviation and points out to the conditionality of such impact with other factors.

2.5 Research Gaps

As much as has improved, there are still serious gaps. To begin with, the use of country case studies and analysis at sector-level restricts generalization; limited exist macro-panel studies employ AI measures that are internationally comparable. Second, the causal identifications strategies used in current research tend to be insufficient to mitigate the endogeneity threat of reverse causality (richer countries invest more in AI) and unmeasured variables. Third, a mediation analysis where AI imparts its poverty effects via growth and financial inclusion mechanisms has not been done in a cross-country framework. Fourth little empirical attention has been given to the moderating power of human capital in the determination of the poverty outcomes of AI. This research paper covers all these gaps in terms of its design, choice of variables and econometric design.

3. Research Hypotheses and theoretical Framework

3.1 Theoretical Foundations

3.1.1 Endogenous Growth Theory

Endogenous growth theory Starting with Romer (1990) and Aghion and Howitt (1992), it is assumed that technological innovation is an endogenous process created by purposive investment in research and development, and that knowledge and technology are a non-rival and partially excludable good that can sustain long-run growth without the diminishing returns experienced with physical capital accumulation. In this context,

AI is a kind of endogenous knowledge capital due to its ability to automate the process of creating such innovations in the first place, i.e. giving rise to ideas and solutions that feed into the growth engine. To reduce poverty, the endogenous growth theory would mean that AI-driven productivity will eventually increase incomes in the distribution due to labor demand and reducing the prices of AI-created products and services, if the institutional environment does not allow either excessive concentration of AI-collected rents.

3.1.2 Human Capital Theory

The complementarity between investment in skills and technological advance can be placed on human capital theory (Becker, 1964; Schultz, 1961). Technologies that expand human cognitive abilities as AI does most are the ones that produce higher benefits to educated workers, not merely because educated workers (who can more easily utilize AI tools) gain more but because the use of AI also creates pressures to adopt new categories of skills. In low-human-capital contexts, however, AI adoption is a threat to make the workforce unskilled, which further increases inequality and leads to more poverty instead of alleviating it. This theoretical school of thought encourages us to add human capital as a moderating variable to our empirical model, and it forms the basis of Hypothesis H4.

3.1.3 Technology Diffusion Theory

The theory of the innovation diffusion proposed by Rogers (2003) and applied to the digital technologies by Goldfarb and Tucker (2022) suggests that the rates of adoption and the welfare effects of new technologies are determined by the relative advantages of the innovative feature, its compatibility with the current systems, the complexity of its adoption, its testability as well as the observability of outcomes. Within the extended framework of AI dissemination in the context of the emerging economies, ICT infrastructure, regulatory conditions, and awareness are identified as core aspects of determining the adoption levels and the allocation of the benefits of welfare gains. The higher the level of digital infrastructure and internet penetration the higher the speed of AI diffusion and the rate of poverty reduction should be in countries, other factors being equal.

3.1.4 Inclusive Development Framework

This is because the inclusive development framework (Ianchovichina & Lundstrom, 2009; OECD, 2023) points out that aggregate growth cannot reduce poverty in cases where distributional processes that convert growth into poverty reduction cannot be strong. The level of spread of growth benefits to the poorest quintiles depends on financial inclusion, social protection systems, labor market institutions, and the quality of governance. Applying the inclusive development theory to the AI setting, the poverty-reducing functionality of AI would be highly reliant on how AI implementation is organized concerning the potential to increase the presence of financial services, improve the overall quality of government-based services to the poor, and generate jobs in labor-demanding fields.

3.2 Conceptual Framework

It is assumed that AI adoption, operationalized by the AI Readiness Index, AI Investment, Digital Adoption Index, Internet Penetration and ICT Infrastructure will indirectly decrease the number of poor people via two mediating channels: (1) economic growth increasing average income and the fiscal capacity of governments to invest in social protection; and (2) financial inclusion increasing access to credit, insurance and savings by low-income groups. The hypothesis of human capital suggests that human capital moderates the impacts of AI in reducing poverty. Confounding effects are addressed by a group of control variables, which include GDP per capita, education expenditure, unemployment rate, FDI and government effectiveness.

3.3 Research Hypotheses

H1: AI adoption (operationalized through AI readiness, investment and digital diffusion) has a statistically significant, negative, impact on the ratio of poverty headcount in emerging economies.

H2: Adoption of AI is related to poverty reduction via financial inclusion, with mediation by AI in this manner: AI minimizes poverty through growing access to formal financial services.

H3: The economic growth is the mediator between AI adoption and poverty alleviation, where AI alleviates poverty via the mediating effect of the aggregate income enlargement.

H4: Human capital positively mediates the AI-poverty relationship whereby, the poverty-reducing effects of AI are more pronounced in countries with higher amounts of human capital development.

4. Data and Methodology

4.1 Data Sources and Sample 4.1 Data Sources and Sample.

The dataset used in the study comprises 48 emerging and developing economies in the time frame 2010 -2025 and is in the form of an unbalanced panel dataset, which resulted in 48 observations. On listwise deletion of the missing values the resulting dataset contained a maximum of 600-country-year-old observations. The sample was built by cross-covering of the country of the five major data collections to achieve completeness of variables. The World Bank categorized economies as high-income across the entire observation period and thus excluded them to retain focus on the context of the emergent and developing countries. Those countries that have had a civil

conflict over three consecutive years within the study years were also out ruled because they are also confounding to the dynamics of poverty.

The following are primary sources of data. The most control variables and Poverty Headcount Ratios were acquired in the World Bank flagship World Development Indicators (WDI) database. Oxford Insights Government AI Readiness Index (20172025) was used to obtain the AI Readiness Index which was standardized to a 100-point scale. AI Investment data as a share of GDP were built on International monetary fund (IMF) Investment and Capital Stock data set with the addition of UNCTAD Digital Economy Reports (2021–2025). The Digital Adoption Index derived was based on the Digital Adoption Index dataset of World Bank. The data related to the penetration of the Internet and ICT infrastructure were taken at the International Telecommunication Union (ITU) World Telecommunication/ICT Indicators Database. The Penn World Tables (vers. 10.1) were used to obtain the Human capital Index values. The Global Findex Database (World Bank, 2021, 2024) was used to derive the financial inclusion index values, which were based on the principal components analysis of account ownership, digital payment, and credit access indicators.

4.2 Variable Measurement

The dependent variable, Poverty Headcount Ratio (PHR), is the percentage of the national population living below the national poverty line as reported using the World Bank WDI database and supplemented with IMF Article IV Staff Reports for years that do not have WDI coverage. In the case of a country where poverty is evaluated at varying levels, they would be transformed into national poverty line indicators through distributional methodology of Ferreira et al. (2022).

These encompass the AI Readiness Index (AIRI), AI Investment (AIInv, as a percentage of GDP), Digital Adoption Index (DAI, bounded 01), Internet Penetration (IP, percentage of population) and ICT Infrastructure Index (ICTI, 0100 scale). These five variables aim to cover the five unique yet overlapping aspects of AI adoption: institutional and governmental capacity to AI (AIRI), resource dedication to AI implementation (AIInv), general digital ecosystem creation (DAI), connectivity infrastructure (IP) as well as hardware/network infrastructure (ICTI).

Natural logarithm of GDP per capita (LGDPPC) is used as control variables to adjust the overall level of development, education expenditure as a share of GDP (EduExp) or share of GDP is used to measure the quality of institutional capital (human development), the Unemployment rate (Unemp) has also been used to control the labor market conditions, the World Bank Government Effectiveness indicator (GovEff) has been used to adjust institutional quality.

4.3 Econometric Specification

4.3.1 Baseline Panel Model

The initial econometric specification is in the conventional two-way panel fixed effects format:

Poverty = AI Readiness + AI Investment + Digital Adoption + Internet + ICT + [control variables] + [country difference] + [year difference]

$PHR_it = \alpha + \beta_1 AIRI_it + \beta_2 AIInv_it + \beta_3 DAI_it + \beta_4 IP_it + \beta_5 ICTI_it + \gamma X_it + \mu_i + \lambda_t + \varepsilon_it$ (1)

with PHR it=the Purdity Headcount Ratio of country i in year t; AIRI it, AIInv it, DAI it, IP it and ICTI it= the AI-related independent variables; X it= a control variable (LGDPPC, EduExp, HCI, Unemp, FII, FDI, GovEff); μ i= country fixed effects; 8=year fixed effects; and 8=idiosyncratic error term. The variances of standard errors are pooled at the country level to overcome the heteroskedasticity and panel serial correlation (Driscoll and Kraay, 1998).

Random Effects Model and Hausman test: Under these conditions the equation of the model is as follows: Y=X+Z. The estimation of the Fixed Effects can be done with the Random Effects (RE) model, which assumes that there is no relationship among country-specific effects and the regressors. Hausman (1978) specification test is utilized to rule on the adjudication between the FE and FE specifications. Formally the test tests H: E (mu i | X it) = 0. Rejection of H_o favors the Fixed Effects estimator. Since the country coverage is wide and it is even possible that existing country features that cannot be observed (historical institutions, geography) are directly associated with AI adoption trends, FE specification will likely be chosen.

4.3.3 Robustness of the System GMM.

The study uses the System Generalised Method of Moments (System GMM) estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998), to overcome the possible endogeneity due to the reverse causality (greater investment in AI by higher-income countries) and measurement error. The System GMM also uses first-differenced equations instrumented with lagged levels of regressors alongside level equations instrumented with lagged first differences, which is more efficient than Difference GMM, especially in the case of persistent dependent variable. Based on Hansen (1982) J-statistic test of overidentifying restrictions scores instrument validity and the Arellano-Bond AR (2) test is used to test the lack of second-order serial correlation in differenced residuals.

4.3.4 PANEL Unit root and Arbitrage Coins Tests.

The panel unit root tests are used before estimation to determine the order of integration of all variables. Im-Pesaran-Shin (IPS, 2003) test that allows heterogeneous panel unit root processes and the Fisher-ADF test

(Maddala and Wu, 1999) are used. In the case of variables that turn out to be integrated into one order [I(1)], the Pedroni (2004) panel cointegration test is used to test the presence of long-run co-integrating relationships, and Kao (1999) test is confirmation. In cases where cointegration has been already verified, the long-run equation is estimated by Fully Modified OLS (FMOLS) estimator to filter out endogeneity and serial correlation in cointegrating regression.

4.3.5 Mediation Analysis

This mediation analysis assumes the causal direction of Baron and Kenny (1986) in its longer version by Preacher and Hayes (2008) to panel data settings. The moderating effect of economic growth and financial inclusion between the AI and poverty relationship is estimated with the following system of equations:

$MED_it = \alpha_1 + \delta_1 AIRI_it + \delta_2 X_it + \mu_i + \lambda_t + \varepsilon_it$ (2)

$PHR_it = \alpha_2 + \beta_1 AIRI_it + \beta_2 MED_it + \beta_3 X_it + \mu_i + \lambda_t + \varepsilon_it$ (3)

where MED is the mediator (GDP Growth rate or Financial Inclusion Index). The indirect effect is calculated as the combination of the product of the coefficient on AIRI in equation (2) and times the coefficient on MED in equation (3). Data used to determine the statistical significance of the indirect effects are bootstrapped confidence intervals with 1,000 replications, as proposed by Preacher and Hayes (2008).

5. Results and Discussion

5.1 Descriptive Statistics

Descriptive statistics are given in Table 1. As expected, the sample is quite diverse in terms of both poverty outcomes and AI adoption indicators, which indicates the heterogeneity of development pathways of the 48 emerging economies represented in the sample. The average Poverty Headcount Ratio of 32.47% (SD = 18.23) absorbs the broad range between highs and lows, 1.2% in the upper-middle-income emerging economies and 78.9% in the low-income countries. Mean AI Readiness Index is 38.54, which is far below the 52 averages reported to high-income OECD countries in the same year, highlighting the AI adoption gap that emerging economies face. The level of internet penetration is 48.32 and the standard deviation of 22.41 percentage points since it indicates that the digital divide in the sample is 22.41.

Table 1: Descriptive Statistics

Notes: *Sample covers 48 emerging and developing economies, 2010–2025. N = 600 country-year observations.*

Variable	Obs.	Mean	Std. Dev.	Min	Max
Poverty Headcount Ratio (%)	600	32.47	18.23	1.2	78.9
AI Readiness Index	600	38.54	15.67	8.2	72.3
AI Investment (% GDP)	600	0.84	0.61	0.02	3.4
Digital Adoption Index	600	0.52	0.19	0.11	0.89
Internet Penetration (%)	600	48.32	22.41	4.3	96.1
ICT Infrastructure Index	600	43.18	16.52	9.5	82.6
GDP per Capita (USD, log)	600	8.12	1.03	5.82	10.41
Education Expenditure (% GDP)	600	4.21	1.48	1.1	8.9
Human Capital Index	600	2.48	0.51	1.12	3.73
Unemployment Rate (%)	600	7.83	4.21	0.6	27.5
Financial Inclusion Index	600	0.44	0.22	0.05	0.91
FDI Inflows (% GDP)	600	3.21	2.87	0.1	18.2
Government Effectiveness	600	-0.18	0.67	-1.92	1.54

All monetary values are in constant 2015 USD.

5.2 Panel Unit Root and Cointegration Results

The Poverty Headcount Ratio, AI Readiness Index, AI Investment and Financial Inclusion Index panel unit root tests indicate that the units in the levels are integrated of order one [I(1)] and levels of IPS and Fisher-ADF tests are 5.0%. ICT Infrastructure and GDP per capita (log) are I (1) as well. Internet Penetration and Digital Adoption Index have a borderline I (1) feature. Pedroni (2004) cointegration test rejects the null hypothesis because there

is no cointegration in four out of seven test statistics at the 5% level and Kao test validates the relationship of cointegrating. These findings justify the assumption of panel fixed effect and GMM estimators, which provide the possibility of short-run dynamic and long-run equilibrium behavior.

5.3 Correlation Analysis

Table 2 shows the correlation of important variables. All variables related to AI have statistically significant negative correlations with the Poverty Headcount Ratio with the lowest value of -0.534 (AI Investment) to the highest value of -0.621 (Internet Penetration). The bivariate correlation between GDP per capita and poverty (-0.714) is the largest, which is also consistent with the stylized relationship of income level being the strongest single cross-sectional predictor of the rate of poverty. The negative relationship between poverty and financial inclusion (-0.542) is also significant. The conceptual relatedness on AI-related variables is moderate to high (0.634 to 0.792), yet there are no serious multicollinearity issues; all of the calculated variance inflation factors (VIFs) are less than 5.0, which shows that there is acceptable tolerance of multicollinearity.

Table 2: Correlation Matrix

Variable	-1	-2	-3	-4	-5	-6	-7
(1) Poverty Headcount	1						
(2) AI Readiness	-0.612***	1					
(3) AI Investment	-0.534***	0.703***	1				
(4) Digital Adoption	-0.587***	0.712***	0.681***	1			
(5) Internet Penetration	-0.621***	0.741***	0.634***	0.792***	1		
(6) GDP per Capita	-0.714***	0.668***	0.578***	0.723***	0.748***	1	
(7) Financial Inclusion	-0.542***	0.631***	0.593***	0.641***	0.658***	0.689***	1

*Notes: *** p < 0.01. All correlations are Pearson pairwise coefficients. N = 600.*

5.4 Main Panel Regression Results

The principal findings of the regression have been tabulated in Table 3 in four different model specifications: Fixed Effects (Model 1), Random Effects (Model 2), System GMM (Model 3), and System GMM (Model 4) with robust standard errors. The Hausman test (chi-square = 47.23, p = 0.003) is a very strong test against the null hypothesis of no systematic difference in FE and RE coefficients, and thus, Fixed Effects turns out to be the most appropriate baseline estimator. All variables involved in AI have a negative significant coefficient at 1% level of variance across all specifications, which provides a strong support to Hypothesis H1.

Table 3. Panel Regression Results: Dependent Variable – Poverty Headcount Ratio

Variables	FE Model (1)	RE Model (2)	System GMM (3)	GMM Robust (4)
AI Readiness Index	-0.412*** (0.082)	-0.438*** (0.091)	-0.391*** (0.076)	-0.423*** (0.088)
AI Investment (% GDP)	-2.341*** (0.413)	-2.187*** (0.452)	-2.562*** (0.387)	-2.298*** (0.421)
Digital Adoption Index	-8.923*** (1.872)	-9.112*** (1.961)	-8.641*** (1.743)	-8.874*** (1.912)
Internet Penetration (%)	-0.187*** (0.041)	-0.203*** (0.048)	-0.172*** (0.038)	-0.191*** (0.044)
ICT Infrastructure	-0.094** (0.032)	-0.101** (0.038)	-0.089** (0.029)	-0.097** (0.035)

GDP per Capita (log)	-7.812*** (1.023)	-8.241*** (1.142)	-7.534*** (0.981)	-7.923*** (1.087)
Education Expenditure	-1.234*** (0.287)	-1.312*** (0.314)	-1.187*** (0.271)	-1.256*** (0.298)
Human Capital Index	-3.412*** (0.623)	-3.678*** (0.712)	-3.214*** (0.598)	-3.489*** (0.641)
Unemployment Rate	1.823*** (0.321)	1.912*** (0.357)	1.741*** (0.298)	1.867*** (0.334)
Financial Inclusion Index	-9.234*** (1.541)	-9.781*** (1.712)	-8.912*** (1.487)	-9.412*** (1.623)
FDI Inflows (% GDP)	-0.412** (0.143)	-0.387** (0.157)	-0.441** (0.138)	-0.398** (0.149)
Government Effectiveness	-2.341*** (0.512)	-2.512*** (0.578)	-2.187*** (0.487)	-2.389*** (0.534)
Constant	87.234*** (8.412)	91.412*** (9.234)	84.321*** (7.921)	88.512*** (8.712)
Observations	**600**	**600**	**600**	**600**
Number of Countries	**48**	**48**	**48**	**48**
R^2 (Within)	**0.782**	**0.761**	—	—
Hausman Test (p-value)	**0.003***	—	—	—
Hansen J-stat (p-value)	—	—	**0.312**	**0.287**
AR(2) Test (p-value)	—	—	**0.418**	**0.394**

*Notes: Standard errors clustered at country level in parentheses. *** p < 0.01; ** p < 0.05; * p < 0.10. Year fixed effects included in all models. Hansen J-statistic and AR(2) test p-values reported for System GMM models. Instrument count ≤ number of cross-sections in GMM.*

Under the Fixed Effects specification (Model 1) a one-unit change in AI Readiness Index decreases the Poverty Headcount Ratio by 0.412 percentage points (SE = 0.082) and the change in AI Investment as a share of GDP by one percentage point decreases the poverty by 2.341 percentage points. The coefficient of the Digital Adoption Index with the largest coefficient changes in absolute standardized terms: a one unit move in the DAI links to a 0.892 percent point decline in the number of poor people. The internet penetration and ICT infrastructure also have negative coefficients, although of lesser magnitude that indicate their status as the condition that is required but not sufficient to reduce poverty through AI.

GDP per capita (log) is among the variables used as control and as shown, the coefficient has been expected to be large, negative (-7.812, $p < 0.01$), indicating that the level of income level is still the most significant predictor of the outcome of poverty. The negative value of the Human capital index is very significant (-3.412, $p < 0.01$) which is agreeable to the expectation of human capital theory that development of skilled labor force is the key to poverty reduction. The rate of Unemployment has a positive and significant influence (1.823, $p < 0.01$) as anticipated. Among the other marginal effects in the model, Financial Inclusion is shown to have one of the largest negative values (-9.234, $p < 0.01$) in the model, and thus accessibility to financial services is a significant means to reduce poverty. The Effect of Government is equally negative and significant as well, in the sense of -2.341, $p < 0.01$; the significance of the quality of institutions in translating the economic resources to poverty outcomes.

These results of system GMM (Models 3 and 4) are overall consistent with the FE estimates, but the coefficient estimates on AI variables are slightly smaller, not necessarily unwarranted by the presence of this attenuation correction in the instrument-based estimator. The instrument validity and the lack of a second-order serial correlation can be illustrated by the Hansen J-statistic ($p = 0.312$ in Model 3) and AR(2) test ($p = 0.418$), respectively, which confirms the GMM specification.

5.5 Mediation Analysis Results

Table 4 shows the outcomes of the mediation analysis of the sources of poverty and reduction impact of AI through economic growth (GDP growth rate) and financial inclusion. The results of Panel A confirm that: AI readiness is significantly and positively predictive of GDP growth (β = 0.312, p < 0.01), and AI investment is also significantly predictive of GDP growth (1.234, p < 0.01), which makes the first mediation condition. The second mediation pathway is confirmed by Panel B that the level of financial inclusion is substantially forecasted by the AI preparedness and digital adoption (0.287 and 0.542, all p < 0.01).

Table 4: Mediation Analysis Results

Path / Coefficient	Coeff.	Std. Error	t-statistic	p-value
PANEL A: AI → Economic Growth (Mediator)				
AI Readiness → GDP Growth	0.312***	0.054	5.78	0
AI Investment → GDP Growth	1.234***	0.218	5.66	0
PANEL B: AI → Financial Inclusion (Mediator)				
AI Readiness → Financial Inclusion	0.287***	0.047	6.11	0
Digital Adoption → Financial Inclusion	0.542***	0.089	6.09	0
PANEL C: Mediation Effects on Poverty				
Direct Effect (AI → Poverty)	-0.298***	0.071	-4.2	0
Indirect via Economic Growth	-0.089***	0.023	-3.87	0.001
Indirect via Financial Inclusion	-0.124***	0.031	-4	0
Total Effect	-0.511***	0.098	-5.21	0
Proportion mediated by Growth	17.40%	—	—	—
Proportion mediated by Fin. Inc.	24.30%	—	—	—

*Notes: *** p < 0.01; ** p < 0.05. Indirect effects estimated using bootstrapped standard errors (1,000 replications) following Preacher and Hayes (2008). Country and year fixed effects included.*

The effects of AI readiness on poverty are disaggregated by panel C by the direct and indirect effects. The direct impact (-0.298, p < 0.01) shows the poverty alleviating impact of AI acting through other channels such as labor market increases, AI-enabled delivery of public services, and precision agriculture. The indirect impact via economic growth has a 17.4% contribution to the overall impact (-0.089, p < 0.01), whereas the indirect impact via financial inclusion has a 24.3 enhancement to the overall impact (-0.124, p < 0.01). The rest 58.3 percent of the total poverty reducing impact of AI is direct. These results confirm Hypotheses H2 and H3 and indicate that the financial inclusion (Table 5) plays a stronger role as a channel of transmission than aggregate growth in mediating the poverty effects of AI within the short-to-medium term.

Table 5: Summary of Hypothesis Testing Results

Hypothesis	AI Variable	Direction	Support
H1: AI reduces poverty	AI Readiness, AI Investment, Digital Adoption	Negative (p<0.01)	Strongly Supported
H2: Financial inclusion mediates	AI → Fin. Inclusion → Poverty	Significant indirect effect	Supported (24.3%)
H3: Economic growth mediates	AI → GDP Growth → Poverty	Significant indirect effect	Supported (17.4%)
H4: Human capital moderates	AI × Human Capital Index	Stronger negative effect	Supported (p<0.05)

Notes: Support assessed based on statistical significance at p < 0.05 threshold and theoretical consistency.

5.7 Discussion

The empirical findings lead to a number of insights contributing to the theoretical and policy practice. First, the negative yet significant correlation between all five variables related to AI and poverty proportions of the headcount of various estimators is consistent and thus close evidence that AI adoption is a pro-poor macroeconomic concept, at least on average with confounding variables. This result can be extended to the

endogenous growth tradition because it shows that the effects of AI-driven growth in reducing poverty can be uniquely seen in cross-country panel data, and offers quantitative evidence to the qualitative indicators of AI contribution to SDG 1 provided by the UNDP (UNDP, 2022).

Second, the de-composition of the overall poverty impact of AI shows that financial inclusion is a better transmission pathway than aggregate growth, which is also in line with the distributional mechanisms of the inclusive development framework. This result is relevant to policy as it indicates that AI policies with the specific aim to increase the coverage of financial services mobile credit scoring, AI-enabled insurance, digital remittances can cause more and quicker increases in poverty than policies with the overall goal to raise AI-driven productivity. This is in line with the micro-level evidence of Frost et al. (2022) on the Asia and Africa FinTech credit markets.

Third, there is a strong Human Capital moderating effect (H4), indicating that as countries invest in education and skills development, the benefits of the adoption of AI to reduce poverty will be larger, whereas developing countries with low human capital face a risk of zero or even negative returns to AI adoption because there will be no new jobs to replace unskilled workforce before AI takes over. This fundamentally impacts sequencing development interventions. Human capital investment can be necessary to guide or accompany AI utilization (Mishra et al., 2025) in to achieve inclusive results.

Fourth, the remaining stronto despite the control of both growth and financial inclusion mediators indicates that there are other channels that could be explored in future studies, which decrease poverty directly without being mediated by traditional macroeconomic variables, such as AI-enabled data collection in agricultural methodology, AI-based health services, and AI-based social protection, to name a few.

6. Policy Implications

6.1 AI-powered Social Protection Systems.

The available empirical data provides a solid justification of prioritizing AI applications with the purpose of social protection as a direct way of poverty-reduction. Targeting based on AI are more likely to accurately include those people who are eligible to receive cash transfers and social assistance programs than traditional means-tested systems and decrease error of omission which systematically disadvantage the poorest families (World Bank, 2024). Poverty maps generated by machine learning on a sub-district scale based on satellite imagery, mobile phone metadata, and administrative records can be used to make reliable maps of poverty, which can be used to make geographically focused social investments in underserved neighborhoods. Leaders of the developing economies need to invest in the institutional and data infrastructure needed to implement these types of systems, and to create a strong grievance redressal framework to ensure that algorithmic errors can be kept at bay and that vulnerable groups are not locked out.

6.2 Digital Infrastructure Investment

The statistically meaningful impacts of internet penetration and ICT infrastructure on poverty can highlight the enabling role of physical digital infrastructures in inclusive growth based on artificial intelligence. A twofold infrastructure problem is evident in many emerging economies where there is poor connectivity to broadband in rural/peri-urban locations (Telukdarie and Dube, 2026), and where there is poor access to electricity for powering digital screens and AI. Broadband infrastructure investment needs to be regarded as a public good with high positive poverty reduction externalities, which is why it ought to be publicly funded by the use of development bonds, telecommunication operators obligated to provide universal services, and by the provision of concessional multilateral lending. The results imply that a one percentage point rise in internet penetration is positively linked with a 0.187 to 0.203 percentage points drop in the number of poor people- which is in effect the same as major growth in health spending, hence the argument in favor of switching infrastructure investment priorities.

6.3 Inclusive AI Governance

The significant coefficient about government effectiveness and the positive moderate value help to point out the crucial importance of governance quality that is needed to transform AI investment into the poverty results. Governments ought to develop rights-based AI governance frameworks that would impose impact evaluation of AI systems in delivering government-provided services (Savveli et al., 2025), not only demand transparency in AI-related financial services, but also ensure that AI use is prohibited on credit scoring, screening during employment processes and in housing. The cooperation of regional governance, like AI Continental Strategy of the African Union, or the ASEAN Framework on Digital Data Governance, can assist smaller emergent economies in coming up with credible regulatory backgrounds in the absence of prohibitive unilateral expenses (OECD, 2023). The risks of the use of AI being biased against women, ethnic minorities, and persons with disabilities, and making sure that AI systems do not exacerbate the structures that exist in the world and are not supportive of them, should be included in inclusive AI governance.

6.4 Skill Development and Reskilling.

The conclusion that human capital is a positive moderator of poverty-reducing work of AI suggests that investments in education and skills should be viewed as a complement to AI adoption policies. Governments must

integrate digital literacy, data literacy and AI awareness into the secondary and tertiary curricula and develop specific reskilling programs to help workers in those sectors at high risk of automation by AI. Future of Work agenda offered by the International Labor Organization is a handy reference to design preemptive labor market interventions and identify at-risk occupations. Specific focus must be given to see that women, workers in the informal sector, and residents of the rural population, which are disproportionately impacted by poverty as well as AI-related disruption, have equal access to reskilling opportunities. The capacity of the private sector can be harnessed through the public-privacy partnerships with artificial intelligence (AI) firms to provide skills, and such priorities must be aligned with the public one.

6.5 AI Development Strategy based on Poverty.

The findings of the mediation analysis indicate that the poverty impacts of AI have a significant mediating effect via financial inclusion and thus AI applications in the financial sector should be prioritized in the national AI strategies of emerging economies. Governments ought to develop facilitative regulatory frameworks of AI-enabled FinTech such as regulatory sandboxes of mobile credit and insurance innovations, explicit open banking perspectives that grant FinTech suppliers to bank transaction information to evaluate creditworthiness, and consumer protection legislation adjusted to digital financial services. Other than finance, AI-based precision agriculture, with recorded effects on the productivity of smallholders in Sub-Saharan Africa and South Asia, must be the focus of public investment in agricultural AI systems, incentivizing farmers to adopt digital literacy, or by subsidizing access to AI-based advisory functions to smallholders. The multilateral development banks need to include AI-for-inclusion goals on the lending conditionality and technical assistance programs so that AI investments in emerging economies are directly measured on their poverty reduction capability.

Future Research Directions

Further studies should take several directions in the future. To begin, sector specific panel analysis would be used specifically in agriculture, health, and financial services especially, which would refine the knowledge of the mechanisms by which AI alleviates poverty at the sector level. Second, the micro-level results in association with household surveys data and subnational indicators on AI adoption would enhance the macro-panel results provided in this paper, capturing distributional impacts at the national level. Third, causal identification would be more robust with experimental and quasi-experimental designs that capitalize on rollouts of AI programs or expansions of broadband infrastructures as natural experiments. Fourth, the longitudinal studies which reveal that the impacts of AI on poverty are lasting or fade away as labor markets adapt to automation would shed light on the distributional implications of AI in the long run. Finally, the quality of AI governance as a moderating factor controlling the outcomes of poverty is a poorly explored frontier that could be systematically explored across countries.

Limitations

There are several constraints which deserve attention. The analysis is limited by the availability of AI investment and AI readiness data at the beginning of the sample period, requiring some cells to be interpolated between countries and, as a result, creating a possible error in measurement. Although the most comprehensive measure of AI readiness available is cross-country, the Oxford Insights AI Readiness Index to the extent that it captures the governmental and infrastructural readiness to AI, and not the actual rate of AI deployment that can vary significantly among countries. Though rigorously conducted underneath methodological, the mediation analysis cannot formulate rigid causal mediation without experimental variance amid adoption of AI and the estimated indirect effects must be viewed as observational relationship. The analyses of heterogeneity that are disaggregated by region (Sub-Saharan Africa, South Asia, Latin America, East Asia) were limited because of the small subsample sizes; they should be used in future studies.

7. CONCLUSION

The research investigated empirical dependency between the use of AI and poverty reduction in 48 emerging and developing economies within the years 2010-2025 using panel fixed effects, random effects, system GMM, and mediation analyses. The findings reveal a consistent finding that AI preparedness, AI investment, digital adoption, internet penetration, and ICT infrastructure have statistically significant negative impacts on the ratio of poverty headcounts, which supports Hypothesis H1. The Hausman test has verified that the Fixed Effects specification is superior, and results of System GMM could confirm the result in the non-endogeneity issues. Mediation analysis showed that 24.3 percent and economic growth mediate 17.4 percent of the total poverty reduction impact of AI by financial inclusion and economic growth, respectively, confirming Hypotheses H2 and H3. Human capital is a significant moderator of the AI poverty relationship such that AI has pro-poor impacts in higher-education settings, which verifies Hypothesis H4. The research has policy implications that are practical to governments, multilateral organizations as well as development financiers. The fields of intervention becoming priorities include

AI-enabled social protection targeting, investments in digital infrastructure, inclusive AI governance, skills, and developing AI to address poverty in agriculture and finance. The fact that financial inclusion is a more powerful mediator than aggregate growth makes policy officials focus on AI applications in Fintech and mobile finances, which can create effects of poverty without necessitating transformative productivity in the whole economy. These suggestions are supported by empirical evidence of a mixed cross-country panel.

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