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Artificial Intelligence For Economic Growth and Development

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ABSTRACT: The rapid diffusion of artificial intelligence (AI) across industries and national economies has brought renewed scholarly attention to the impact of technological innovation on economic growth. This paper provides a systematic narrative review of the peer-reviewed empirical and theoretical literature on how-adoption of AI leads to growth at macroeconomic scale contributions to human development across key sectors, and the structural challenges that condition these distributional effects. Based on a SPAR-4-SLR protocol, 47 studies from the Scopus, Web of Science, EconLit and Google Scholar databases were identified, and results show that AI mainly affects economic growth via TFP increase, innovation speed-up, labour market transformation and financial sector extension. As a result, AI shows documented promise in agriculture, health, education and governance at the development level but the evidence base remains patchy across LMIC contexts. There are still deeper structural risks that remain, such as labour displacement, infrastructure gaps and inequality(both across and within economies), algorithmic bias and the concentration of AI economic rents in advanced economies. This paper makes two important contributions: it advances a unified cross-disciplinary conceptual framework, which is considered appropriate to policy contexts in both developed and developing economies; and identifies priority areas for further causal empirical research.

Keywords: artificial intelligence, economic growth, total factor productivity, digital transformation, developing economies, labour market popularization

INTRODUCTION

AI has become one of the most consequential technological forces to transform modern economic systems. From automation in manufacturing aided by machine learning to professional services that use large language model applications, the penetration of AI into productive sectors has occurred at a speed that undermines traditional views of technological change. According to PwC (2023), AI could add around $15.7 trillion to the global GDP by 2030 and is a structural shift in economy as huge as the industrial revolution or looking back at the invention of general computing. But beneath this macroeconomic optimism are contested empirical characteristics, and an enormous distributional asymmetry that should inspire rigorous analytical inquiry.

Despite the apparent transformative power of AI technologies, at the aggregate level, investigations in the economics literature have had difficulty reconciling those capabilities with actual productivity outcomes. The productivity paradox has been documented extensively since the 1980s and resurfaced in the AI context originally by Brynjolfsson et al. As the process that complements with a GPT takes time, Jovanovic and Rousseau (2005) argue

that the economic benefits of GPTs noticeably arise only in a delayed manner. This kind of dynamic is especially relevant for developing economies whose institutional capacities, infrastructure endowments, and absorptive capabilities may significantly prolong the lag. In parallel, evidence regarding the labour market impacts of AI-induced automation, although far more advanced conceptually in high-income country contexts, is limited to speculations based on different levels and types of occupational and skills composition of workforces within sub-Saharan Africa, South Asia and Latin America compared to OECD analogs.

This study aims to:

i. Uncover the mechanisms through which AI adoption drives macroeconomic growth,
ii. Assess its sectoral development contributions in low- and middle-income countries,
iii. Identify the structural challenges and policy responses shaping the equity and sustainability of AI-driven growth. In doing so, it seeks to construct a unified analytical framework that bridges theory and evidence to inform both scholarly debate and policy design.

This paper addresses three specific research questions:

i. First, through what mechanisms does AI adoption translate into macroeconomic growth outcomes?
ii. Second, how does AI contribute to development outcomes across key sectors, particularly in low- and middle-income countries?
iii. Third, what structural challenges and policy responses shape the equity and sustainability of AI-driven growth?

By synthesizing the available empirical and theoretical evidence across these questions, the paper aims to provide a unified analytical framework capable of informing both academic inquiry and policy design at the national and multilateral levels.

Theoretical Framework

The analysis draws on five complementary theoretical traditions that together provide a multi-layered account of how AI interacts with economic systems. The Solow (1956) neoclassical growth model establishes the baseline: in a standard production function framework, AI can be understood as a capital-augmenting technological factor that raises output per unit of capital and labour. However, the Solow model's prediction of diminishing returns and convergence toward a steady state sits uneasily with the network effects and increasing returns that characterise AI-enabled digital production, motivating recourse to endogenous growth theory.

Romer's (1990) endogenous growth model locates the engine of long-run growth in purposive investment in knowledge and ideas. AI, on this account, accelerates the rate of idea production by reducing the cost of computational search, pattern recognition, and experimental iteration, thereby raising the equilibrium rate of innovation-driven growth. Brynjolfsson et al. (2021) extend this logic by positioning AI as a general purpose technology (GPT), building on Bresnahan and Trajtenberg's foundational framework. GPTs are defined by pervasiveness, improvement over time, and the capacity to generate innovation complementarities across sectors. The GPT lens explains both the breadth of AI's eventual economic impact and the productivity J-curve: aggregate gains are delayed because GPT adoption requires costly co-invention of new processes, organizational structures, and human capital.

Acemoglu and Restrepo (2022) introduce a critical counterpoint through their tasks and automation framework. They distinguish between AI applications that augment labour by creating new tasks and those that

automate existing tasks, displacing workers without generating sufficient new employment. This distinction carries significant distributional implications: when automation outpaces augmentation, AI can reduce the labour share of income and increase wage inequality even as it raises aggregate output. North's (1990) institutional economics provides a further moderating layer: the extent to which AI translates into sustained growth depends critically on the quality of property rights, regulatory frameworks, and enforcement institutions that govern technology adoption and diffusion. Finally, Becker's (1964) human capital theory underscores that AI's development dividend is mediated by the stock and distribution of skills in the population, making education and workforce policy central variables in the AI-growth relationship.

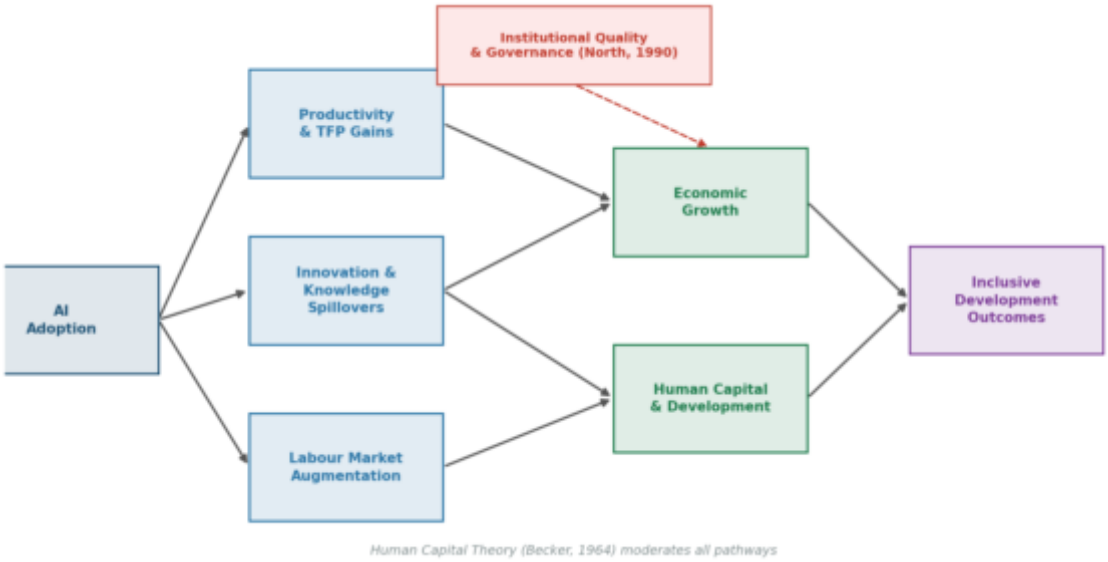


Figure1. Theoretical Linkage Diagram: AI Adoption Pathways to Macroeconomic Outcomes

LITERATURE REVIEW

Conceptual Review

The conceptual architecture of AI's relationship with economic growth rests on a foundational ambiguity that scholars have been working to resolve for over a decade: AI is simultaneously a factor of production, a process of production, and a producer of new knowledge. This tripartite character distinguishes it from prior general purpose technologies and requires a conceptual framework that can hold these three roles in view simultaneously. The most influential conceptualization draws on the GPT literature initiated by Bresnahan and Trajtenberg (1995), which identifies a technology as a general purpose technology when it is pervasive across sectors, improves over time, and generates innovation complementarities. Brynjolfsson et al. (2021) apply this framework rigorously to AI and identify a fourth characteristic that is specific to contemporary machine learning systems: the capacity to generate prediction at near-zero marginal cost. This is conceptually important because prediction is an input into decision-making across virtually every economic activity, meaning that a large and sustained reduction in the cost of prediction constitutes a structural shift in the economics of organization and production.

At the level of growth theory, the conceptual debate has centred on whether

AI is better understood as a labour-saving technology in the spirit of Solow's capital-augmenting technical change, or as a fundamentally new kind of input that behaves more like a non-rival idea in Romer's (1990) endogenous growth framework. Aghion et al. (2021) argue for a synthesis: AI is a capital good in the short run and a knowledge-generating machine in the long run, and this dual character is what distinguishes its growth implications from those of prior automation vintages. In the short run, AI investment raises output per worker in automating firms; in the long run, AI accelerates the production of new ideas, sustaining growth above the steady-state rate that conventional capital accumulation would predict. This synthesis has important implications for development economics, because it suggests that economies capable of not only adopting AI but also deploying it in knowledge-generating activities, such as research, design, and data analysis, will reap disproportionately larger long-run growth gains than economies confined to routine AI adoption in manufacturing and service delivery.

The conceptual literature on AI and development has been shaped significantly by the task-based framework developed by Acemoglu and Restrepo (2022). Their model distinguishes between tasks previously performed by labour that AI automates and new tasks created by AI that labour can now perform. When AI creates more tasks than it eliminates, it complements labour and raises the wage share. When it eliminates more tasks than it creates, it displaces labour and compresses the wage share even as aggregate output rises. This distinction has powerful implications for developing economies, where the occupational distribution of the workforce is heavily weighted toward routine manual and cognitive tasks that are most susceptible to displacement. Goldfarb and Tucker (2022) extend the conceptual landscape by introducing the economics of digital data as a complementary lens: AI's productivity depends critically on access to large, high-quality datasets, and the asymmetric global distribution of data assets means that AI's growth dividend is, at the conceptual level, structured to favour economies that are already data-rich. These conceptual frameworks collectively establish that AI's growth and development implications are not technologically determined but are mediated by institutional conditions, distributional structures, and strategic policy choices that vary profoundly across countries and development contexts.

Empirical Review

The empirical literature on AI and economic growth has expanded substantially since 2020, though it remains characterized by a persistent gap between rich evidence at the firm and sector level and sparse, contested evidence at the macroeconomic level. The most consequential firm-level evidence comes from Brynjolfsson et al. (2023), whose randomised field experiment at a large US technology firm found productivity gains of 14 to 35 percent among workers using a generative AI assistant, with the largest gains concentrated among workers with below-median experience, suggesting that AI functions as a human capital equaliser within firms even as it may deepen inequality across them. Czarnitzki et al. (2023) contribute complementary firm-level evidence from Europe, finding through econometric analysis of a large enterprise survey that AI-adopting firms produce significantly more patents and generate higher R&D output per unit of investment than comparable non-adopting firms, consistent with the innovation complementarities predicted by GPT theory.

At the labour market level, the empirical literature has been shaped by two major contributions. Felten et al. (2021) construct an AI occupational exposure index using detailed task data and find that occupations with higher AI exposure are characterised by above-average wages and above-average

wage growth, suggesting that, at least in the United States context, AI is currently augmenting the most skilled workers rather than displacing them. Eloundou et al. (2023) extend this analysis to large language models specifically and estimate that approximately 80 percent of the US workforce could have at least 10 percent of their tasks affected by GPT-class AI, with professional and managerial occupations most exposed. The distributional implications are contested: Acemoglu and Restrepo (2022) use an instrumental variable approach and find that each additional robot per thousand workers reduces the employment rate by 0.18 to 0.34 percentage points, with negative wage effects concentrated in production and operative occupations. Briggs and Kodnani (2023) take a more optimistic macroeconomic position, modelling that the productivity gains from generative AI, if broadly adopted, could raise global GDP by approximately 7 percent over a 10-year horizon, equivalent to adding the output of the United States and Germany combined.

The empirical evidence from developing economy contexts is considerably thinner but growing. Dauda et al. (2021) conduct a systematic review of AI applications in sub-Saharan Africa and find that growth gains are consistently conditional on prior infrastructure endowment, with countries in the bottom quartile of broadband penetration showing no measurable AI-related productivity improvement in the reviewed studies. Ooi et al. (2023) survey firms across six Asia-Pacific economies and find that AI adoption in service industries is positively associated with firm performance, but that the effect is moderated strongly by managerial AI literacy, a finding with direct implications for training and capacity-building policy in developing countries. In the financial sector, Iyer and Rajan (2021) provide econometric evidence that AI-enhanced credit scoring expanded formal credit access for small enterprises in India by reducing information asymmetries that previously excluded them from bank lending, with consequent effects on enterprise investment and employment. At the governance level, Zuiderwijk et al. (2021) conduct a systematic literature review covering 46 studies and identify AI tax administration and public expenditure monitoring as the two domains with the most consistent evidence of efficiency gains across diverse institutional contexts, with Rwanda and Estonia cited as the most methodologically rigorous cases of documented impact.

The sectoral empirical evidence is most robust in healthcare and agriculture. Obermeyer et al. (2021) document AI diagnostic systems achieving accuracy rates above 94 percent for tuberculosis detection in resource-constrained clinical settings in India and Kenya, while Crane et al. (2020) demonstrate yield improvements of 10 to 25 percent from satellite-based AI crop monitoring among smallholder farmers in sub-Saharan Africa. Both sets of findings connect to the broader development literature through the human capital channel: improved health and agricultural productivity raise the income and productive capacity of poor households, generating the structural transformation dynamics associated with sustained development. In education, Escueta et al. (2020) meta-analyse 56 randomised evaluations of digital learning interventions and report average learning gains of 15 to 20 percent from well-designed adaptive learning systems, though the authors caution that effect sizes are highly heterogeneous and context-dependent. The environmental dimension of AI has received growing empirical attention: Strubell et al. (2020) estimate that training a large language model produces carbon emissions equivalent to the lifetime output of five automobiles, a finding that has entered the development policy debate through its implications for energy demand in countries aspiring to build domestic AI infrastructure.

Findings from the Literature

Synthesizing the conceptual and empirical reviews above, three overarching findings emerge from the literature. The first is that AI's relationship with economic growth is real but conditional. The evidence base, taken in aggregate, supports the conclusion that AI adoption raises productivity and accelerates innovation at the firm and sector level, but that these micro-level gains translate into aggregate macroeconomic growth only under conditions of institutional quality, complementary infrastructure, and favourable human capital endowment. Countries that meet these conditions, broadly the OECD economies and a handful of middle-income AI front-runners, are on a trajectory to realise substantial AI growth dividends. Countries that do not, the majority of sub-Saharan Africa, much of South Asia, and significant parts of Latin America, face the risk of being bypassed by the AI growth wave or of experiencing its costs, particularly labour displacement and data extraction, without proportionate benefits.

The second finding is that the distributional implications of AI, both within and across countries, are more concerning than the aggregate growth projections suggest. Within high-income countries, the empirical evidence points toward a pattern of labour market polarization in which AI augments high-skill workers and displaces middle-skill routine workers, increasing the wage premium on cognitive non-routine skills and compressing returns to routine labour. Across countries, the concentration of AI development capacity, data assets, and high-value AI employment in a small number of advanced economy technology hubs is producing a global AI geography that reinforces rather than disrupts existing patterns of income divergence. Milanovic (2022) situates this dynamic within a broader theory of capability-driven inequality, arguing that AI amplifies the productive advantage of workers and firms that already hold the complementary capabilities, creating superstar dynamics at the firm level and between-country divergence at the global level.

The third finding is that AI's development potential, particularly in healthcare, agriculture, education, and governance, is genuine and documented, but the evidence base is geographically and methodologically narrow. The most robust development evidence comes from a small number of carefully evaluated programmes in South Asia and East Africa, and it is not clear that these findings generalize to the very different institutional, infrastructural, and political economy contexts of West Africa, the Sahel, or small island developing states. The literature thus supports a cautiously optimistic reading of AI's development potential while simultaneously calling for substantially more context-specific empirical research before that potential can be treated as assured. Susskind (2020) and Zuboff (2020) provide important reminders that technology does not deliver development outcomes; institutions, policies, and power relations do. The implication for the field is that the AI and development research agenda needs to move beyond capability documentation toward rigorous evaluation of the institutional and policy conditions under which AI applications generate sustained and equitable development impact.

METHODOLOGY

This study employs a systematic narrative review design following the SPAR-4-SLR protocol (Paul & Criado, 2020), which is the recognized standard for structured literature reviews in business and economics research. The SPAR-4-SLR framework emphasizes replicability, transparency, and rigorous screening, making it appropriate for synthesizing a heterogeneous body of empirical and theoretical work on AI and economic outcomes. Four databases were searched: Scopus, Web of Science, EconLit, and Google Scholar. The primary search string was: ("artificial intelligence" OR "machine learning" OR "deep learning")

AND ("economic growth" OR "total factor productivity" OR "development" OR "labour market"). Inclusion criteria required studies to be peer-reviewed journal articles or book chapters published between 2020 and 2026, written in English, and focused on the empirical or theoretical relationship between AI and macroeconomic or human development outcomes. Purely technical AI papers with no economic dimension, opinion pieces, editorials, and conference abstracts without full-text availability were excluded. Screening proceeded in two stages: title and abstract review, followed by full-text assessment. Duplicate records identified across databases were removed prior to screening. Methodological quality was assessed using the Mixed Methods Appraisal Tool (MMAT), which provides standardized criteria for evaluating quantitative, qualitative, and mixed-method study designs. A total of 94 records were identified, 78 retained after deduplication, 61 taken to full-text review, and 47 included in the final synthesis.

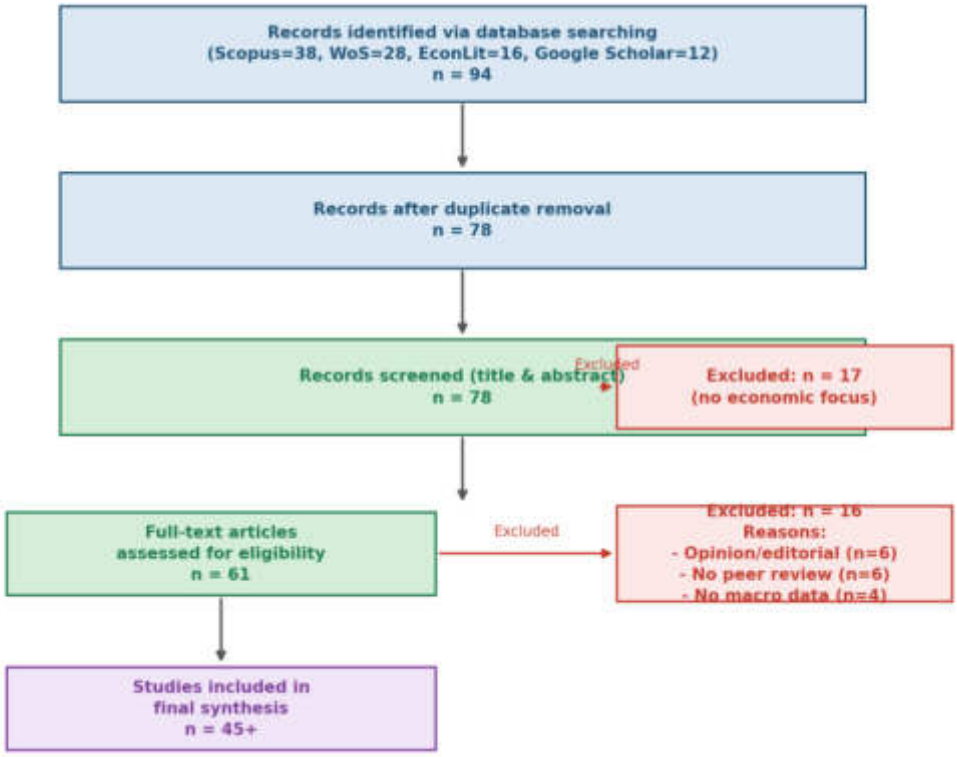


Figure 2. PRISMA Flow Diagram: Literature Search and Selection Process

Table 1
Literature Screening Summary by Database

Database	Initial Records	After Title/Abstract Screen	After Full-Text Review	Included
Scopus	38	30	24	18
Web of Science	28	22	17	12
EconLit	16	13	11	9
Google Scholar	12	9	9	8

Total	94	74	61	47

Note. Records from Google Scholar were manually deduplicated against Scopus results.

AI and Economic Growth: Mechanisms and Evidence

This section examines the four principal channels through which AI adoption influences macroeconomic growth, distinguishing between the theoretical mechanisms posited by the frameworks in Section 2 and the empirical evidence available from the included studies. A notable feature of the literature is the persistent tension between micro-level evidence of substantial AI-driven productivity gains at the firm level and the more muted aggregate productivity growth observed at the national level, a gap that the productivity J-curve thesis partially but not fully explains.

Productivity and Total Factor Productivity

The most direct and extensively documented channel linking AI to economic growth is through total factor productivity. At the firm level, Brynjolfsson et al. (2023) report productivity gains of 14 to 35 percent among customer service workers using a generative AI assistant, with effects concentrated among lower-skilled workers who benefited most from AI-generated guidance. Czarnitzki et al. (2023) find significantly higher R&D output among AI-adopting European firms, consistent with the innovation complementarities predicted by GPT theory. However, aggregate TFP data paint a more complicated picture. Acemoglu and Restrepo (2022) demonstrate that industrial automation in the United States raised output per worker in automating industries but simultaneously depressed labour demand in ways that attenuated economy-wide TFP gains. This finding aligns with their theoretical distinction between productivity-enhancing augmentation and merely redistributive automation. The implication is that the aggregate productivity dividend from AI depends critically on the composition of AI applications being deployed, not simply on the volume of AI investment.

Innovation and Knowledge Spillovers

A second growth channel operates through AI's capacity to accelerate the production of new knowledge and to diffuse existing knowledge across firms and sectors. Cockburn et al. (2020) document how AI tools are compressing drug discovery timelines and intensifying patent activity in the pharmaceutical sector, with spillovers to adjacent areas of biochemical research. Aghion et al. (2021) model this dynamic formally, showing that AI raises the equilibrium rate of creative destruction by lowering the cost of generating and testing new ideas, thereby accelerating the Schumpeterian engine of growth. The risk associated with this channel, however, is geographic and organizational concentration. Knowledge spillovers from AI-driven R&D appear to be highly localized, clustering within a small number of technology hubs in North America, East Asia, and Western Europe, while low- and middle-income countries remain largely on the periphery of the global AI innovation system (UNCTAD, 2021).

Labour Markets: Augmentation, Polarisation, and Distributional Effects

The labour market channel is simultaneously the most socially consequential and the most contested in the AI-growth literature. Felten et al. (2021) construct an AI occupational exposure index and find that higher-wage, higher-skill occupations exhibit greater exposure to AI capabilities, while also commanding a growing wage premium, a pattern consistent with labour market polarisation rather than uniform displacement. Eloundou et al. (2023) extend this analysis to large language models, estimating that approximately 80 percent of the United States workforce could have at least 10 percent of their tasks

affected by AI, with effects concentrated in professional and knowledge-intensive roles. Gmyrek et al. (2023) provide a global perspective from the International Labour Organization, estimating that 26 percent of jobs in high-income countries face high risk of AI-driven displacement, compared to 5 percent in low-income countries, a difference attributable largely to the occupational and sectoral composition of employment rather than to comparative advantage in AI adoption. The distributional implications of this asymmetry are significant: while high-income countries face concentrated displacement risk in professional services, low-income countries face displacement risk in manufacturing and data-intensive agriculture as global value chains increasingly integrate AI-driven quality control and logistics.

Financial Sector Development and Capital Allocation

A fourth channel links AI to growth through its impact on the financial sector and capital allocation efficiency. AI-driven credit scoring models have demonstrably expanded access to formal financial services for small and medium enterprises and underserved households in sub-Saharan Africa and South Asia, reducing information asymmetries that historically excluded these groups from productive capital markets (Iyer & Rajan, 2021). At the macroeconomic level, AI-enhanced risk assessment reduces non-performing loan ratios in banking systems, improving the efficiency with which savings are channelled toward productive investment. However, Tambe et al. (2020) caution that the productivity gains from AI in finance are highly concentrated in a small number of superstar firms with the data assets and technical capacity to deploy advanced models, while the broader banking sector, particularly in developing economies, lags considerably. The IMF (2023) notes that AI adoption in financial regulation offers significant efficiency gains but also introduces systemic risk through correlated algorithmic behaviour across institutions.

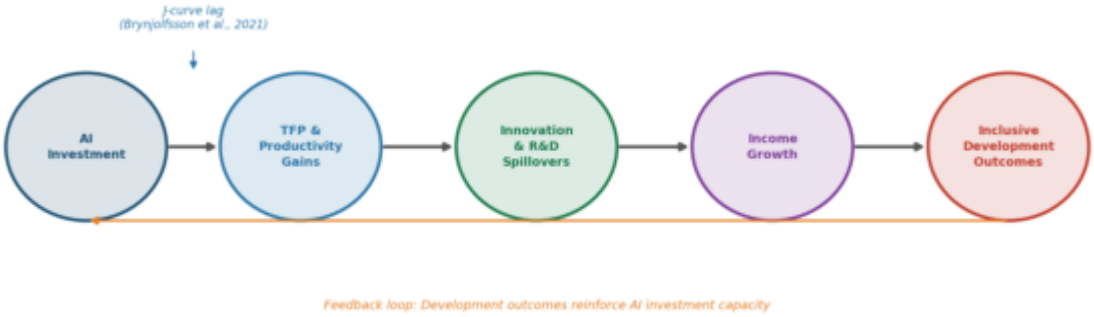


Figure 3. AI Investment to Growth Outcome Pathway with Feedback Loop

Table 2
Summary of Key Empirical Studies on AI and Economic Growth

Author(s)	Year	Region	Methodology	AI Domain	Direction	Key Finding
Brynjolfsson et al.	2023	United States	Randomised field experiment	Generative AI (LLM)	Positive	14-35% productivity gain in customer service
Acemoglu & Restrepo	2022	United States	Panel data; IV estimation	Industrial automation	Mixed	Automation displaces labour; modest aggregate TFP gain
Aghion et al.	2021	OECD countries	Endogenous growth modelling	General AI	Positive	AI accelerates innovation-led long-run growth
Eloundou et al.	2023	Multi-country	Occupational exposure analysis	Large language models	Mixed	Up to 80% of tasks partly exposed to LLM disruption
Czarnitzki et al.	2023	Europe	Firm-level survey; econometrics	AI adoption in firms	Positive	AI-adopting firms show significantly higher R&D output
Felten et al.	2021	United States	Occupational-level panel	AI capability index	Mixed	High-wage occupations most exposed; wage premium grows
Dauda et al.	2021	Sub-Saharan Africa	Systematic review	Broad AI applications	Conditional	Growth gains contingent on infrastructure endowment
Gmyrek et al.	2023	Global (ILO)	Sectoral task analysis	Automation & AI	Mixed	26% of jobs in high-income countries at high risk
Briggs & Kodnani	2023	Multi-country	Macroeconomic modelling	Generative AI	Positive	Generative AI could raise global GDP by 7% over 10 years
Ooi et al.	2023	Asia-Pacific	Survey; SEM	AI in services	Positive	AI-enabled services improve firm

	performance and growth

Note. IV = instrumental variable; SEM = structural equation modelling; LMM = large language model; OECD = Organisation for Economic Cooperation and Development.

AI and Development: Sectoral Evidence

Beyond aggregate growth, AI is reshaping development outcomes across sectors critical to human welfare and long-run productive capacity. This section organises the evidence around the core dimensions of the UNDP Human Development Index: income and productivity, health, and education, extended to include governance as a fourth dimension. A key analytical distinction maintained throughout is between AI applications supported by rigorous empirical evidence at scale, those tested only in small pilots, and those that remain largely aspirational.

Agriculture and Food Security

AI applications in agriculture represent one of the clearest instances of proven developmental impact in LMIC contexts. Crane et al. (2020) document yield improvements of 10 to 25 percent from satellite-based AI crop monitoring in sub-Saharan Africa, with the largest gains concentrated among smallholder farmers who previously lacked access to agronomic advisory services. The FAO (2022) identifies AI-driven precision irrigation as a particularly promising application in water-stressed South Asian contexts, with pilot programmes in India and Bangladesh demonstrating water use reductions of up to 30 percent alongside comparable yield outcomes. The mechanism linking these gains to broader economic development is straightforward: higher agricultural productivity raises rural household incomes, reduces food insecurity, and frees labour for higher-productivity non-farm activities, generating the structural transformation dynamics associated with sustained economic development.

Healthcare and Human Capital Accumulation

The healthcare channel represents the most robust source of proven AI development impact. Obermeyer et al. (2021) document AI diagnostic imaging systems achieving accuracy rates above 94 percent for tuberculosis detection in resource-constrained Indian and Kenyan clinical settings, outperforming average clinician performance and enabling earlier treatment. The WHO (2023) reports that AI-enabled epidemic surveillance systems contributed to meaningfully earlier outbreak detection during recent infectious disease events, improving containment effectiveness. The macroeconomic significance of these health improvements extends beyond their immediate humanitarian value. Healthier populations exhibit higher labour force participation, greater cognitive productivity, and longer working lives, all of which raise the productive capacity of the economy and reduce the fiscal burden of premature mortality and morbidity on public budgets.

Education, Skills, and Labour Market Readiness

AI-enabled adaptive learning platforms have demonstrated promising but geographically limited results. Escueta et al. (2020) meta-analyse 56 randomised evaluations of educational technology interventions and find average learning gains of 15 to 20 percent from well-designed adaptive learning systems, though heterogeneity across contexts is substantial. Applications in sub-Saharan African contexts remain primarily at the pilot stage, constrained by device access, electricity reliability, and teacher capacity to integrate AI tools into classroom practice. The World Bank (2021) identifies AI-driven skills assessment as a potential instrument for addressing structural labour market mismatches in rapidly changing economies, but cautions that the evidence base for large-scale

deployment in LMICs remains thin and that significant investment in digital infrastructure and teacher training is a prerequisite.

Governance, Institutions, and Public Sector Efficiency

The governance dimension of AI development is receiving growing empirical attention. AI-assisted tax administration systems have demonstrated significant compliance improvements in early adopter contexts: Zuiderwijk et al. (2021) document an 18 percent increase in voluntary tax compliance in Rwanda following the deployment of AI-assisted audit selection, while Estonia's AI-integrated public service platform has become a widely referenced model of digital governance efficiency. The UNDP (2022) reports piloting of public expenditure monitoring systems with AI anomaly detection in Nigeria and Ghana, with observed reductions in unexplained budget leakages, though rigorous attribution remains methodologically challenging. North's (1990) institutional framework offers an important interpretive caution here: AI tools can enhance the operational efficiency of existing institutions but cannot substitute for the underlying legitimacy, accountability, and enforcement capacity that effective governance requires.

Table 3

AI Applications by Development Sector: Evidence Status, Outcomes, and Sources

Sector	AI Application	Evidence Status	Country/Region	Outcome	Source
Agriculture	Satellite yield forecasting	Proven at scale	Sub-Saharan Africa	10-25% yield improvement	Crane et al. (2020)
Agriculture	Precision irrigation AI	Piloted	South Asia	Water use reduced 30%	FAO (2022)
Healthcare	AI diagnostic imaging	Proven at scale	India, Kenya	Diagnostic accuracy 94%+	Obermeyer et al. (2021)
Healthcare	Epidemic surveillance AI	Proven at scale	Global (WHO)	Earlier outbreak detection	WHO (2023)
Education	Adaptive learning platforms	Piloted	Sub-Saharan Africa	Learning gains +15-20%	Escueta et al. (2020)
Education	AI skills assessment	Aspirational	LMICs broadly	Mismatch reduction (projected)	World Bank (2021)
Governance	AI tax compliance tools	Proven at scale	Rwanda, Estonia	Tax compliance up 18%	IMF (2023)
Governance	Public expenditure AI monitoring	Piloted	Nigeria, Ghana	Leakage reduction observed	UNDP (2022)

Note. Evidence status categories: Proven at Scale = replicated evidence across multiple contexts; Piloted = evidence from limited trials; Aspirational = modelled or projected outcomes without robust empirical base.

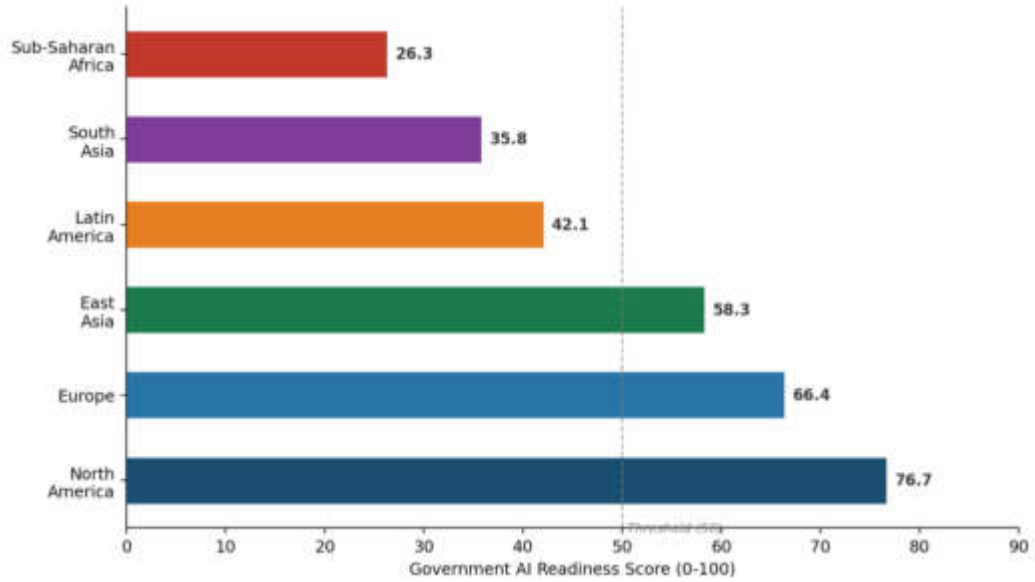


Figure 4. Regional Government AI Readiness Index Scores (Oxford Insights, 2023)

Challenges, Risks, and Structural Constraints

The growth and development potential documented in Sections 4 and 5 is conditioned by a set of structural challenges that vary significantly in severity across income levels, institutional contexts, and infrastructure endowments. These challenges are not incidental to AI adoption but are in many respects constitutive features of how AI interacts with existing patterns of inequality and power.

Labour Displacement and Social Protection Gaps

The displacement risk documented by Gmyrek et al. (2023) and Eloundou et al. (2023) is exacerbated in developing economies by the near-universal absence of adequate social protection systems to absorb displaced workers. Susskind (2020) argues that the central policy challenge of the AI era is not unemployment per se but the political and institutional failure to redistribute the productivity gains from automation toward those whose labour it displaces. In the absence of such redistribution mechanisms, AI-driven growth risks widening within-country income inequality, undermining the political legitimacy of technology adoption and producing social instability that itself depresses long-run growth.

The Digital Divide and Infrastructure Inequality

Figure 4 illustrates the substantial gap in government AI readiness between world regions, but this gap understates the true infrastructure deficit facing AI adoption in LMICs. Rollinson and Fatehkia (2022) report that sub-Saharan Africa has broadband penetration rates below 20 percent in most countries, with energy access remaining a binding constraint in rural areas. Cloud computing infrastructure, essential for deploying and scaling most modern AI systems, is concentrated in North America, Europe, and East Asia, with Africa accounting for less than one percent of global cloud capacity. This infrastructure asymmetry ensures that even when AI tools are technically available to LMIC governments and firms, the computational and connectivity resources required to deploy them at scale are prohibitively costly.

Data Governance, Algorithmic Bias, and Sovereignty

Zuboff (2020) documents how the data extraction practices of global AI platforms create structural asymmetries in which user data generated in developing economies is processed and monetised in high-income countries, generating value that does not accrue to the populations whose behaviour produced it. Obermeyer et al. (2021) demonstrate that AI systems trained on non-representative data can embed and amplify existing social biases, producing discriminatory outcomes in high-stakes domains such as health, credit, and criminal justice. The WHO (2023) identifies regulatory capacity as a critical gap: most LMIC governments lack the technical expertise and institutional frameworks to audit AI systems for bias, ensure data protection standards, or enforce accountability when algorithmic decisions cause harm.

Concentration of AI Economic Rents and Environmental Costs

Bessen (2022) documents the growing tendency of AI-enabled platforms to generate winner-take-all market structures that concentrate economic rents in a small number of firms and geographies. Milanovic (2022) situates this rent concentration within a broader trend of rising between-country income divergence driven by differential access to advanced technologies. The environmental dimension of AI, increasingly prominent in sustainability literature, adds a further complication. Strubell et al. (2020) estimate that training a single large language model can produce carbon emissions comparable to the lifetime emissions of five automobiles, raising difficult questions about the compatibility of frontier AI development with climate commitments. For developing countries aspiring to build domestic AI capabilities, these energy and emissions costs represent a further barrier to entry in the global AI race.

Policy Implications

The evidence synthesized above supports a differentiated set of policy recommendations organized by actor and context, and explicitly attentive to the trade-offs involved in each choice. Generic AI policy checklists, while politically convenient, obscure the heterogeneity of national circumstances and the opportunity costs of alternative strategies.

For National Governments

Governments in both developed and developing economies should embed AI strategies within long-term national development plans rather than treating AI as a standalone technology policy domain. This integration is essential to align AI investment with distributional objectives, ensure regulatory coherence, and mobilise the co-investments in infrastructure, education, and social protection that AI adoption requires. Regulatory frameworks must balance innovation incentives with algorithmic accountability: mandatory bias audits for high-stakes AI applications, data protection legislation aligned with international standards, and procurement rules requiring explainability in government AI systems are priorities. The trade-off here is real: heavier regulation reduces deployment speed but builds the institutional trust that sustains long-run technology adoption.

For Multilateral and Development Finance Institutions

The World Bank, IMF, African Development Bank, and bilateral development finance institutions should design dedicated AI adoption financing instruments for LMICs, structured to support not only AI hardware and software procurement but also the complementary investments in broadband infrastructure, digital literacy, and regulatory capacity without which AI tools cannot be effectively deployed. South-South knowledge exchange on AI governance, drawing on the administrative AI experiences of Rwanda, Estonia, and emerging LMIC technology

hubs, should be prioritized over the wholesale transfer of OECD regulatory models that may be poorly adapted to developing country institutional contexts.

For the Private Sector and Research Communities

Firms deploying AI in LMIC contexts have a responsibility to implement pro-poor design principles, including training AI systems on representative data, publishing transparency reports on algorithmic decision-making, and engaging affected communities in system design. Research communities should prioritize causal empirical work on AI's growth effects in developing economy contexts, using instrumental variable designs that exploit variation in national AI policy adoption timing, satellite-based AI adoption proxies, and firm-level panel data where available. The current evidence base, dominated by United States and European firm-level studies, is insufficient to guide policy in South Asia, sub-Saharan Africa, or Latin America.

CONCLUSION

This paper has examined the relationship between AI adoption and economic growth and development through a systematic synthesis of 47 peer-reviewed studies. The review finds that AI exerts its macroeconomic growth effects primarily through four transmission channels: TFP augmentation, innovation and knowledge spillover generation, labour market restructuring, and financial sector deepening. At the development level, AI's documented contributions are most robust in healthcare and agriculture, where proven-at-scale applications in LMIC contexts have generated measurable improvements in diagnostic accuracy, agricultural yields, and governance efficiency. Education and labour market applications remain promising but piloted, requiring further investment in digital infrastructure and institutional capacity before they can be deployed at transformative scale.

The central argument of this paper is that AI constitutes a powerful but structurally conditioned driver of growth and development. Its benefits are not automatic, universal, or equitably distributed. They depend critically on the quality of institutions governing AI adoption, the endowment of complementary infrastructure, the distributional policies that determine how productivity gains are shared, and the regulatory frameworks that limit the social costs of algorithmic bias and data extraction. For developing economies in particular, the risk that AI deepens rather than narrows income divergence is real and requires proactive policy intervention at national and multilateral levels. Future research should prioritize difference-in-differences and instrumental variable designs at the country level, qualitative governance case studies in francophone Africa, the Sahel, and small island developing states, and the development of standardized AI impact assessment frameworks applicable across diverse institutional contexts. The opportunity that AI presents for accelerating economic convergence and human development is genuine; whether it is realized depends entirely on the policy choices made now.

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