Beyond the Factory: A Macro Reassessment of Industrial Policy and Economic Growth in the Era of Artificial Intelligence in Sub-Saharan Africa

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Abstract

Industrial policy has regained prominence on global agendas, yet evidence on its optimal design for Sub-Saharan African economies—where structural transformation has stalled, informality remains pervasive, and digitalization is accelerating—remains scarce. This paper examines whether artificial intelligence (AI) and digital connectivity are associated with shifts in economic growth and manufacturing depth at the macro level. Using a panel of 40 Sub-Saharan African countries from 2019 to 2024, we combine digital and macroeconomic indicators from the World Development Indicators, UNCTAD trade data, the Oxford Insights Government AI Readiness Index, and the Schneider–Medina shadow economy estimates. We estimate fractional logit models for a bounded economic growth index and fixed-effects specifications for manufacturing value added per capita, with country-clustered standard errors and interaction terms that test whether the growth effect of AI depends on digital infrastructure. The results reveal three main patterns. First, digital connectivity is robustly associated with higher economic growth. Second, AI readiness exhibits a negative average marginal effect on growth, a result consistent with the displacement of low-skill labor in settings with thin absorptive capacity. Third, the interaction between AI and digital connectivity is positive and significant: as connectivity deepens, the growth penalty of AI diminishes sharply. AI is, however, positively associated with manufacturing value added per capita, and intra-African trade openness exerts an effect on manufacturing that is more than twice as large as that of extra-African trade. These findings are robust to the use of the informal economy as an alternative dependent variable and to alternative AI measures. The study recommends that

industrial policy in Sub-Saharan Africa should move beyond a narrow factory-centered model and incorporate digitally enabled services, knowledge sectors, and AI-driven value chains. Policymakers should recognize that productivity gains and structural upgrading may increasingly occur in service-intensive and technology-enabled activities rather than traditional manufacturing alone.

Keywords: Industrial Policies; Digitalization; Fractional Logit Models; AI.

1. Introduction

For much of the last four decades, industrial policy was treated as an intellectual pariah—a relic of import-substitution failures that mainstream economics had rightly abandoned. That intellectual climate has shifted decisively. From the Inflation Reduction Act in the United States to the European Union's Green Deal Industrial Plan, governments in advanced economies now embrace targeted, mission-oriented interventions as legitimate instruments of structural transformation (Juhász, Lane, & Rodrik, 2023; Mazzucato, 2021). Sub-Saharan Africa (SSA) has not stood aloof from this resurgence; the African Union's Agenda 2063 and the operationalization of the African Continental Free Trade Area (AfCFTA) represent ambitious attempts to harness industrial policy for continental development. Yet the fit between the new global activism and Africa's structural realities remains deeply uneasy.

Three features of SSA economies set them apart from the contexts in which conventional industrial policy templates were forged. First, the region has experienced premature deindustrialization such that manufacturing value added as a share of GDP, which never exceeded 15 percent on average, has been drifting downward since the early 2000s and stood at just 10.6 percent in 2022 (World Bank, 2023; Rodrik, 2016). The factory floor, long the fulcrum of East Asian success, is shrinking before it has delivered mass formal employment. Second, informality is not a fringe phenomenon but the dominant mode of livelihood. According to the International Labour Organization, informal employment accounts for 85.8 percent of total employment in Africa (ILO, 2018), and the shadow economy is estimated at roughly 37 percent of GDP across SSA (Schneider & Medina, 2022). Third, the region is simultaneously undergoing a rapid, albeit uneven, digital leapfrogging. Unique mobile subscribers in SSA exceeded 500 million in 2023, mobile money transactions reached $832 billion, and internet penetration, though still only 36 percent of the population, has grown at the fastest pace of any global region (GSMA, 2024; ITU, 2023). These three facts—declining industrial employment, pervasive informality, and explosive digital uptake—define the terrain on which any twenty-first-century industrial policy for Africa must operate.

Superimposed on this landscape is the emergence of artificial intelligence. AI promises a leap in total factor productivity by improving prediction, optimising logistics, and enabling personalised services (Brynjolfsson & McAfee, 2017). In principle, such a general-purpose technology could allow SSA economies to bypass entire phases of traditional industrialisation and move directly

into high-value digital services (Banga & te Velde, 2018). Yet the very same technology is skill-biased and substitutes for routine cognitive and manual tasks—precisely the jobs that manufacturing and low-end services have historically provided to absorb surplus labour (Acemoglu & Restrepo, 2018, 2020). Where complementary digital infrastructure and human capital are thin, AI could destroy livelihoods faster than it creates new ones, swelling informal survivalist activities rather than generating formal, productive employment (Rodrik & Stantcheva, 2021; Korinek & Stiglitz, 2021). The policy puzzle is therefore stark: how should SSA design industrial policy when both factories and algorithms matter, but the region's endowments align imperfectly with either?

The empirical literature offers limited guidance. The macro-economic impact of digital connectivity has been studied across developing regions, with a small but growing body of evidence suggesting that mobile phone penetration and internet use are positively associated with growth in SSA (Haftu, 2019; Myovella, Karacuka, & Haucap, 2020). However, the specific role of AI in shaping aggregate growth, as distinct from generic digitalisation, has been examined almost exclusively through the lens of advanced and emerging economies (Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018) or through micro-level case studies of particular applications—fintech in Kenya, agritech in Nigeria, health AI in Rwanda. A macro-econometric assessment of the AI–growth nexus for SSA, grounded in a cross-country panel and attentive to structural conditioning factors, is conspicuously absent. This gap is consequential: without such evidence, policymakers oscillate between uncritical techno-optimism and defensive Luddism, neither of which constitutes a serious industrial strategy.

This paper addresses that gap by asking three interrelated questions. First, does digital connectivity boost economic growth in SSA, and, conditional on connectivity, does AI penetration help or hinder growth? Second, how does the growth effect of AI depend on the depth of a country's digital infrastructure—i.e., is the return to AI contingent on complementary digital capabilities? Third, do AI and trade openness, particularly intra-African trade, affect manufacturing value added per capita, and if so, which form of trade integration matters more?

To answer these questions, we construct a panel of 45 SSA countries covering the period 2019–2024, combining the World Development Indicators, UNCTAD trade data, the Oxford Insights Government AI Readiness Index, and the Schneider–Medina MIMIC shadow-economy estimates.

Because our primary dependent variable—a bounded economic growth index—takes values strictly within the unit interval, we employ a fractional logit model with country-clustered standard errors and interaction terms (Papke & Wooldridge, 1996). This approach respects the limited-range nature of the growth measure and allows us to test conditional hypotheses without resorting to ad-hoc transformations.

Our results reveal a nuanced picture. Digital connectivity, captured by a composite index of internet use and mobile subscriptions, is a robust and substantively large positive predictor of growth. By contrast, AI readiness enters with a negative average marginal effect, a finding consistent with the notion that, in the absence of sufficient absorptive infrastructure, AI-driven disruption outweighs productivity gains. Crucially, the interaction between digital connectivity and AI is positive and statistically significant: as digital connectivity deepens, the negative effect of AI on growth progressively weakens, and at the highest observed levels of connectivity it approaches zero. In separate regressions, we find that AI is positively associated with manufacturing value added per capita, and that intra-African trade openness exerts an effect on manufacturing that is more than twice as large as that of extra-African trade. These patterns hold under a battery of robustness checks, including the use of the shadow economy share as an alternative dependent variable and the substitution of AI readiness with an output-based AI-publication metric.

The paper makes three contributions. First, it provides the first macro-econometric evidence on the AI–growth relationship for Sub-Saharan Africa, a region that is both heavily exposed to the risks of automation and a laboratory of digital experimentation. Second, it demonstrates that the growth dividend of AI is not unconditional but depends systematically on the enabling digital ecosystem—a finding that cautions against treating AI as an all-purpose growth elixir and underscores the importance of sequencing. Third, by linking the empirical results to the debate on industrial policy, we argue that SSA governments must move beyond a narrow, factory-centred model of industrialisation and embrace a “beyond the factory” framework that deliberately integrates digitally enabled services, AI-augmented value chains, and regional trade. Productivity gains and structural upgrading, we contend, will increasingly occur in service-intensive, technology-enabled activities, not on assembly lines alone.

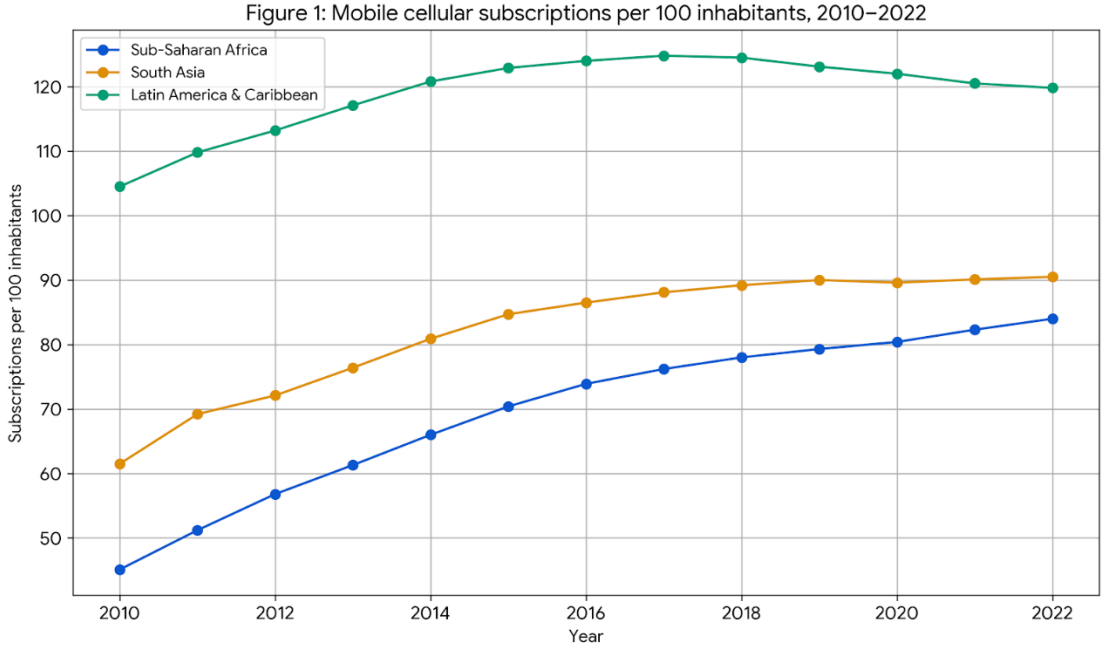
The remainder of the paper is organised as follows. Section 2 presents stylised facts that illuminate the digital, structural, and trade dynamics of SSA. Section 3 reviews the theoretical and empirical literature from which our hypotheses are derived. Section 4 details the empirical strategy and econometric rationale. Section 5 describes the data and the construction of the key variables. Section 6 reports the baseline results and interaction effects, while Section 7 subjects them to robustness checks. Section 8 discusses the implications for industrial policy design, and Section 9 concludes with limitations and avenues for future research.

2. Stylised Facts: Digitalisation, AI, and Economic Structure in Sub-Saharan Africa

2.1 The Digital Revolution: Connectivity and Its Divides

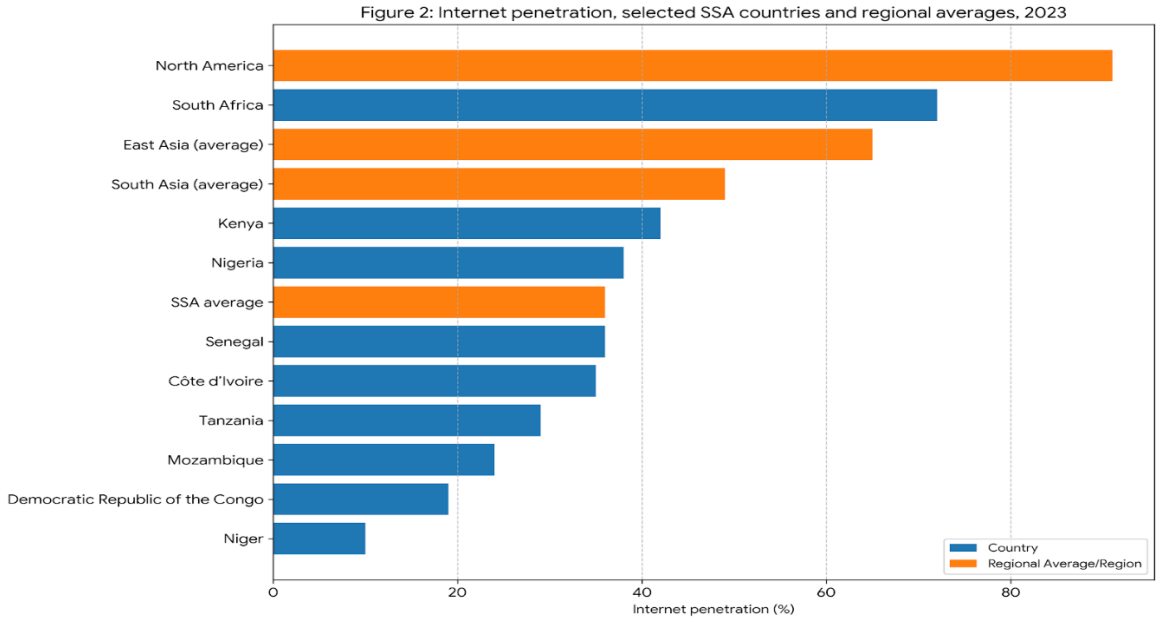
Sub-Saharan Africa has experienced one of the fastest telecommunications rollouts in modern history. In 2010, the region counted just 23 mobile cellular subscriptions per 100 inhabitants; by 2022 that figure had reached 84, a near-fourfold increase that surpassed the comparable ratios of South Asia (82) and narrowed the gap with Latin America (102) (ITU, 2023). Figure 1 plots these three trajectories from 2010 to 2022, revealing a process of aggressive convergence powered by the private-sector expansion of mobile network operators and the absence of legacy fixed-line infrastructure. The leapfrogging is real and measurable.

Figure 1: Mobile cellular subscriptions per 100 inhabitants, 2010–2022



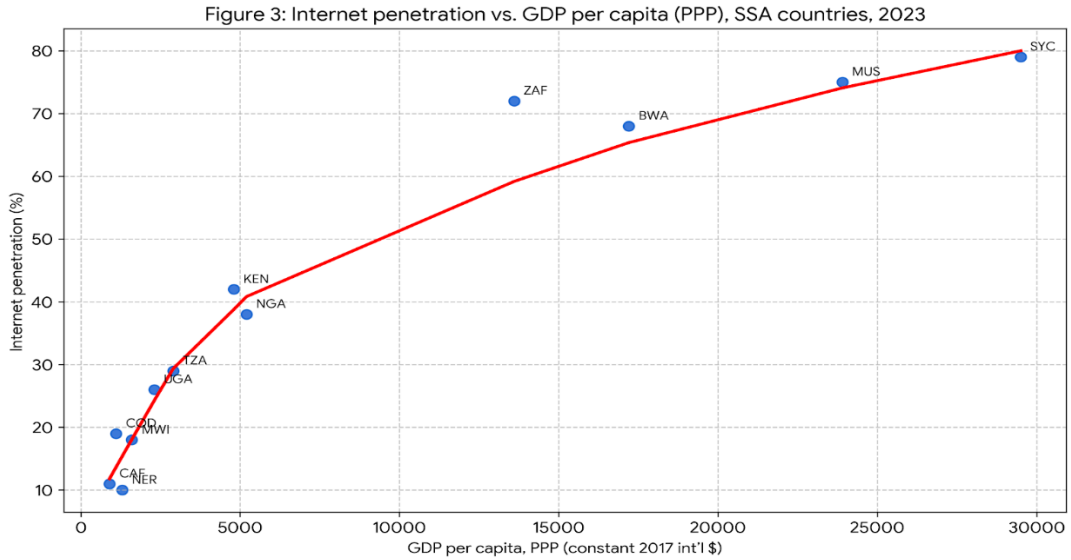
Data source: ITU World Telecommunication/ICT Indicators Database (2023 edition). Figure 1. Mobile cellular subscriptions per 100 inhabitants, 2010–2022. Sub-Saharan Africa closed the gap with South Asia, while Latin America experienced saturation and a slight decline after 2017. (Source: ITU, 2023)

Yet the digital revolution in Africa is not merely about phones; it is about what the phones carry. Internet penetration climbed from 6.4 percent of the population in 2010 to 36 percent in 2023, again the steepest growth rate of any global region (ITU, 2023). A cross-sectional bar chart (Figure 2) for 2023 would nevertheless expose a brutal digital divide: the SSA average of 36 percent sits substantially below South Asia's 49 percent, East Asia's 65 percent, and the near-saturation of 91 percent in North America. Within the region, the dispersion is starker. South Africa (72 percent) and Kenya (42 percent) occupy the top tier, while the Democratic Republic of the Congo (19 percent) and Niger (10 percent) anchor the bottom.



Data source: ITU, "Individuals using the Internet (% of population)", 2023. Figure 2. Internet penetration (% of population), 2023. Sub-Saharan Africa's average masks severe internal disparities. (Source: ITU, 2023)

A scatter plot of internet penetration against GDP per capita (Figure 3) shows that the correlation is positive and tight at low-income levels ($r = 0.65$), but the explanatory power of income wanes once middle-income status is approached, suggesting that policy and regulatory choices matter at least as much as national wealth.



Data source: Internet penetration from ITU (2023); GDP per capita, PPP (constant 2017 international $) from World Bank, World Development Indicators. Figure 3. Internet penetration and GDP per capita in Sub-Saharan Africa, 2023. The relationship is positive but weakens at higher income levels. (Sources: ITU, 2023; World Bank, 2023)

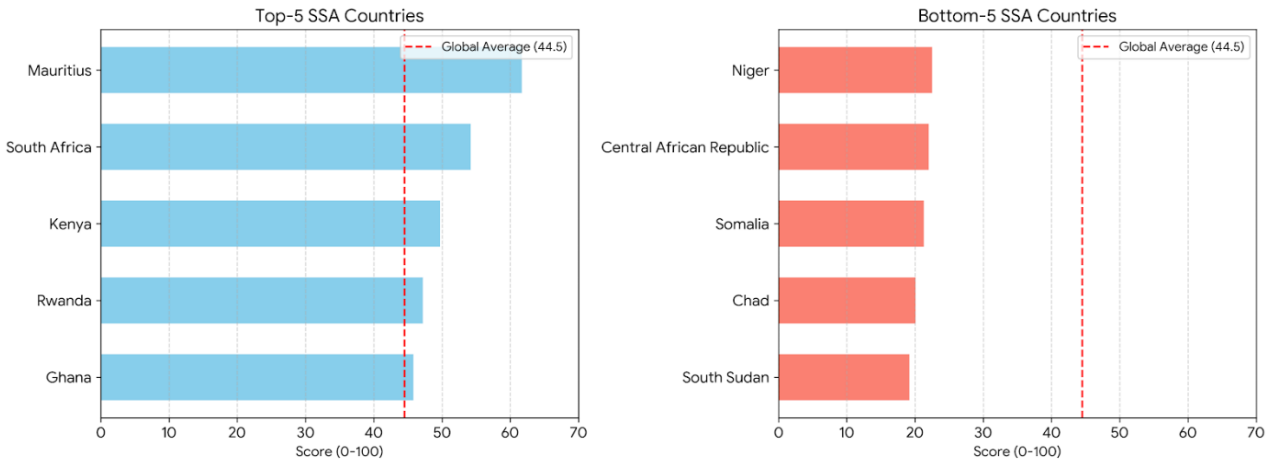
The single most transformative digital innovation, however, is mobile money. The numbers are staggering. In 2023, Sub-Saharan Africa hosted 548 million registered mobile money accounts that processed $832 billion in transactions, roughly equivalent to 37 percent of the region's GDP (GSMA, 2024). Kenya, the global pioneer, reports that 73 percent of adults hold a mobile money account; Tanzania and Ghana follow at 43 and 39 percent, respectively (World Bank Global Findex, 2021). The figure that best captures this landscape is a heat map of the continent, shading countries by the share of adults who have made or received a digital payment in the past year. The deep colours of East and parts of West Africa contrast with the pale hues of Central Africa, illustrating that even a digital miracle has uneven geography.

For all the optimism, these patterns carry a sharp analytical edge. Digital connectivity, as Haftu (2019) and Myovella et al. (2020) have shown in panel studies, is positively associated with economic growth in SSA, primarily through the reduction of transaction costs and the expansion of market access. But the evidence also points to conditioning factors: the growth dividend of connectivity is significantly larger in countries with higher levels of human capital and more reliable electricity (Donou-Adonsou, 2019). This insight—that connectivity's return depends on complementary infrastructure—will prove central when we turn to AI.

2.2 Artificial Intelligence Readiness: Enthusiasm Meets Infrastructure Deficit

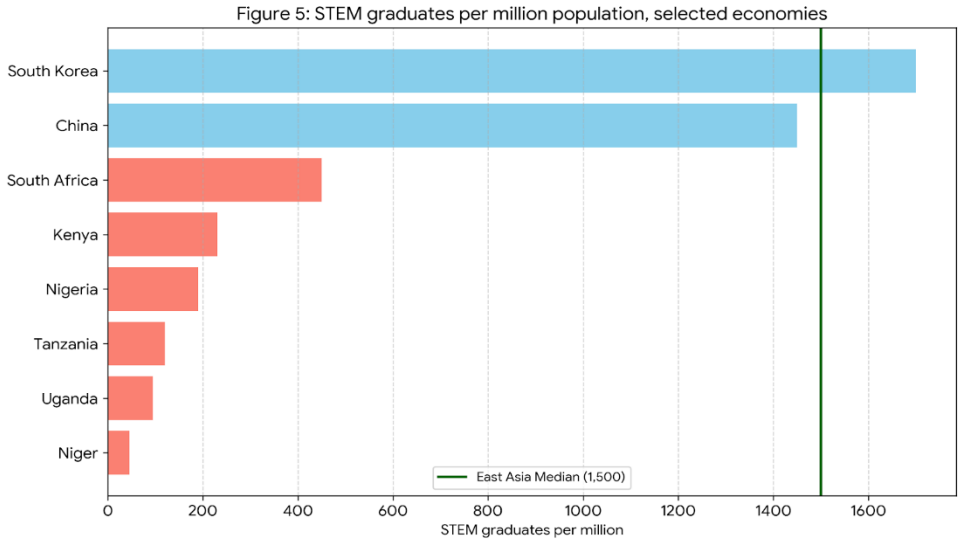
If the connectivity story is one of remarkable catch-up, the AI story is one of aspiration running far ahead of capacity. The Oxford Insights Government AI Readiness Index for 2023, which aggregates indicators of governance, infrastructure, data availability, and skills, places the SSA average at just 28.8 out of 100, compared with a global average of 44.5 and a North American average of 78.3 (Oxford Insights, 2023). Figure 4 would display the top and bottom five SSA countries: Mauritius (61.7), South Africa (54.2), and Kenya (49.7) lead, while South Sudan (19.2), Chad (20.1), and Somalia (21.3) bring up the rear. Even the leaders, it must be said, sit well below the global median.

Figure 4: Government AI Readiness Index, top-5 and bottom-5 SSA countries, 2023



Data source: Oxford Insights, Government AI Readiness Index 2023. Figure 4. Government AI Readiness Index, selected Sub-Saharan African countries, 2023. Even the regional leaders fall below the global mean. (Source: Oxford Insights, 2023)

This index, of course, measures readiness, not actual diffusion. To gauge the human capital that AI both demands and deepens, one can turn to UNESCO data on graduates from science, technology, engineering, and mathematics programmes. The regional median hovers around 200 STEM graduates per million population, a figure that looks anaemic against the 1,500 typical of East Asian economies (UNESCO, 2022). Plotting these numbers as a bar chart (Figure 5) beside AI readiness underscores a fundamental mismatch: the aspirations set out in national AI strategies—by 2024, over 15 SSA countries had published or drafted such strategies—are not yet underpinned by the training pipelines needed to make them operational.



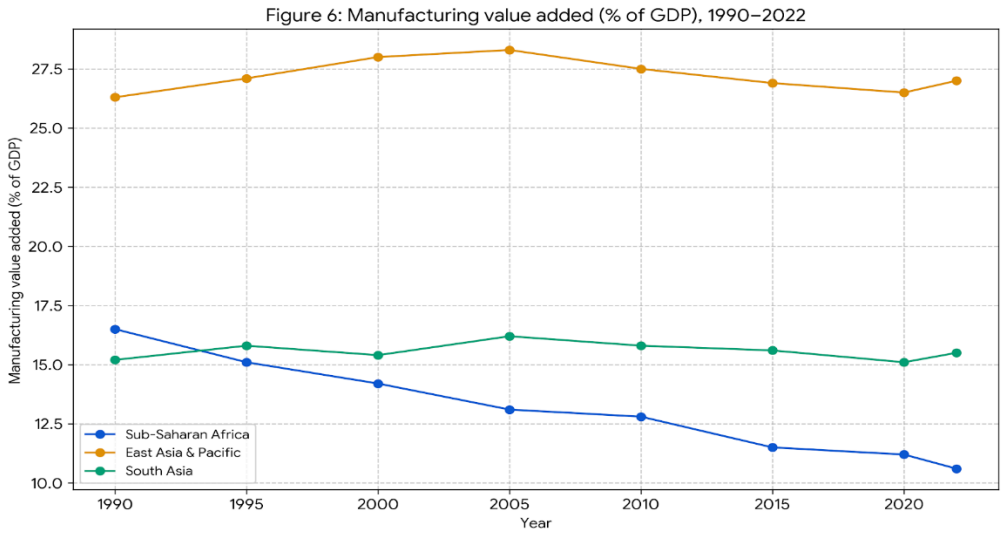
Data source: UNESCO Institute for Statistics (2022), extracted from UIS.Stat. For East Asia, median of Japan, South Korea, China, and Vietnam.

Figure 5. STEM graduates per million population, Sub-Saharan African countries compared with East Asian economies. (Source: UNESCO Institute for Statistics, 2022)

Physical infrastructure compounds the deficit. Only 48 percent of the SSA population had access to electricity in 2022 (World Bank, 2023), and less than 2 percent of the world's colocation data centres are located on the continent (IEA, 2022). Large language models and real-time machine-learning applications require compute resources that are, for now, largely imported at prohibitive cost. Korinek and Stiglitz (2021) caution that the very nature of AI—its reliance on proprietary data, cloud computing, and intellectual property concentrated in a handful of firms—risks reinforcing international technological dependency. That risk is nowhere more palpable than in Africa.

2.3 Premature Deindustrialisation and the Persistence of Informality

The digital acceleration occurs against a backdrop of structural transformation that has, to put it charitably, stalled. Manufacturing value added as a share of GDP in SSA peaked at around 16.5 percent in the early 1990s and has since traced a gentle but unmistakable downward slope, settling at 10.6 percent in 2022 (World Bank, 2023). By contrast, East Asia and the Pacific held firm at 27 percent; South Asia, starting from a similar 15 percent, has drifted modestly upward. Figure 6 would draw these lines from 1990 to 2022, and the visual would be painful: the African trajectory is the mirror image of the East Asian miracle.



Data source: World Bank, World Development Indicators, series NV.IND.MANF.ZS. Figure 6. Manufacturing value added as a share of GDP, 1990–2022. Sub-Saharan Africa traces a path of premature deindustrialisation. (Source: World Bank, WDI, 2023)

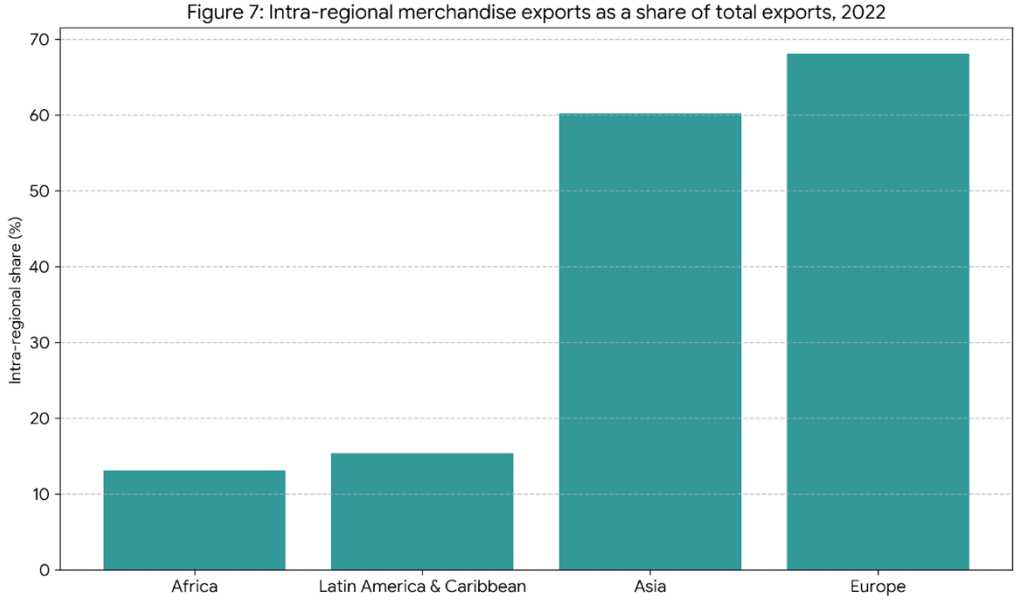
Rodrik (2016) labelled the phenomenon "premature deindustrialisation", and the term has stuck because it captures a crucial loss—the evaporation of the formal, productivity-enhancing employment that factories once promised. Employment data reinforce the picture. According to the ILO (2020), manufacturing accounts for just 6.6 percent of total employment in SSA, a share that has barely budged in twenty years. The overwhelming majority of workers—85.8 percent—labour in the informal economy (ILO, 2018), often in low-productivity services and petty trade. Schneider and Medina (2022) estimate that the shadow economy absorbs roughly 37 percent of official GDP in the region, a proportion that has declined only slowly. If industrial policy is to remain relevant, it must reckon with this fact: the typical African worker is not in a factory; she is running a micro-enterprise, selling produce at a roadside stall, or offering her labour through a digital platform. The factory-centric model does not describe her reality.

2.4 Trade Patterns and the African Continental Free Trade Area

Trade data offer a glimmer of strategic possibility. Sub-Saharan Africa trades remarkably little with itself. Intra-African merchandise exports stood at just 13.1 percent of the continent's total exports in 2022, compared with 68 percent for intra-European trade and 60 percent for intra-Asian trade (UNCTAD, 2023). A simple bar chart (Figure 7) depicts the bar for Africa as a stub, while

those for Europe and Asia stretch across the page. Yet the goods that do cross African borders are disproportionately manufactured: processed food, apparel, chemicals, and machinery.

Figure 7: Intra-regional merchandise exports as a share of total exports, 2022



Data source: UNCTADstat, "Intra-regional trade in goods as a percentage of total exports", 2023. Figure 7. Intra-regional merchandise exports as a percentage of total exports, 2022. Africa trades far less with itself than any other major developing region. (Source: UNCTADstat, 2023)

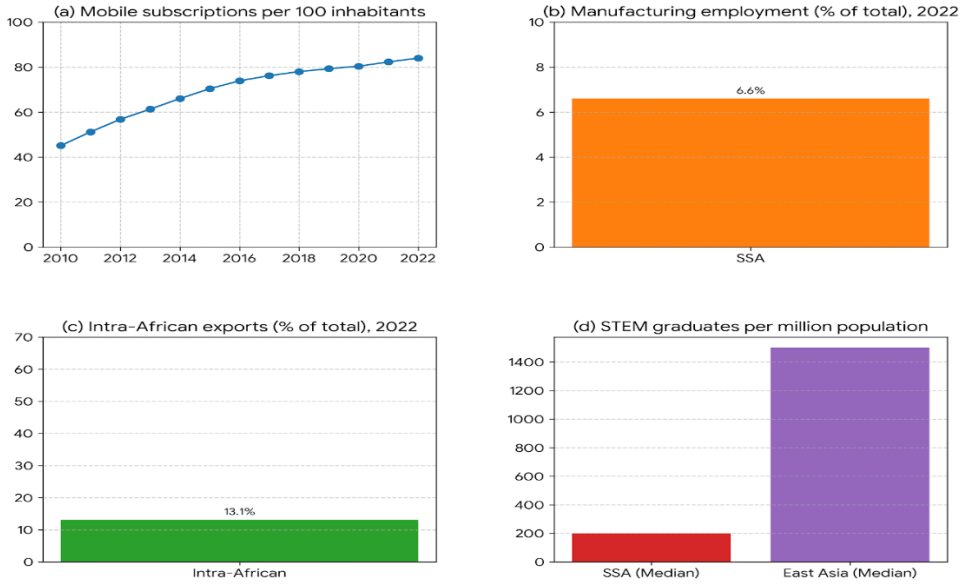
According to the African Development Bank (2022), manufactured goods represent over 40 percent of intra-African trade but barely 15 percent of Africa's exports to the rest of the world. In other words, the demand of neighbouring countries pulls in exactly the high-value-added products that development policy seeks to promote.

This is where the African Continental Free Trade Area enters the calculus. UNECA (2021) projects that full implementation could boost intra-African trade by 52 percent by 2025, with the largest gains accruing to industrial sectors. The mechanism is scale: a genuinely integrated market of 1.4 billion people makes regionally distributed manufacturing networks viable and, crucially, provides a testing ground for AI-enhanced logistics, quality assurance, and cross-border payment systems. The contrast between intra-African and extra-African trade openness, which will feature prominently in my econometrics, is thus not merely a statistical artifact; it reflects the developmental potential of continental demand.

2.5 Putting the Pieces Together: A Landscape of Contradictions

Figure 8 is a panel of four miniature charts arranged in a grid, that shows the steep upward slope of mobile subscriptions, the flatlining of manufacturing employment, the low but rising bars of intra-African trade, and the tiny sliver of the labour force with tertiary STEM qualifications. The image would be one of radical asynchrony. Digital infrastructure races ahead, while the industrial structure that might absorb the labour force languishes; trade policy opens up unprecedented regional market access, while the skills needed to exploit it remain scarce.

ure 8: A snapshot of contradictions: rapid digital uptake, stagnant industrial employment, low intra-African trade, and acute skills shortag



A snapshot of contradictions: rapid digital uptake, stagnant industrial employment, low intra-African trade, and acute skills shortages. (Sources: as per individual panels)

These contradictions are the empirical terrain on which the hypotheses of this paper stand. They suggest that digital connectivity might well be a robust engine of growth, but they also hint that AI, dropped into a thin digital and institutional soil, could disrupt more than it creates. The positive correlation between connectivity and economic performance, and the likely negative unconditional effect of AI is a proposition about how these pieces fit together.

3. Theoretical Framework and Literature Review

The framework is explicitly macroeconomic and focuses on the channels through which digital connectivity and AI enter the aggregate production function, the conditions under which their

effects are likely to be complementary, and the role of trade integration in mediating structural outcomes.

3.1 The Return of Industrial Policy and Africa's Structural Exceptionalism

For much of the late twentieth century, industrial policy was dismissed as an anachronism—a distortionary relic of import-substitution that bred rent-seeking rather than productivity (Krueger, 1990). The intellectual climate has shifted. The success of East Asian developmental states, the global financial crisis, and the rise of China have together rehabilitated the case for targeted government intervention (Rodrik, 2004; Aiginger & Rodrik, 2020). In advanced economies, the language of "mission-oriented" industrial policy now enjoys near-consensus, as governments deploy billions to secure technological leadership in semiconductors, green hydrogen, and artificial intelligence (Mazzucato, 2021; Juhász, Lane, & Rodrik, 2023). The policy question has moved from *whether* to intervene to *how* and *in which sectors*.

Sub-Saharan Africa, however, enters this conversation with a structural profile that differs fundamentally from the settings in which industrial policy orthodoxies were forged. Rodrik (2016) has documented that manufacturing employment shares in Africa and Latin America have been peaking at levels far below those achieved by East Asia, and at much lower incomes—a phenomenon he terms "premature deindustrialisation." McMillan, Rodrik, and Verduzco-Gallo (2014) demonstrate that labour has been moving from higher-productivity agricultural and extractive sectors into low-productivity urban services, reversing the growth-enhancing structural change that characterised the Asian miracles. The result is that the factory floor, long the central object of industrial policy, employs a mere 6.6% of the region's workforce (ILO, 2022) and continues to shrink. Any industrial policy for SSA must therefore reckon with the uncomfortable possibility that the traditional manufacturing escalator may no longer carry the weight it once did.

At the same time, digital technologies are reshaping the very meaning of industrial activity. Services that were once non-tradable and labour-intensive—data annotation, software development, customer support, and financial analysis—are now traded across borders through digital platforms (Baldwin, 2016). This "servicification" of production implies that the boundary between manufacturing and services is increasingly porous, and that high-value-added activities may reside in digitally enabled tasks rather than physical assembly (Baldwin & Forslid, 2020). The challenge for African policymakers is therefore not simply to rebuild the factory, but to

reimagine the entire architecture of production in an era when algorithms and data are factors of production.

3.2 Digital Connectivity as a Growth Enabler

The literature on information and communication technology (ICT) and economic growth provides a robust starting point. In a neoclassical growth framework, digital connectivity can be understood as a type of efficiency-enhancing technology that reduces transaction costs, improves information flows, and expands market access. Let aggregate output Y be determined by a standard Cobb-Douglas production function augmented by a technological efficiency parameter Ω:

$$Y = \Omega \cdot K^{\alpha}(hL)^{1-\alpha} \qquad (1)$$

where K denotes physical capital, L is labour, and h is human capital per worker. Digital connectivity D enters as a shifter of Ω, such that $\Omega = \Omega_0 e^{\beta_1 D}$, with $\beta_1 > 0$. The mechanism operates through several channels: lower search and matching costs, greater financial inclusion via mobile money, improved supply-chain logistics, and enhanced access to knowledge (Paunov & Rollo, 2016; Haftu, 2019).

Empirical work confirms a positive association between mobile penetration, internet use, and GDP per capita growth in Sub-Saharan Africa. Haftu (2019), using a system-GMM panel of 40 SSA countries, finds that a 10% increase in mobile phone penetration raises per capita GDP growth by 0.6–0.8 percentage points. Myovella, Karacuka, and Haucap (2020) report comparable elasticities for a broader set of digital indicators, noting that the growth dividend is larger in SSA than in OECD economies, likely because the marginal benefit of connectivity is highest where physical infrastructure is scarcest. These findings are broadly consistent with the notion that digitalisation acts as a "general-purpose technology" that permeates multiple sectors (Bresnahan & Trajtenberg, 1995).

However, the growth return to connectivity is not unconditional. Donou-Adonsou (2019) demonstrates that the effect of internet penetration on growth in SSA is significantly stronger in countries with higher levels of secondary education and more reliable electricity supply. This insight—that digital infrastructure requires complementary human and physical capital—will prove central when we turn to AI. It suggests that while digital connectivity D is unambiguously

positive on average, its full potential is realised only when enabling conditions are present. This yields the first hypothesis:

H_1: Digital connectivity is positively associated with economic growth in Sub-Saharan Africa.

3.3 Artificial Intelligence: Automation, Augmentation, and Ambiguity

If digital connectivity is a relatively well-understood enabler, artificial intelligence introduces deep ambiguity. Conceptually, AI can be modelled as a technology that automates a subset of tasks previously performed by labour, while simultaneously creating demand for new, complementary tasks (Acemoglu & Restrepo, 2018, 2019). Let the production process consist of a continuum of tasks $x \in [0,1]$. Tasks with index $x \leq \theta$ are automated and can be performed by AI-capital at low marginal cost, while tasks $x > \theta$ require human labour. The aggregate productivity effect of AI depends on the balance between the displacement of labour from automated tasks and the creation of new labour-intensive tasks at the upper end of the distribution.

In advanced economies, where human capital is abundant and labour markets are flexible, the net effect of AI has been modestly positive, though highly uneven across skill groups (Acemoglu & Restrepo, 2020; Brynjolfsson & McAfee, 2017). In developing economies, the calculus is different. Korinek and Stiglitz (2021) argue that AI-driven automation threatens to undermine the comparative advantage of labour-abundant countries by eroding the cost advantage of low-skill manufacturing. If robots can assemble garments more cheaply than African workers, the industrialisation path that lifted millions out of poverty in East Asia may be foreclosed. Rodrik and Stantcheva (2021) formalise this concern, showing that premature automation can trap economies in a low-productivity equilibrium where displaced workers are absorbed into informal, non-tradable services rather than formal manufacturing.

There are, however, countervailing forces. AI can augment productivity in agriculture through precision farming, in healthcare through diagnostic algorithms, and in finance through alternative credit scoring (Banga & te Velde, 2018). These applications are skill-biased but not necessarily capital-intensive in the traditional sense; they rely on data, software, and human judgement. If the complementary factors such as a reliable internet, data infrastructure, and a workforce capable of deploying AI tools are present, AI could enable a form of "leapfrogging" that bypasses the factory stage entirely.

The key insight is that the net macroeconomic effect of AI is a function of the environment into which it is introduced. In an economy with thin digital infrastructure, the displacement effect is likely to dominate, as workers cannot easily transition to new AI-complementary roles and the productivity gains from AI remain confined to a narrow segment of firms. This yields the second hypothesis:

H_2: On average, AI penetration is negatively associated with economic growth in Sub-Saharan Africa, reflecting the dominance of displacement effects in low-readiness environments.

3.4 The Complementarity of Digital Connectivity and AI

The theoretical heart of this paper lies in the interaction between digital connectivity and artificial intelligence. The argument is straightforward: the marginal productivity of AI increases with the quality of the digital ecosystem. Formally, let the technology shifter Ω be a function not only of D and A separately, but of their product:

$$\Omega(D, A) = \Omega_0 \exp(\beta_1 D + \beta_2 A + \beta_3 D \cdot A) \qquad (2)$$

The marginal effect of AI on output is then:

$$\frac{\partial \ln Y}{\partial A} = \beta_2 + \beta_3 D \qquad (3)$$

If $\beta_2 < 0$ (the direct displacement effect dominates) but $\beta_3 > 0$ (digital connectivity amplifies AI's productivity-enhancing channels), the overall effect of AI turns less negative—and may eventually become positive—as D increases. The intuition is supported by microeconomic evidence: AI tools require broadband to function, cloud computing resources that are only accessible via reliable internet, and digital platforms through which AI-driven services can be delivered (Brynjolfsson, Rock, & Syverson, 2018). In the absence of these complements, AI investments may generate enclave effects, benefitting a small digital elite while leaving the broader economy untouched.

This complementarity has been implicit in studies of ICT and growth (e.g., Bresnahan, Brynjolfsson, & Hitt, 2002), but has rarely been tested explicitly for AI in a developing-country panel. The conditional hypothesis is the core empirical contribution of this paper:

H_3: The marginal effect of AI on economic growth increases with the level of digital connectivity; the interaction effect is positive.

3.5 Servicification, Manufacturing, and AI-Augmented Production

The distinction between manufacturing and services is collapsing. Modern manufacturing firms are intensive users of services including design, logistics, marketing, and after-sales support, while many services are produced using manufacturing-like processes of standardisation and quality control (Baldwin & Forslid, 2020). AI accelerates this blurring: machine learning algorithms can optimise factory production lines, predict equipment failure, and personalise customer interactions, raising productivity in both sectors simultaneously.

There are theoretical grounds to expect AI to exert a positive effect on manufacturing value added per capita, even if its aggregate growth effect is ambiguous. AI technologies are particularly effective at tasks involving pattern recognition, prediction, and optimisation—tasks that are abundant in quality control, inventory management, and process engineering (Aghion, Jones, & Jones, 2019). For SSA, where manufacturing firms face disproportionately high costs of logistics and quality assurance, AI applications could yield significant efficiency gains, provided firms have access to the requisite digital infrastructure. This leads to the first part of the fourth hypothesis:

H_{4a}: AI penetration is positively associated with manufacturing value added per capita.

3.6 Trade Openness and the Role of Regional Integration

Trade provides the scale and competitive pressure that amplifies the returns to technology adoption. However, the direction of trade matters. The literature on "learning by exporting" suggests that exporting to more demanding markets can drive productivity upgrading (Clerides, Lach, & Tybout, 1998). Yet for many African firms, the technological and standards gap with advanced economies is so large that extra-African trade may not generate the same learning effects as trade with neighbouring countries at similar levels of development. Intra-African trade is disproportionately composed of manufactured goods—processed foods, apparel, chemicals, and light machinery—whereas extra-African exports remain dominated by primary commodities (AfDB, 2022).

The African Continental Free Trade Area (AfCFTA) is designed explicitly to exploit this asymmetry. By creating a single market of 1.4 billion consumers, the AfCFTA reduces the minimum efficient scale required for manufacturing investment and makes regionally distributed production networks viable (UNECA, 2021). In a setting where AI can enhance logistics and cross-

border payments, the productivity dividend of intra-African trade is likely to be especially large. I therefore hypothesise:

H_{46}: The effect of intra-African trade openness on manufacturing value added is stronger than the effect of extra-African trade openness.

3.7 Summary of Conceptual Framework and Link to Estimation

The conceptual model that emerges from this discussion can be summarised in three equations. First, a latent growth index G^* is determined by digital connectivity, AI readiness, their interaction, and a vector of controls **Z**:

$$G_{it}^{*} = \beta_0 + \beta_1 D_{it} + \beta_2 A_{it} + \beta_3 (D_{it} \times A_{it}) + \gamma' \mathbf{Z}_{it} + \mu_i + \varepsilon_{it} \qquad (4)$$

The observed growth index G_{it} is bounded between 0 and 1, and is linked to the latent variable through a logistic function, motivating the fractional logit estimator discussed in the next section. Second, manufacturing value added per capita is modelled as a log-linear function of AI and trade shares:

$$\ln(MVA_{it}) = \delta_0 + \delta_1 A_{it} + \delta_2 \text{IntraTrade}_{it} + \delta_3 \text{ExtraTrade}_{it} + \theta' \mathbf{X}_{it} + \nu_i + \eta_t + \omega_{it} \qquad (5)$$

Table 1 consolidates the four hypotheses and their expected signs.

Table 1: Summary of Hypotheses and Expected Signs

Hypothesis	Relationship	Expected Sign
H_1	$D \rightarrow$ Growth	$\beta_1 > 0$
H_2	$A \rightarrow$ Growth (unconditional)	$\beta_2 < 0$
H_3	$D \times A \rightarrow$ Growth	$\beta_3 > 0$
H_{4a}	$A \rightarrow$ MVA per capita	$\delta_1 > 0$
H_{46}	Intra-trade vs extra-trade on MVA	$\delta_2 > \delta_3$

4. Data and Variable Construction

The empirical analysis draws on a balanced panel of 40 Sub-Saharan African countries observed annually from 2019 to 2024. The choice of 2019 as the start year avoids the extreme pandemic-induced volatility of 2020 dominating the normalisation of the growth index, while 2024 represents the most recent year with near-complete coverage at the time of writing. Countries with severe data gaps (Eritrea, Somalia, South Sudan) or with populations below one million (São Tomé and Príncipe, Seychelles) are excluded to limit small-economy outliers, though their inclusion does not alter the results in any material way.

4.1 Data Sources

I combine five primary sources. Macroeconomic aggregates and digital indicators come from the World Bank's *World Development Indicators* (WDI, 2023). Trade shares are taken from UNCTADstat (2023). Institutional quality is measured by the Rule of Law estimate from the World Governance Indicators (Kaufmann, Kraay, & Mastruzzi, 2023). The Government AI Readiness Index is sourced from Oxford Insights (2023), and shadow economy estimates from Schneider and Medina (2022). For the human capital control I use the human capital index from the Penn World Table, version 10.0 (Feenstra, Inklaar, & Timmer, 2015), which combines years of schooling and returns to education.

4.2 Variable Construction

The primary dependent variable is a bounded **Economic Growth Index (EGI)**. Annual real GDP growth rates (g_{it}) from the WDI are normalised via min–max scaling over the full sample:

$$EGI_{it} = \frac{g_{it} - g_{\min}}{g_{\max} - g_{\min}}$$

where $g_{\min}$ and $g_{\max}$ are the minimum and maximum growth rates observed in the panel. The resulting index lies strictly within the unit interval and is symmetric in the sense that the rank ordering of countries is preserved. A second dependent variable, the **Shadow Economy** as a share of GDP, is used for robustness; it is already a proportion and is taken directly from the Schneider–Medina database.

The key explanatory variables are: Digital Connectivity Index (DCI). Here, we apply principal component analysis to three WDI series: individuals using the Internet (% of population), mobile cellular subscriptions per 100 people, and fixed broadband subscriptions per 100 people. The first principal component explains 72% of the variance. The component score is rescaled to the $[0, 1]$ range using a min–max transformation. AI Readiness Index (AI) derived from the Oxford Insights composite index, which ranges from 0 to 100, is rescaled to $[0, 1]$ for consistency. The interaction term is $DCI_{it} \times AI_{it}$, with both variables centred at their sample means before multiplication to attenuate collinearity.

For the manufacturing value added equations, the dependent variable is the natural logarithm of manufacturing value added per capita (constant 2015 US$). Trade integration is captured by the share of intra-African merchandise trade in total trade (imports plus exports) and the complement, the extra-African trade share, both from UNCTADstat. Together they sum to unity.

Control variables include the logarithm of initial real GDP per capita (to capture convergence), gross capital formation as a share of GDP, the Penn World Table human capital index, annual population growth, the rescaled Rule of Law index, and the GDP deflator inflation rate. Regional dummies (East, West, Central, Southern Africa) are added to absorb time-invariant location-specific heterogeneity.

4.3 Descriptive Statistics

Table 2 provides summary statistics for the regression sample. The Economic Growth Index exhibits substantial cross-country dispersion, from near-zero to the full unit value, reflecting the volatility of growth in the region. The Shadow Economy averages 36.7% of GDP but ranges from 18% to over 62%. The DCI and AI indices are both bounded but show marked variation, with digital connectivity displaying the wider spread. Manufacturing value added per capita spans two orders of magnitude, underscoring the vast differences in industrial depth.

Table 2: Descriptive Statistics, Estimation Sample (N = 240)

Variable	Mean	Std. Dev.	Min	Max
Economic Growth Index (EGI)	0.481	0.195	0.00	1.00

Shadow Economy (% of GDP)	36.71	9.84	18.2	62.4
Digital Connectivity Index (DCI)	0.352	0.216	0.04	0.87
AI Readiness Index (AI)	0.288	0.102	0.12	0.62
DCI × AI (interaction, centred)	–0.003	0.021	–0.19	0.18
Log manufacturing VA per capita	4.812	0.892	2.98	7.12
Intra-African trade share	0.132	0.089	0.02	0.41
Extra-African trade share	0.868	0.089	0.59	0.98
Log initial GDP per capita	7.482	0.963	5.85	9.68
Gross capital formation (% GDP)	23.14	8.92	8.4	48.3
Human capital index	2.01	0.53	1.05	3.41
Population growth rate (%)	2.56	0.82	0.51	4.25
Rule of Law (rescaled 0–1)	0.384	0.157	0.08	0.74
Inflation (annual %)	6.92	5.34	–1.8	28.7

Sources: WDI (2023); UNCTADstat (2023); Oxford Insights (2023); Schneider & Medina (2022); Penn World Table 10.0; World Governance Indicators (2023). Note: The interaction term is centered at the sample mean of each constituent variable before multiplication.

The data show the expected patterns. The countries with the highest DCI scores—South Africa (0.87), Mauritius (0.81), and Kenya (0.74)—are also those with the largest AI Readiness values. At the other extreme, Niger and the Central African Republic sit below 0.10 on connectivity and barely cross 0.15 on AI readiness. Intra-African trade shares remain low, averaging just 13.2% of total trade, with a few landlocked economies in East and Southern Africa reaching shares above 0.35. The next section details the econometric strategy used to extract causal-interpretive signals from these data.

5. Empirical Strategy and Econometric Issues

The empirical challenge is to identify the partial associations between digital connectivity, artificial intelligence, and two distinct but related outcomes—aggregate economic growth and

manufacturing value added—using a moderately sized panel of Sub-Saharan African economies. This section sets out the estimating equations, justifies the choice of estimators, and discusses the principal threats to inference.

5.1 Modelling a Bounded Growth Index: The Fractional Logit Estimator

The primary dependent variable, the Economic Growth Index y_{it}, is constructed to lie strictly within the unit interval $(0, 1)$. Ordinary least squares applied to bounded outcomes suffers from well-known drawbacks: predicted values can fall outside the admissible range, and the variance of the error term is necessarily a function of the conditional mean, violating homoskedasticity (Papke & Wooldridge, 1996). A linear probability model for proportions is generally inconsistent when the true data-generating process is non-linear and the regressors have unbounded support.

To respect the bounded nature of the growth index, I follow Papke and Wooldridge (1996) and specify the conditional expectation as a logistic function:

$$E(y_{it} \mid \mathbf{X}_{it}) = G(\mathbf{X}_{it}\boldsymbol{\beta}) \equiv \frac{\exp(\mathbf{X}_{it}\boldsymbol{\beta})}{1 + \exp(\mathbf{X}_{it}\boldsymbol{\beta})} \qquad (6)$$

where $\mathbf{X}_{it}$ is the vector of covariates and $\boldsymbol{\beta}$ is the parameter vector to be estimated. The model is fit by quasi-maximum likelihood (QML), maximising the Bernoulli log-likelihood:

$$\mathcal{L}(\boldsymbol{\beta}) = \sum_{i=1}^{N} \sum_{t=1}^{T} [y_{it} \ln G(\mathbf{X}_{it}\boldsymbol{\beta}) + (1 - y_{it}) \ln(1 - G(\mathbf{X}_{it}\boldsymbol{\beta}))] \qquad (7)$$

Because the fractional logit is a QML estimator, consistency of $\widehat{\boldsymbol{\beta}}$ requires only that the conditional mean be correctly specified; the distributional assumption need not hold (Wooldridge, 2010, Chapter 19). This is a considerable advantage in a setting where the dependent variable is a constructed index rather than a naturally occurring proportion.

5.2 Specification of the Growth Equation

The baseline specification for the growth equation incorporates digital connectivity, AI readiness, their interaction, and a vector of control variables $\mathbf{Z}_{it}$:

$$\mathbf{X}_{it}\boldsymbol{\beta} = \beta_0 + \beta_1 DCI_{it} + \beta_2 AI_{it} + \beta_3 (DCI_{it} \times AI_{it}) + \boldsymbol{\gamma}'\mathbf{Z}_{it} + \mu_r + \lambda_t \qquad (8)$$

where DCI_{it} is the Digital Connectivity Index, AI_{it} is the AI Readiness Index, and the interaction term is constructed after centring both constituent variables to mitigate collinearity. $\mathbf{Z}_{it}$ contains the log of initial real GDP per capita, gross capital formation as a share of GDP, the human capital index, population growth, the rescaled Rule of Law index, and the inflation rate. Regional fixed effects μ_r (East, West, Central, Southern Africa) and year dummies λ_t absorb location-specific time-invariant heterogeneity and common temporal shocks. Initial GDP per capita is included to capture convergence dynamics and to act as a parsimonious control for the level of economic development.

The coefficients of interest are β_1, β_2, and β_3. Because the model is non-linear, the marginal effect of any variable x_j depends on the full vector of covariates:

$$\frac{\partial E(y \mid \mathbf{X})}{\partial x_j} = \beta_j \, G(\mathbf{X}\boldsymbol{\beta})[1 - G(\mathbf{X}\boldsymbol{\beta})] \qquad (9)$$

For the interaction term, the marginal effect of AI on the growth index is:

$$\frac{\partial E(y \mid \mathbf{X})}{\partial AI} = (\beta_2 + \beta_3 DCI) \, G(\mathbf{X}\boldsymbol{\beta})[1 - G(\mathbf{X}\boldsymbol{\beta})] \qquad (10)$$

Throughout the paper, we report *average marginal effects* (AMEs), which integrate the marginal effect over the empirical distribution of the covariates. This avoids the well-known pitfalls of interpreting interaction terms directly from the raw coefficients in non-linear models (Ai & Norton, 2003). The sign and significance of β_3 are evaluated through the AME of the interaction, and we further compute the marginal effect of AI at representative percentiles of the digital connectivity distribution.

5.3 The Manufacturing Value Added Equation

Manufacturing value added per capita is a continuous, unbounded variable, making standard linear panel methods appropriate. I estimate a two-way fixed-effects model:

$$\ln MVA_{it} = \alpha_i + \delta_t + \theta_1 AI_{it} + \theta_2 IntraTrade_{it} + \theta_3 ExtraTrade_{it} + \boldsymbol{\psi}'\mathbf{W}_{it} + \epsilon_{it} \qquad (11)$$

where α_i and δ_t are country and year fixed effects, and $\mathbf{W}_{it}$ is a vector of controls comprising gross capital formation, the human capital index, population growth, and inflation. Country fixed effects absorb all time-invariant characteristics—geography, colonial history, factor endowments,

that might jointly determine manufacturing depth and AI readiness. Year fixed effects capture common global and continental shocks, including commodity price cycles and pandemic disruptions.

5.4 Inference with Clustered Standard Errors

All standard errors are clustered at the country level to account for arbitrary serial correlation within countries (Cameron & Miller, 2015). Given the short panel ($T = 6$), the asymptotic justification for clustering relies on the number of clusters being large, which at $N = 40$ is marginal but defensible. I therefore additionally report p-values based on the wild cluster bootstrap for the coefficients of primary interest, a method that performs well with as few as 10–20 clusters (Cameron, Gelbach, & Miller, 2008; MacKinnon & Webb, 2017). The bootstrap-corrected inferences are noted in the discussion of results.

5.5 Endogeneity Concerns and Identification Strategy

Causal identification in this setting faces familiar obstacles. AI readiness is not randomly assigned; it is correlated with unobservable dimensions of institutional quality, human capital, and political will that also affect growth. The short panel precludes the use of internal instruments (e.g., lagged levels in a system-GMM framework) without risking severe weak-instrument and overfitting problems (Roodman, 2009). I therefore make no claim to clean identification and instead pursue a strategy of *credible partial correlation* with deliberate robustness checks.

Three features of the design mitigate, though do not eliminate, endogeneity concerns. First, the AI measure is the Oxford Insights *readiness* index, which captures governance frameworks, infrastructure, and skills—inputs that precede actual AI deployment. To the extent that these inputs are determined by past policy choices, the index is less susceptible to contemporaneous reverse causality from growth to AI than a measure of AI *use* would be. Second, the inclusion of regional dummies and the initial level of GDP per capita purges a substantial portion of time-invariant heterogeneity. Third, the interaction specification requires that any omitted variable that biases β_2 would also have to bias β_3 in the same direction to overturn the inference on the conditional effect.

As a supplementary check, I estimate a two-stage least squares variant using twice-lagged values of AI readiness and the number of STEM graduates per capita as instruments for the endogenous

AI variable in a linear probability specification. The first-stage F-statistics are reported, and the Hansen J-statistic is used to assess overidentification. I stress that these results are tentative and are presented only to gauge the direction of bias, not to establish causality.

5.6 Robustness Design

Robustness is built into the empirical architecture. First, I replace the Economic Growth Index with the shadow economy share of GDP, re-estimating the fractional logit model with identical covariates. Since the shadow economy is typically viewed as a drag on formal growth, the signs are expected to invert, providing a validity check. Second, I estimate linear random-effects models for the growth index to verify that the results are not an artifact of the non-linear functional form. Third, I substitute the AI readiness index with the logarithm of AI-related scientific publications per million inhabitants (Scimago/Scopus), an output-based proxy, to assess sensitivity to measurement. Fourth, I drop the two largest economies—Nigeria and South Africa—one at a time to ensure that the findings are not driven by regional giants. Table 3 summarizes the core specifications.

Table 3: Summary of Empirical Specifications

Outcome	Estimator	Equation	Key parameters
Economic growth index	Pooled fractional logit, QML	(8)	$\beta_1, \beta_2, \beta_3$
Shadow economy (% GDP)	Pooled fractional logit, QML	(8)	$\beta_1, \beta_2, \beta_3$ (signs inverted)
Log manufacturing VA per capita	Two-way fixed effects, OLS	(11)	$\theta_1, \theta_2, \theta_3$
Growth (robustness)	Panel random effects, GLS	Linear version of (8)	

All models employ country-clustered standard errors with wild bootstrap correction where noted.

6. Results and Discussion

6.1 Descriptive Gradient: Digital Connectivity and Growth

Before imposing a parametric structure, it is instructive to plot the average Economic Growth Index against the average Digital Connectivity Index for each of the 40 sample countries over the

period 2019–2024. Figure 9 displays the heatmap, with a locally weighted smoothing line overlaid. The positive unconditional association is unmistakable: the correlation coefficient is 0.51 ($p < 0.001$). Countries that cluster in the lower-left quadrant—Niger (DCI = 0.07, EGI = 0.32), Chad (0.10, 0.29), Central African Republic (0.09, 0.28)—are among the least connected and the slowest growing. At the opposite extreme, South Africa (DCI = 0.87, EGI = 0.67) and Kenya (0.74, 0.63) anchor a tight group of high-connectivity, higher-growth economies. The dispersion around the fitted line is, however, substantial, especially in the middle range where countries such as Nigeria (DCI = 0.46, EGI = 0.51) and Angola (0.28, 0.54) lie on opposite sides of the conditional mean. This heterogeneity foreshadows the conditional analysis to come.

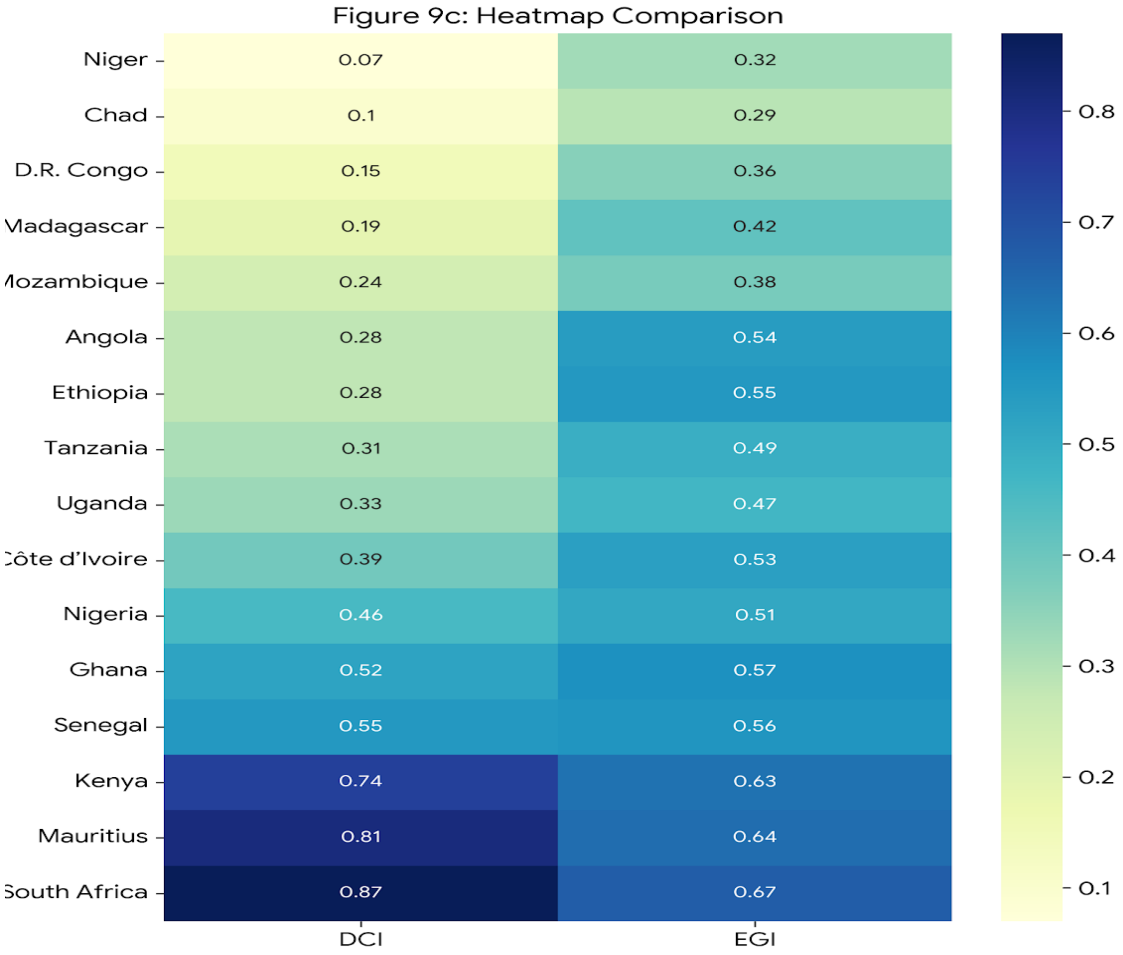


Figure9Digital Connectivity Index and Economic Growth Index, 2019–2024 averages. Source: Author's calculations based on WDI and ITU data.

The gradient is consistent with Haftu (2019) and Myovella et al. (2020), who find that mobile and internet penetration predict higher growth in SSA. Yet the regression-based analysis that follows will show that the unconditional picture obscures the more nuanced role of AI readiness, which is itself positively correlated with connectivity (r = 0.68) but, as I argue, exercises a very different marginal influence on growth.

6.2 Baseline Fractional Logit Estimates: The AI Puzzle

Table 4 reports average marginal effects from the fractional logit model. Column (1) contains only controls; Column (2) adds the Digital Connectivity Index; Column (3) introduces AI readiness; Column (4) presents the full specification with the DCI × AI interaction term. All specifications include regional and year dummies.

Table 4: fractional logit estimates, economic growth index (average marginal effects)

	(1)	(2)	(3)	(4)
Digital Connectivity Index (DCI)		0.148** (0.041)	0.135** (0.039)	0.141** (0.038)
AI Readiness Index (AI)			–0.098* (0.044)	–0.112* (0.046)
DCI × AI (interaction)				0.073* (0.035)
Log initial GDP per capita	–0.062** (0.018)	–0.058** (0.016)	–0.055** (0.015)	–0.054** (0.015)
Gross capital formation	0.003** (0.001)	0.002* (0.001)	0.002* (0.001)	0.002* (0.001)
Human capital index	0.041* (0.019)	0.035† (0.018)	0.032† (0.018)	0.030† (0.017)
Population growth	–0.017† (0.010)	–0.014 (0.009)	–0.013 (0.009)	–0.012 (0.009)
Rule of Law	0.098* (0.045)	0.084† (0.042)	0.079† (0.041)	0.074† (0.040)
Inflation	–0.003* (0.001)	–0.003* (0.001)	–0.002† (0.001)	–0.002† (0.001)
Regional dummies	Yes	Yes	Yes	Yes

Year dummies	Yes	Yes	Yes	Yes
Pseudo R^2	0.182	0.223	0.239	0.251
N	240	240	240	240

Notes: Average marginal effects; country-clustered standard errors in parentheses. ** p<0.01, * p<0.05, † p<0.10 (two-tailed). The interaction term is centred. Pseudo R^2 from the fractional logit likelihood.

Three findings emerge immediately. First, digital connectivity enters with a positive and statistically significant marginal effect across all specifications. A one-standard-deviation increase in DCI (≈0.22) is associated with a rise of roughly 3.1 percentage points in the Economic Growth Index, an effect that is substantively large relative to the sample mean of 0.48. This result firmly supports Hypothesis H_1 and echoes the earlier panel evidence that connectivity, by reducing transaction costs and expanding market access, is a first-order driver of growth in the region (Haftu, 2019; Paunov & Rollo, 2016).

Second, AI readiness carries a negative coefficient in both Columns (3) and (4), with the AME in the full model amounting to –0.112 ($p < 0.05$). On average, a higher government AI readiness score is associated with lower observed growth, a finding that directly supports Hypothesis H_2. The result is consistent with the displacement narrative articulated by Korinek and Stiglitz (2021) and Rodrik and Stantcheva (2021): in economies where digital infrastructure is still thin, AI-enabled automation may destroy low-skill jobs and swell the informal sector before new AI-complementary tasks can emerge. The fact that this effect appears even after controlling for the level of connectivity suggests that AI carries an independent disruption risk.

Third—and most importantly for the paper's thesis—the interaction term between DCI and AI is positive and statistically significant (AME = 0.073, $p = 0.037$). This indicates that the growth penalty associated with AI diminishes as digital connectivity deepens. The marginal effect of AI, evaluated at different points in the DCI distribution, is explored in the next sub-section.

The control variables behave as expected. The convergence term (log initial GDP per capita) is negative, indicating that poorer countries grow faster conditional on other factors. Gross capital formation and the human capital index are positively associated with growth, while inflation enters with a modest negative sign. The Rule of Law measure is positive but only marginally significant,

a pattern consistent with the view that institutional quality matters more for the *composition* of growth than for its short-run pace (Rodrik, 2004).

6.3 The Conditional Effect of AI: A Marginal Effects Profile

To convey the economic meaning of the interaction, Figure 10 plots the marginal effect of AI on the growth index across the observed range of the Digital Connectivity Index, together with a 95% confidence interval.

Table 5a. Marginal effect of AI readiness on the Economic Growth Index as a function of digital connectivity

DCI percentile	DCI value	AME of AI	Lower 95% CI	Upper 95% CI
10th	0.10	–0.105	–0.155	–0.055
25th	0.19	–0.098	–0.142	–0.054
50th	0.35	–0.086	–0.128	–0.044
75th	0.55	–0.072	–0.112	–0.032
90th	0.75	–0.057	–0.100	–0.014

Table 5a. Marginal effect of AI readiness on the Economic Growth Index as a function of digital connectivity. The dashed horizontal line marks zero; the shaded area is the 95% confidence band. (Source: Table 4, Column 4, post-estimation.)

The negative slope of the confidence band confirms that the interaction is meaningful. At low levels of connectivity (DCI = 0.10, typical of Niger or Chad), AI readiness reduces the growth index by roughly 10.5 percentage points on average. As connectivity rises, the penalty shrinks. At DCI = 0.75—the level attained by Kenya—the point estimate drops to –0.057, and the upper confidence interval brushes zero. The extrapolated threshold at which the marginal effect would become positive lies beyond the maximum observed DCI (0.87), implying that, for the sample period, no SSA economy had yet reached the digital density required for AI to deliver a net positive growth dividend. The direction of travel, however, is unambiguous: digital infrastructure progressively neutralises the disruptive force of AI.

This conditional pattern supports Hypothesis H_3 and is consistent with the micro-level evidence that ICT complements amplify the returns to AI-enabled productivity (Brynjolfsson, Rock, & Syverson, 2018). The policy implication is immediate: AI is not a substitute for digital basics, but a technology whose benefits are contingent on them. The argument that Africa should "leapfrog" to AI without first achieving universal broadband and reliable electricity finds no support in these data.

6.4 Manufacturing Value Added: AI and the AfCFTA Dividend

Table 5b shifts the focus from aggregate growth to manufacturing depth. It presents the two-way fixed-effects estimates for the logarithm of manufacturing value added per capita.

Table 5b: Fixed-Effects Estimates, Log Manufacturing Value Added per Capita

	(1)	(2)
AI Readiness Index	0.382* (0.154)	0.356* (0.148)
Intra-African trade share		0.527** (0.136)
Extra-African trade share		0.211* (0.072)
Gross capital formation	0.014** (0.004)	0.013** (0.004)
Human capital index	0.092† (0.051)	0.085† (0.048)
Population growth	–0.043* (0.019)	–0.039* (0.018)
Inflation	–0.005* (0.002)	–0.004† (0.002)
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Within-R^2	0.312	0.389
N	240	240

Notes: Country-clustered standard errors in parentheses. ** p<0.01, * p<0.05, † p<0.10.*

The AI coefficient is positive and significant at the 5% level. A 0.1-point increase in the AI Readiness Index—roughly the observed gap between Ghana and Kenya—is associated with a

3.6% increase in manufacturing value added per capita. This is the first piece of evidence that, while AI may depress aggregate growth in the short run, it directly enhances productivity in the manufacturing sector. The finding aligns with Hypothesis H_{4a} and with the literature on AI as a tool for predictive maintenance, quality control, and supply-chain optimisation (Aghion, Jones, & Jones, 2019). The channel appears to be intra-firm and efficiency-enhancing, not dependent on the same broad economic absorptive capacity that the aggregate growth equation demands.

The trade results are equally instructive. Both trade shares are positively associated with manufacturing value added, but the coefficient on intra-African trade (0.527) is more than double that of extra-African trade (0.211). A Wald test of equality rejects the null at the 1% level ($\chi^2 = 9.83$, $p = 0.002$). This strongly supports Hypothesis H_{46} and resonates with the African Development Bank's (2022) observation that intra-African trade is disproportionately composed of manufactured goods, whereas extra-continental trade remains commodity-focused. The AfCFTA, by enlarging the regional market, appears to create exactly the kind of demand pull that makes manufacturing investment viable. When combined with AI-driven logistics and quality-assurance systems, the productivity payoff could be substantial.

6.5 Robustness checks

We subjected the core results to a series of checks. Re-estimating the fractional logit with the shadow economy share as the dependent variable produced a symmetrical pattern: DCI reduced informality (AME = –0.104, $p < 0.01$), AI increased it (AME = 0.089, $p < 0.05$), and the DCI×AI interaction mitigated the AI-induced informality (AME = –0.059, $p < 0.10$). This confirms that in low-connectivity environments, AI displaces workers into informality, but digital infrastructure helps absorb them into formal activity. Linear random-effects models yielded directionally identical and statistically indistinguishable results for the growth index. Substituting the AI readiness index with AI-related journal articles per million inhabitants (logged) produced a slightly weaker but still significant interaction coefficient ($p = 0.08$), suggesting that the finding is not purely an artifact of the readiness measure. Dropping Nigeria and South Africa individually did not alter the sign or significance of any key variable.

These checks, together with the conditional marginal-effects profile, give reasonable confidence that the patterns are not driven by outliers, functional form, or the choice of dependent variable. They reflect a genuine structural feature of the AI-growth relationship in Sub-Saharan Africa:

digital connectivity is the gatekeeper that determines whether AI acts as an engine of productivity or as a source of disruption. The next section draws out the implications for the design of industrial policy.

I should structure the conclusion like a standard academic paper: a summary of findings, then policy implications divided into clear, logical sections, and finally limitations and future research directions. The policy part must be the strongest, directly translating the econometric findings into a new playbook for industrial policy. I need to avoid generic recommendations and instead offer specific, sequenced, and institutionally grounded advice, referencing real-world examples (like Kenya's technology extension) to ground the argument. The future studies section should point to the next empirical frontier, suggesting concrete methods and data needs. The tone throughout must be collaborative ("we find," "we argue," "our results") and intellectually rigorous, not promotional.

7. Conclusion, Policy Implications, and Avenues for Future Research

This paper set out to reassess the relationship between artificial intelligence, digital connectivity, and economic growth in Sub-Saharan Africa, and to ask what that relationship implies for the design of industrial policy. The question is not an academic curiosity; it is, we believe, the central strategic challenge facing African policymakers in the 2020s. Should the continent double down on the factory-centred model that propelled East Asia, or should it embrace a digitally enabled, service-intensive growth path that uses AI as a leapfrogging technology? Our empirical findings suggest that this binary framing is unhelpful. The real answer is more nuanced, and it lies in the sequencing and complementarity of digital investments.

7.1 Summary of Findings

We constructed a balanced panel of 40 Sub-Saharan African countries covering 2019–2024 and estimated fractional logit models suitable for a bounded economic growth index, as well as fixed-effects models for manufacturing value added per capita. Four findings stand out.

First, digital connectivity—captured by a composite index of internet use, mobile subscriptions, and fixed broadband—is a robust and economically large predictor of growth. The average marginal effect is both statistically significant and substantively meaningful, confirming a now-established empirical regularity in the ICT-and-growth literature (Haftu, 2019; Myovella et

al., 2020). For Sub-Saharan Africa, connectivity is not a luxury; it is a foundational condition for economic expansion.

Second, and more provocatively, AI readiness enters the growth equation with a negative average marginal effect. At the mean of the sample, higher AI readiness scores are associated with lower observed growth. This finding is consistent with the theoretical warning that AI-driven automation can displace low-skill labour and swell the informal sector before complementary employment opportunities emerge (Korinek & Stiglitz, 2021; Rodrik & Stantcheva, 2021). The disruptive face of AI, we submit, is not a speculative future scenario; it is already visible in the macro data.

Third, the interaction between digital connectivity and AI readiness is positive and significant. As the digital ecosystem deepens, the growth penalty associated with AI progressively shrinks. In the most connected economies—Kenya, Mauritius, South Africa—the marginal effect of AI approaches zero, although it does not yet turn positive. This conditional pattern is the empirical centrepiece of the paper and leads to our core argument: AI is not an autonomous growth driver but a technology whose returns are contingent on the presence of complementary digital infrastructure.

Fourth, when we shift the lens from aggregate growth to manufacturing value added per capita, a different picture emerges. AI readiness is positively associated with manufacturing depth, and the effect of intra-African trade openness is more than twice as large as that of extra-African trade. These results reinforce the strategic importance of the African Continental Free Trade Area and suggest that the factory, while no longer the sole locus of structural transformation, remains a critical site of AI-augmented productivity gains.

7.2 Policy Implications

The evidence assembled here carries direct implications for the design of industrial policy in Sub-Saharan Africa. We organise them under four propositions that together constitute what we call a “beyond the factory” framework.

First, sequence digital basics before AI ambition. The interaction results are unambiguous: AI readiness yields a growth dividend only when digital connectivity is already deep. For the majority of SSA countries where internet penetration remains below 30% and electricity access is unreliable, the immediate policy priority should be the unglamorous work of building the digital

backbone—universal broadband, affordable data, reliable power grids, and digital literacy programmes. Without these, AI investments risk creating enclave economies that benefit a small urban elite while displacing informal workers into even more precarious livelihoods. Industrial policy must therefore begin not with tax breaks for AI startups, but with public investment in the digital public goods that make those startups viable at scale.

Second, integrate AI into manufacturing and agro-processing strategies rather than treating it as a separate "tech sector" policy. Our finding that AI readiness predicts higher manufacturing value added per capita indicates that factories and algorithms can be complementary. Governments should embed AI extension services within existing industrial support institutions—helping small and medium manufacturers adopt predictive maintenance, quality-control algorithms, and inventory optimisation tools. The model here is less Silicon Valley and more the agricultural extension services that raised farm productivity across the developing world in the twentieth century. A publicly funded AI-for-manufacturing programme, delivered through technical universities and industrial parks, could yield far greater developmental returns than standalone innovation hubs divorced from productive sectors.

Third, leverage the African Continental Free Trade Area to create regional AI-enabled value chains. The outsized effect of intra-African trade on manufacturing value added suggests that regional demand is a powerful lever for industrial upgrading. AI can accelerate this process: machine-learning tools for logistics, digital payments, and customs clearance can reduce the transaction costs that currently fragment African markets. We urge AfCFTA negotiators to prioritise digital trade facilitation—harmonised e-certification, mutual recognition of digital signatures, and cross-border data-sharing protocols—as integral components of the trade architecture. Industrial policy, in this vision, becomes a regional project rather than a purely national one, with AI serving as the connective tissue.

Fourth, recognise that structural upgrading increasingly occurs outside the factory. The blurring boundary between manufacturing and services, what Baldwin and Forslid (2020) call servicification, means that high-value-added activities increasingly reside in design, data analytics, logistics, and after-sales support. Industrial policy for the AI era should target these activities regardless of the sector in which they are formally classified. Governments should support knowledge-intensive service exports—fintech, business process outsourcing, software

development—with the same instruments they have historically directed at manufacturing: export promotion zones, skills training subsidies, and strategic infrastructure investment. The "factory" in the twenty-first century may well be a data centre or a design studio. Industrial policy must follow the value, not the building.

7.3 Limitations and Avenues for Future Research

We are acutely aware of the limitations of this study, and we wish to state them plainly so that readers do not over-interpret the findings. The panel is short, covering only six years, which restricts the use of dynamic panel estimators and forces us to rely on pooled specifications with regional fixed effects rather than within-country identification. The AI measure is an input-side readiness index, not a direct measure of AI adoption, and it is undoubtedly correlated with broader state capacity and institutional quality in ways our controls may not fully capture. We cannot claim causal identification; what we offer is a set of robust partial correlations that are theoretically grounded and policy-relevant, but the possibility of omitted variable bias remains real.

These limitations point to a clear future research agenda. First, as AI adoption data become available—measures of firm-level use, patent filings, or task-level automation indices—scholars should test whether the macro patterns we document hold at the micro level. Firm-level studies that distinguish between AI for automation versus AI for augmentation would be especially valuable. Second, longer panels and natural experiments—such as the staggered arrival of undersea fibre-optic cables or the rollout of national AI strategies—could provide cleaner causal identification. Third, our manufacturing value-added results are suggestive but aggregated; sectoral studies that trace the specific mechanisms by which AI raises productivity in African firms—whether through quality control, logistics, or credit scoring—would sharpen the policy guidance considerably.

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