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Unlocking the Potential: AI in Sub-Saharan Africa

Prepared by an IMF team led by Martin Schindler and Andrew Tiffin, under the general guidance of Andrea Richter Hume, and comprising Kamil Dybczak, Marwa Ibrahim, Youssouf Kiendrebeogo, Jacinta Bernadette Shirakawa, Nikola Spatafora, and Solo Zerbo

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Executive Summary

Artificial intelligence (AI) is emerging as a general-purpose technology with the potential to reshape productivity, labor markets, and growth trajectories worldwide. For Sub-Saharan Africa, the central concern is not the risk of technological disruption, but whether countries will be able to adopt, adapt, and scale AI quickly enough to capture its benefits and avoid falling further behind. This paper contributes to the policy debate by applying recent AI exposure and productivity methods to Sub-Saharan Africa, combining country-level estimates with adoption scenarios and evidence from emerging African use cases. At present, the region's capacity to adopt AI is constrained by structural bottlenecks—unreliable and insufficient electricity, limited digital infrastructure, scarce technical skills, and gaps in regulatory and institutional capacity. However, AI gains are within reach if countries move quickly to strengthen the foundations for adoption.

Depending on policy choices and AI's ultimate economic effect, AI adoption in Sub-Saharan Africa could increase productivity between 0.2 percent and 2.1 percent over the next decade, potentially adding up to nearly ½ percentage point to annual GDP growth over the same time period, or about 4 percent cumulatively. A smaller effect would materialize under current conditions—including low adoption rates, a large share of employment in low-exposure sectors such as agriculture, and limited access to complementary or necessary inputs (energy, internet, and human capital)—and help explain why estimated gains are lower than in more advanced economies. Without policy action in Sub-Saharan Africa, continued AI adoption in other parts of the world could therefore reinforce rather than narrow the region's productivity gaps. But the current-conditions estimate is neither a forecast of AI's technological potential nor the region's endgame. Estimated gains could rise by an order of magnitude under a high-adoption scenario characterized by faster diffusion, broader sectoral penetration, and improved enabling conditions; AI has the potential to significantly increase productivity in Sub-Saharan Africa—with estimated effects in some cases (similar to those for more advanced economies). The scale of the increase reflects the region's large structural gaps and its significant scope for catch-up, underscoring the importance of policies. The region's AI trajectory is not predetermined: Policy choices will shape whether AI supports convergence or deepens divergence.

Sectoral evidence underscores where AI could deliver the largest development gains. In agriculture—where productivity gaps are widest—AI-enabled advisory tools, including low-cost mobile- and short message service–based systems, have already demonstrated double-digit yield and income gains. Similar early successes are emerging in education and health care, where AI can augment scarce human capital and expand service delivery, including in low-connectivity settings. AI can also increase productivity in the public sector, including domestic revenue mobilization, customs administration, expenditure control, and service delivery—areas where even modest efficiency gains could have an important economic effect.

Sub-Saharan Africa has an encouraging track record of adoption of new technologies. For example, it bypassed fixed telephone lines in favor of mobile networks with lower fixed costs—a technological shift that has delivered substantial economic gains, connecting previously isolated informal sectors to more efficient formal markets, and providing "gig economy" opportunities that often represent a significant improvement over traditional, informal livelihoods. A similar dynamism is emerging now with AI in Africa. Across the region, governments, firms, and research ecosystems are embarking on the AI journey. Several countries have adopted, or are preparing, national AI strategies, digital transformation plans, data protection frameworks, and sectoral pilots. Private sector applications are also expanding, including in agritech, fintech, healthtech, language technologies, and public service delivery. These developments show that AI adoption in Sub-Saharan Africa is already under way. The policy challenge is to move from pilots and isolated use cases to broader diffusion and institutional adoption.

Realizing this potential requires policies and investments to overcome key barriers, which include

- electricity deficits, which limit both basic digital adoption and energy-intensive AI infrastructure;
- connectivity gaps and their high costs, especially outside urban centers;
- limited human capital and compute access, exacerbated by a self-reinforcing cycle of brain drain;
- shallow and concentrated investment ecosystems, restricting economies of scale; and
- weak governance, including on data protection, cybersecurity, and regulation.

Without deliberate policy action, these constraints will make adoption slow and uneven. They could also reinforce inequality, as advanced firms, skilled workers, and urban hubs benefit, whereas informal sectors, smaller firms, and lower-income populations are left behind. Additional risks include increased dependence on foreign providers of AI tools and underlying data infrastructure, as well as vulnerabilities related to data governance, misinformation, and cyber threats. Even where open-source models and AI as a service can lower entry barriers, access to infrastructure needed to run advanced AI systems—such as cloud services, data centers, or specialized chips—may remain expensive, concentrated, and shaped by geopolitical fragmentation.

The policy agenda is therefore not simply about promoting AI adoption but about enabling broad-based, inclusive diffusion. AI adoption should be understood as part of a broader structural reform agenda, not as a stand-alone technology agenda, and regional cooperation will be especially important to foster adoption and good governance. Priorities include

- scaling reliable and affordable electricity and digital infrastructure;
- investing in skills and human capital at all levels;
- supporting local innovation ecosystems and access to finance;
- leveraging regional integration to achieve scale in data, compute, and regulation; and
- establishing credible governance frameworks to build trust and manage risks.

A pragmatic approach combines near-term "quick wins" with longer-term investments in infrastructure and institutions. Given long implementation lags, especially in energy and connectivity, early action is critical: Delays risk locking in a widening productivity divergence that may prove difficult to reverse.

In sum, AI presents a narrow but meaningful window of opportunity for countries in Sub-Saharan Africa to accelerate growth and improve living standards. The region does not need to be at the technological frontier to benefit—but it must be able to adopt, adapt, and scale AI rapidly and inclusively. The difference between a low- and high-adoption path is substantial. Policy choices made now will determine whether AI becomes a force for convergence or a driver of further divergence in global incomes.

Abbreviations

AI	artificial intelligence
AIPI	Artificial Intelligence Preparedness Index
EMDE	emerging market and developing economy
GNI	gross national income
GPT	general-purpose technology
ILO	International Labour Organization
LAC	Latin America and the Caribbean
LICs	low-income countries
MENA	Middle East and North Africa
PPP	purchasing power parity
SMS	short message service
TFP	total factor productivity

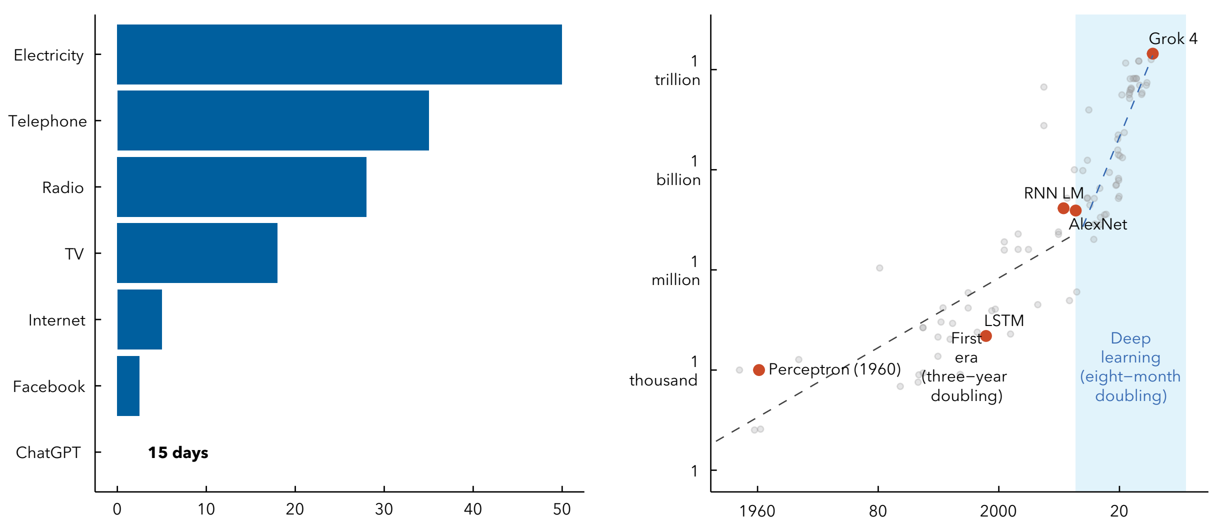
1. Introduction

Artificial intelligence (AI) represents the most profound technological advance of the current age. Even at this early stage, the pace of change is without precedent. ChatGPT reached 1 million users in two weeks—a milestone that took the telephone 35 years, television 18 years, and even Facebook over two years. Behind the adoption curve, the computational capacity driving frontier AI models has been doubling every eight months. These are not incremental advances within an existing technology; they signal the emergence of a general-purpose technology on the scale of electricity or the internet—one whose effects will reshape productivity, labor markets, and competitive dynamics across every sector of the global economy. Recent academic and policy work suggests that AI could support growth in Sub-Saharan Africa and other developing economies, but that the gains are likely to depend heavily on complementary conditions—especially skills, connectivity, reliable power, institutional quality, and the capacity to absorb and adapt the technology—whereas weak infrastructure and capabilities could also limit adoption and widen gaps.[1]

Figure 1. Recent Developments in AI

1. An Unprecedented Technology
(Years to reach 1 million users)

2. Frontier AI Model Size, 1950–2025
(Parameters, log scale)



Sources: Epoch.ai; OpenAI (2023); and Our World in Data (2023).
Note: AI = artificial intelligence.

The global implications are already visible. The five largest technology companies—Google, Microsoft, Meta, Amazon, and Oracle—are projected to spend approximately US$700 billion on AI infrastructure in 2026. And although this investment could raise productivity growth materially over the next decade, the gains are unlikely to be evenly distributed. In advanced economies, AI is already augmenting professional services, automating routine tasks, and restructuring entire industries. In Sub-Saharan Africa, by contrast, adoption capacity remains constrained. Critical inputs, such as reliable electricity, high-capacity connectivity, technical skills, and functioning institutions, are often absent, suggesting that AI-related productivity

[1] Examples include Khan, Umer, and Faruqe (2024) on artificial intelligence (AI) in low-income countries, Mienye, Sun, and Ileberi (2024) on AI and sustainable development in Africa, and the World Bank's WDR 2026a Concept Note on AI for development.

gains may remain limited. At the same time, AI could help bypass (leapfrog) existing bottlenecks, like mobile phone technology in the past (*The Economist* 2025). For Sub-Saharan Africa, the main risk is not disruption but irrelevance, with economies better positioned to exploit AI pulling further ahead, whereas less-prepared countries fall ever farther behind.

This report examines how Sub-Saharan Africa could achieve a high-growth path under accelerated AI adoption. The constraints across the region are substantial, but they are not immutable. In the past, the region has demonstrated that structural disadvantage does not preclude rapid adoption when enabling conditions are in line. Policy can relax the binding constraints in skills and institutional capacity; investment can build the power, connectivity, and compute infrastructure that AI requires; and regional coordination—on data standards, shared infrastructure, and harmonized regulation—can achieve the scale that no single country in the region can reach alone. The sections that follow discuss the region's AI readiness and quantify the potential effect of AI adoption on productivity and growth, taking individual countries' current circumstances and readiness into account. After providing an overview of the barriers, risks, and opportunities that currently confront the region's policymakers, the paper then considers the gains that could be realized if existing obstacles were addressed. Finally, it sets out a pragmatic policy agenda grounded in a simple premise: The region's preparedness deficit is largely a policy problem, not a capability constraint. However, with long implementation lags in energy and digital infrastructure, each year of inaction risks entrenching a productivity divergence that may prove difficult to reverse. Importantly, the key to benefitting from AI is not (necessarily) to be at the frontier of AI development but to be able to adopt AI quickly and broadly (Sunak 2025).

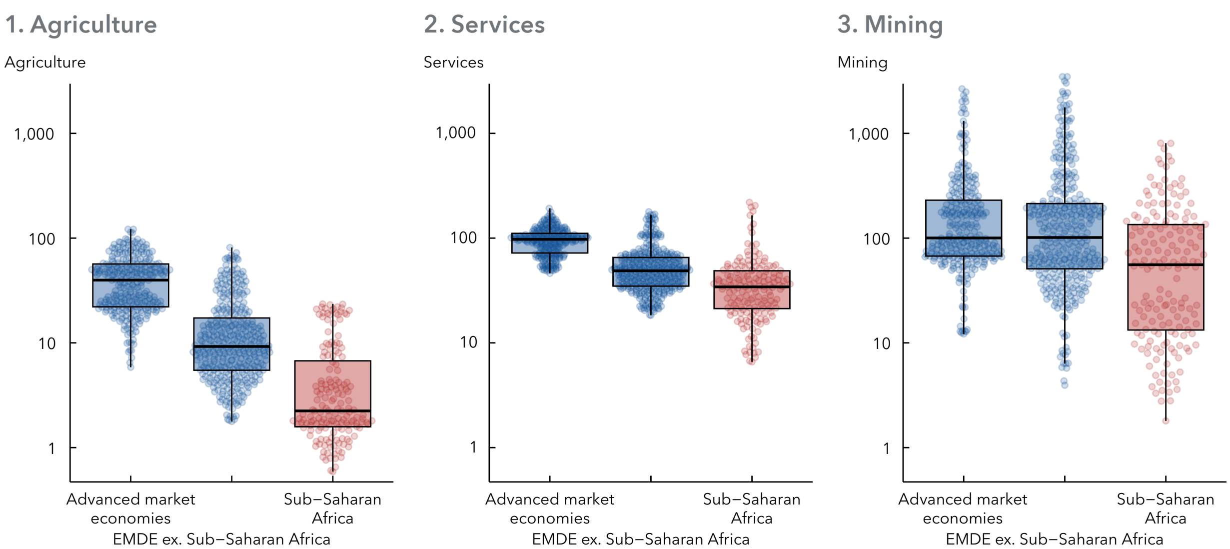
2. AI in Sub-Saharan Africa: Where We Stand

To better assess what AI can deliver in Sub-Saharan Africa, it is important to first assess where the region stands, including in regard to productivity gaps, overall preparedness, and the region's track record of technological adoption. All these will shape how AI is likely to land.

A. Low Productivity

First, general labor productivity in Sub-Saharan Africa is low by global standards and varies widely across countries. The region's productivity shortfall is large and has consistently lagged global benchmarks across key sectors, reflecting entrenched structural hurdles: limited technology diffusion, shallow financial intermediation, and overreliance on low-skill, informal activities that stifle efficiency gains. The gap is particularly stark in agriculture. In many countries, agriculture employs the majority of the population but often functions as a reservoir for underemployed workers who supply fewer annual hours than those in modern activities.

Figure 2. Labor Productivity Distribution Across Regions, 2010–18
(Thousands of US dollar per worker, 2011 PPP exchange rates)



Sources: World Bank Cross-Country Database of Sectoral Labor Productivity; and IMF staff calculations.
Note: EMDE = emerging market and developing economy; PPP = purchasing power parity.

At the firm level, infrastructure deficiencies, limited access to finance, corruption, and human capital constraints remain among the most frequently cited impediments to firm performance and growth in Sub-Saharan Africa, particularly for small and medium enterprises (World Bank 2026b; Dinh, Mavridis, and Nguyen 2010; Amine and others 2025). These constraints are often more acute for smaller firms, which face tighter financing conditions and weaker managerial and training capacity, limiting their ability to invest, grow, and adopt new technologies (Beck and Cull 2014).

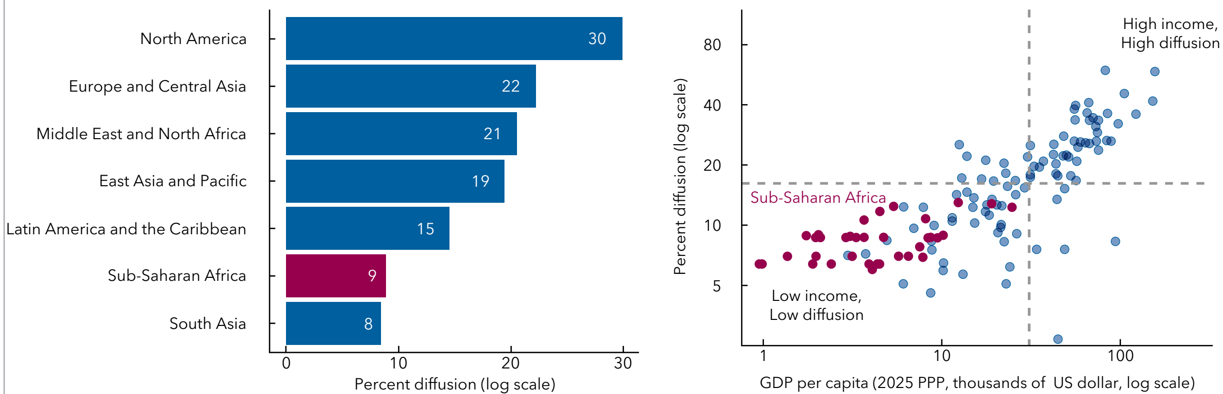
B. Slow Diffusion of AI

Although the uptake of AI has been swift in more advanced market countries, Sub-Saharan Africa has lagged behind. Measured by the prevalence of AI-related activity on Windows devices, AI diffusion in Sub-Saharan Africa remains low relative to most other regions, lagging significantly behind North America, Europe and Central Asia, Middle East and North Africa, and East Asia and Pacific, marginally ahead only of South Asia (Microsoft Data 2025; IMF staff calculations). As other economic centers rapidly scale up AI-enabling systems, the region's productivity gap may widen even further.

Figure 3. AI Diffusion across Regions

(Percent)

1. By Region **2. By Income Per Capita**



Sources: Microsoft Data (2025); and IMF staff calculations. AI diffusion is measured based on the prevalence of AI-related activity on Windows devices, combined with third-party data on Windows market share and the relative distribution of desktop versus mobile usage. The data set encompasses activity from all major AI models.

Note: AI = artificial intelligence; PPP = purchasing power parity.

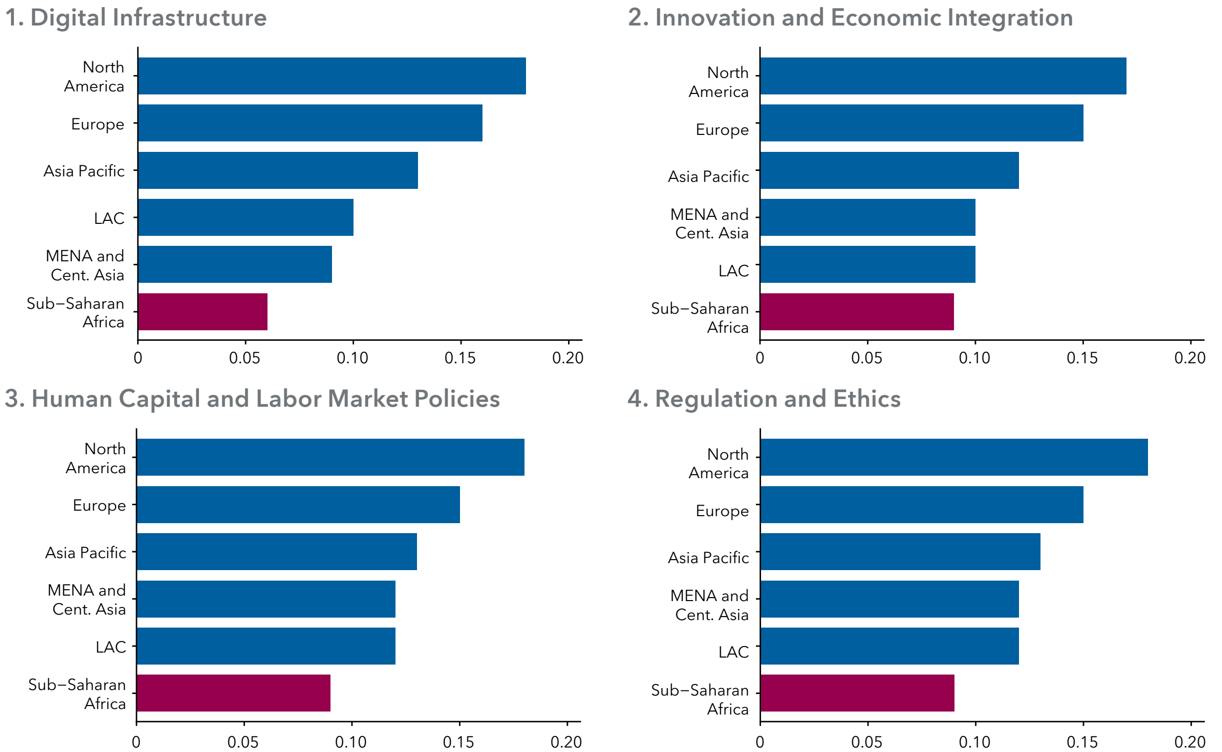
C. Lagging Preparedness

Sub-Saharan Africa's relatively low AI adoption reflects more than just late entry. It stems from a set of structural handicaps that continue to narrow the region's capacity to absorb this particular technology. The IMF's AI Preparedness Index[2] places Sub-Saharan Africa below all other regions, owing to gaps in digital infrastructure, skills, and regulatory capacity, which all serve to limit both AI adoption and resilience to labor market disruption (Figure 4).

However, regional averages conceal wide variation. A small set of economies—Kenya, Mauritius, Rwanda, the Seychelles, and South Africa—demonstrate how targeted investment, institutional commitment, and proactive policy stances can deliver comparatively advanced information and communications technology sectors. But when measured against global frontier cases such as Singapore, even these better-positioned countries face a steep climb.

[2] The AI Preparedness Index offers a simple but useful lens on how well countries are positioned to harness AI (Cazzaniga and others 2024). Built as an average of four pillars—digital infrastructure, human capital, technological innovation, and legal frameworks—it distills a complex landscape into a score between 0 and 1. The index is best viewed as a diagnostic, not as a ranking. It flags where state capacity needs strengthening and where investment would yield the highest returns.

Figure 4. Average AIPI Components by Region
(Index)

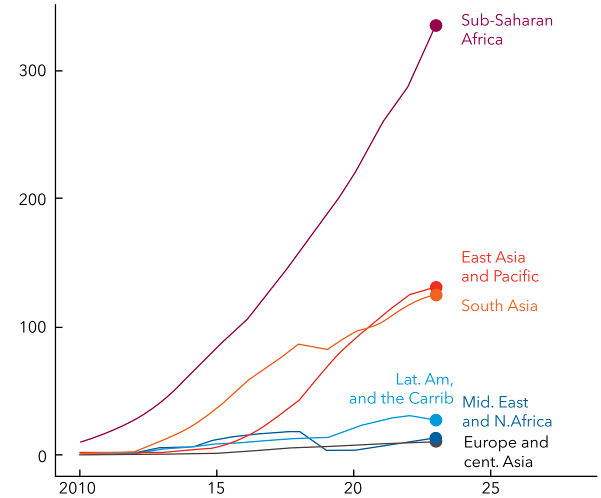


Source: IMF AIPI database.
Note: AIPI = Artificial Intelligence Preparedness Index; LAC = Latin America and the Caribbean; MENA = Middle East and North Africa.

D. Rapid Growth in Digital Tools

The earlier discussion notwithstanding, the region has an encouraging track record of past technology adoptions. Sub-Saharan Africa bypassed fixed telephone lines in favor of mobile networks with lower fixed costs. This technological shift has delivered substantial economic gains, with digital tools acting as a powerful conduit for structural transformation, connecting previously isolated informal sectors to more efficient formal markets, and providing "gig economy" opportunities that often represent a significant improvement over traditional informal livelihoods.

Figure 5. Active Mobile Money Accounts, 2010–23
(Millions)



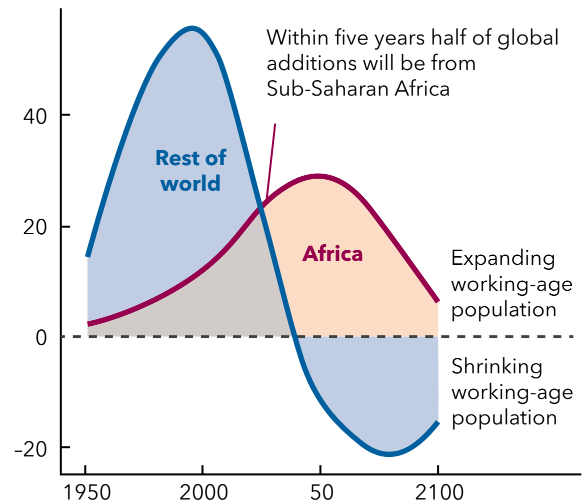
Source: GSMA.

Mobile systems have been a backbone of financial innovation. In the payment and financial landscape, Sub-Saharan Africa has emerged as a world leader in mobile money (Figure 5). Innovations like Kenya's M-Pesa have provided millions of people with their first access to essential financial services—providing low-cost payment rails, enabling a more inclusive financial ecosystem able to reach households and firms that traditional banking never served. And with mobile coverage touching most of the population, small-scale digital tools in agriculture, health, education, and social protection have spread quickly.

3. AI and the Economy: Modeling the Effect on Growth

The preparedness gaps are clear. The next question is: What do they imply for growth? This section estimates the productivity effect of AI under current conditions, using a task-based framework that measures which jobs are exposed, how adoption rates compare across regions, and what the payoff might look like when applied to Sub-Saharan Africa's present economic structure.

Figure 6. Annual Additions to Global Working-Age Populations, 1950–2100
(Millions of people per year, ages 15–64)



Sources: UN World Population Projections; and IMF staff calculations.

The productivity question is urgent because of the region's demography (Figure 6). By 2030, Sub-Saharan Africa will account for roughly half of all new entrants into the global labor force—equivalent to up to 15 million new jobs each year (IMF 2025c). Meeting this demographic challenge will require not only more jobs but also better, more productive jobs capable of supporting sustainable development, allowing workers to escape a frequent regional pattern of low wages and pervasive informality.

Previous technology waves provide some basis for optimism. Beyond improving connectivity and contributing to lowering communication costs, past technological innovations—such as the internet, broadband, and mobile cellular technology—have made existing jobs more productive and have allowed for the creation of new, previously unthought-of jobs and business models. For instance, the introduction of submarine cables in Africa allowed for expanded and more affordable access to information and communications, boosting employment between 4 percent and 10 percent in connected areas, and raising firm entry, productivity, and exports (Hjort and Poulsen 2019).

A. AI's Effect Will Vary from Job to Job

Similar to the effect of previous technological innovations, AI will likely have varying effects on different sectors, jobs, and tasks, boosting productivity in some cases, replacing human effort in others, and creating completely new jobs within a rapidly evolving economic environment. The effect of AI will hinge on the composition of tasks that define different occupations. AI can reshape how work is performed—automating some tasks while complementing others—with an a priori ambiguous effect on overall employment and wages.[3] Current estimates of the effect of AI, therefore, rely on the extent to which different tasks are exposed to replacement or augmentation (Box 1 and Figure 7).

Box 1. Defining and Measuring Artificial Intelligence (AI) Exposure

This paper measures AI exposure using the framework of Felten, Raj, and Seamans (2021, 2023) and Pizzinelli and others (2023). Felten's AI Occupational Exposure (AIOE) index captures the degree of overlap between AI capabilities and the human abilities required to perform tasks within each occupation. Occupations are first decomposed into underlying tasks, which are then assessed against the capabilities of a *current-generation* AI system. This provides an occupation-level indicator of current AI exposure, differentiating between jobs with relatively high exposure and those with relatively low exposure. At present, low-exposure jobs usually involve physical labor, whereas high-exposure occupations rely more on information processing tasks.

Pizzinelli and others (2023) extend the Felten framework by developing a complementarity-adjusted measure of exposure (C-AIOE). Based on the existing social, ethical, and physical context of occupations, the extended index identifies tasks that cannot be delegated to a current-generation AI without human oversight, indicating lower replacement risk. As a result, the C-AIOE index distinguishes between jobs that may face AI-driven displacement (high exposure with low complementarity) and those that may instead gain through AI integration (high exposure with high complementarity).

Following this framework, we classify occupations into three categories: (1) low exposure, (2) high exposure with high complementarity (labor augmenting), and (3) high exposure with low complementarity (labor substituting). Occupations are first divided into low- and high-exposure groups using the median AIOE index as a threshold. High-exposure occupations are then sorted using the median C-AIOE score. Industries, dominated by professional and cognitive-intensive occupations, such as finance, exhibit both high exposure and high complementarity. In contrast, agriculture, manufacturing, and construction are currently classified as predominantly low-exposure sectors.

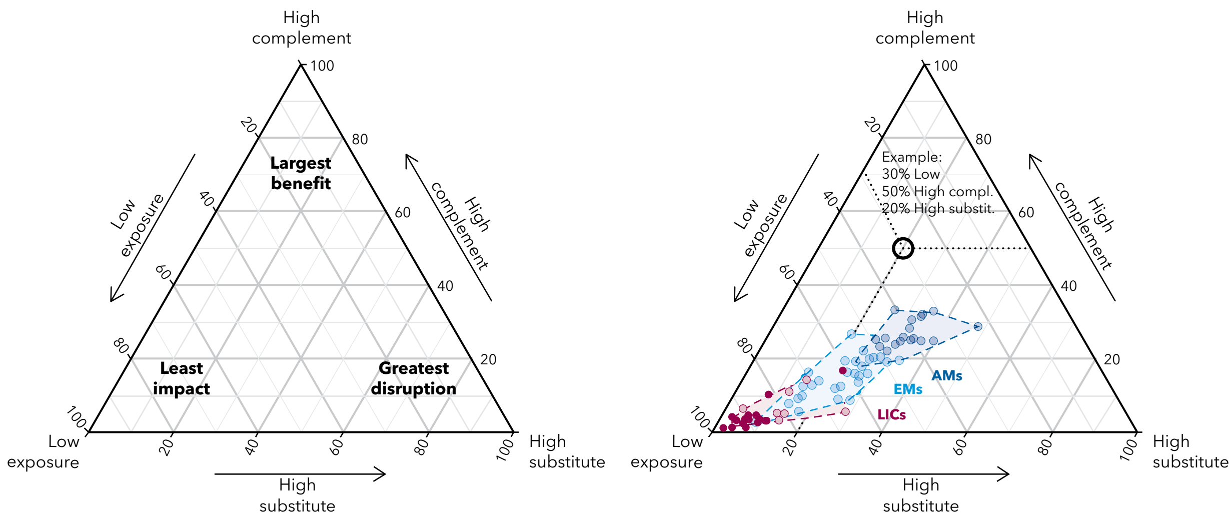
Although this classification approach is used widely, several caveats apply. Although the AIOE framework implicitly assumes that the tasks and work context of occupations are comparable across countries, the task bundles associated with a given occupation may differ substantially, as may the current labor-capital split across tasks within that occupation. Second, in the African context, lower prevailing automation levels and higher labor shares could imply more room for productivity gains from automation, but higher capital costs could dampen that effect. The type of job affected is also likely to shift quickly as AI capabilities expand. Finally, the analysis relies on the International Labour Organization's occupational data, which offer limited granularity. For full methodological detail, see Felten, Raj, and Seamans (2021) and Pizzinelli and others (2023).

[3] Acemoglu and Restrepo (2019) provide a conceptual framework to analyze the potential "displacement effect" as tasks previously performed by labor are taken over by capital and a counterbalancing "reinstatement" effect as new technologies create new tasks where labor has a comparative advantage. The net effect would depend on the speed of displacement and reinstatement as new technologies affect the underlying tasks in production.

Figure 7. AI Exposure Categories

1. Conceptual
(Percent of total)

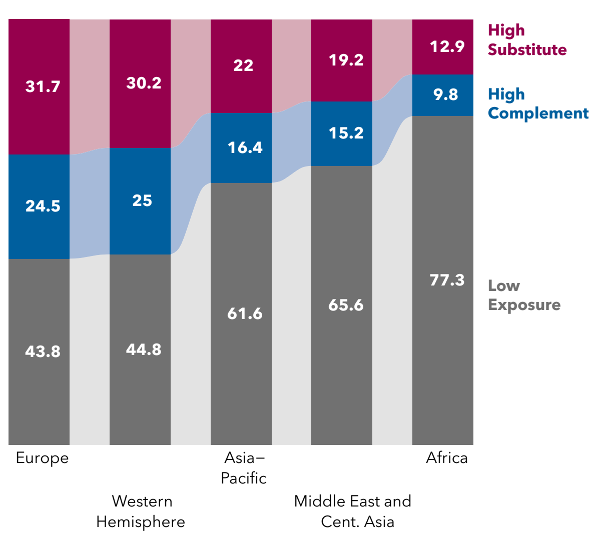
2. Empirical
(Percent of total, solid point = Sub-Saharan Africa)



Sources: Felten, Raj, and Seamans (2021); Pizzinelli and others (2023); International Labor Organization database; and IMF staff calculations.
Note: Based on latest available country data in the ILO database. AI = artificial intelligence; ILO = International Labour Organization; LICs = low-income countries.

Our estimates suggest that, with existing technology, about four-fifths of jobs in sub-Saharan Africa have limited exposure to AI (Figure 8). The share of low-exposure jobs is significantly larger than in Europe and the Western Hemisphere (about 45 percent), and also more than in the Asia Pacific and Middle East (both around 60–65 percent). On the one hand, a high share of low-exposure jobs suggests that AI is less likely to cause labor market disruption in the near term. On the other hand, low exposure also implies that Sub-Saharan Africa, as of now, may benefit less from AI's productivity and growth gains. Among the jobs that are likely to be affected by AI (about 22 percent of total employment), about 13 percent of all jobs are at significant risk of being replaced, whereas almost 10 percent of all jobs are instead likely to benefit.

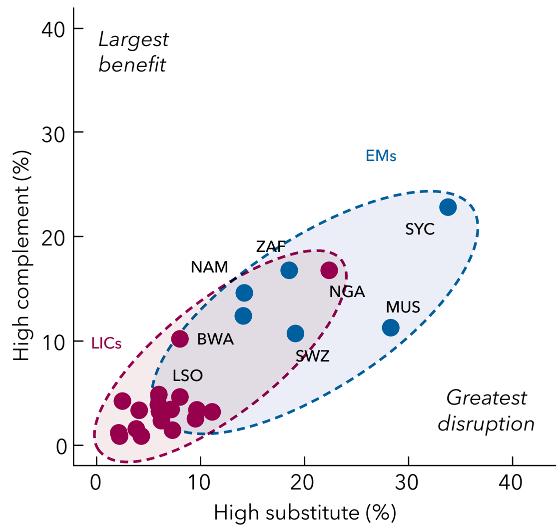
Figure 8. AI Exposure Categories by Region
(Percent of employment)



Sources: Felten, Raj, and Seamans (2021); Pizzinelli and others (2023); International Labor Organization database; and IMF staff calculations.
Note: Based on latest available country data in the ILO database; AI = artificial intelligence; ILO = International Labour Organization.

The low exposure of jobs in Sub-Saharan Africa reflects the sectoral composition of its economies. Regionwide, employment remains concentrated in agriculture, informal services, and other labor-intensive activities where tasks are predominantly manual, routine, or context-specific and therefore less amenable to general-purpose AI applications. Agriculture in particular has a large weight in both employment and value added, with both generally exceeding levels in other regions, especially in advanced economies. Agriculture's share ranges widely—South Africa's is below 5 percent, whereas Guinea-Bissau's is above 50 percent (for both employment and value added).

Figure 9. AI Exposure Categories: Sub-Saharan Africa
(Percent of employment)



Sources: Felten, Raj, and Seamans (2021); Pizzinelli and others (2023); International Labor Organization database; and IMF staff calculations.

Note: Low-exposure share is omitted (determined by the other two categories); Based on latest available country data in the ILO database; AI = artificial intelligence; ILO = International Labour Organization; LICs = low-income countries.

Sectors with higher AI exposure, such as information and communication technology, finance, and professional services, account for a relatively small share of total Sub-Saharan Africa employment.

In addition, exposure rates differ significantly across the region. Although low-exposure jobs dominate in around three-quarters of the region's countries, there are some exceptions. Job composition in Botswana, Mauritius, Namibia, Nigeria, the Seychelles, and South Africa more closely resembles the patterns observed in emerging market economies.

B. Aggregate Effect on Productivity and Growth

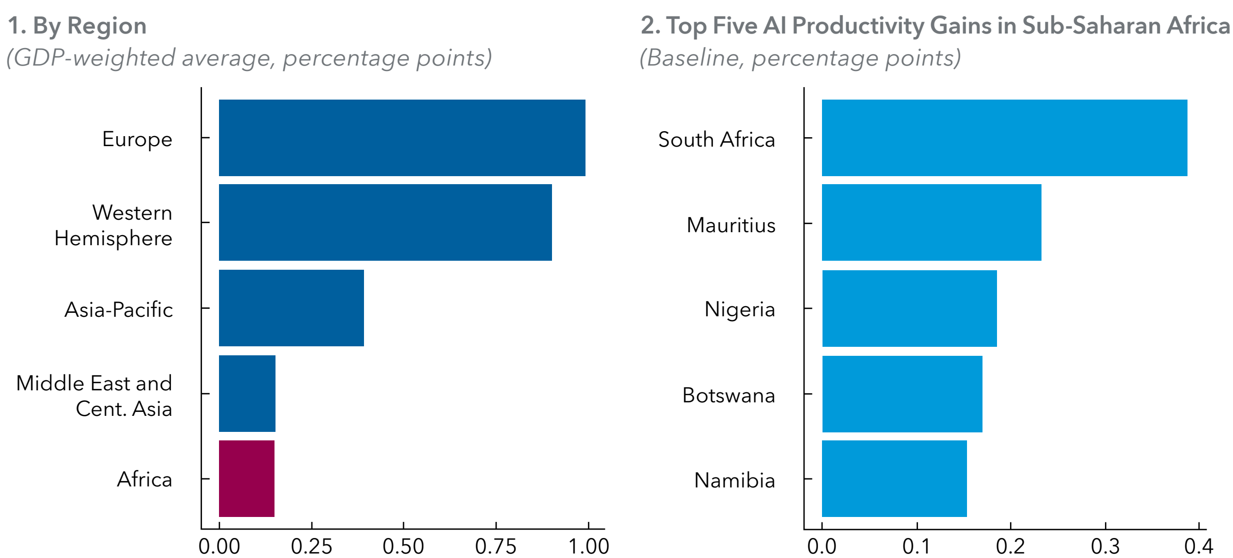
Under Acemoglu's (2024) and Filippucci, Gal, and Schief (2024) task-based framework, aggregate productivity gains depend on three key parameters: (1) the share of tasks affected by AI, (2) the pace of AI adoption across the economy, and (3) the labor cost savings (productivity gains) generated at the task level. Applying this approach, Acemoglu (2024) finds that AI-driven productivity gains are likely to be modest even in advanced economies, with total productivity in the United States increasing by slightly less than 1 percent over a decade. Using a similar methodology and calibration, Misch and others (2025) estimate that on average AI could raise productivity in European economies by about 1 percent cumulatively over five years.

Structural characteristics of less-developed regions suggest that AI-related benefits may be lower than in more advanced regions. Given a substantially lower fraction of jobs exposed to AI, a lower level of preparedness, more limited access to data, and lower incentives to substitute capital for labor because of cheap and abundant labor, the effect of AI on productivity in Sub-Saharan Africa is expected to be limited. In this context, Cerutti and others (2025) employ a global macroeconomic model suggesting that, unless preparedness for and access to AI improve substantially in low-income countries, AI might further exacerbate cross-country income inequality, with growth gains in advanced economies more than double those in less-developed regions.

Applying the standard task-based approach to Sub-Saharan Africa yields an initial estimate of the potential effect of AI on productivity and growth.[4] These estimates are based on three key parameters (see Box 2): (1) *AI exposure*—the share of economically relevant tasks currently seen to be affected by AI; (2) *AI adoption rate*—the share of workers/firms who implement, integrate, or actively use AI in their operations; and (3) *Productivity gains from adoption of AI*—the magnitude of task-level cost savings.

Under current conditions, estimated productivity gains in Sub-Saharan Africa are small—well below those estimated for more advanced economies, with productivity in Sub-Saharan Africa projected to rise by only 0.2 percent cumulatively over the next decade, compared with about 1 percent in Europe and the Western Hemisphere (Figure 10). At the same time, reflecting Sub-Saharan Africa's significant heterogeneity, the estimated effect on productivity spans a wide range, from negligible gains in several low-exposure economies to increases of around 0.4 percentage point in South Africa (an outcome more in line with those for some more advanced economies). These estimates should be interpreted as a current-conditions diagnostic rather than a forecast of AI's technological potential. They reflect today's low adoption, infrastructure gaps, and sectoral structure; they do not capture the full range of gains that could arise from faster diffusion, structural transformation, public sector applications, or AI-enabled innovation.

Figure 10. Potential Productivity Effect of AI

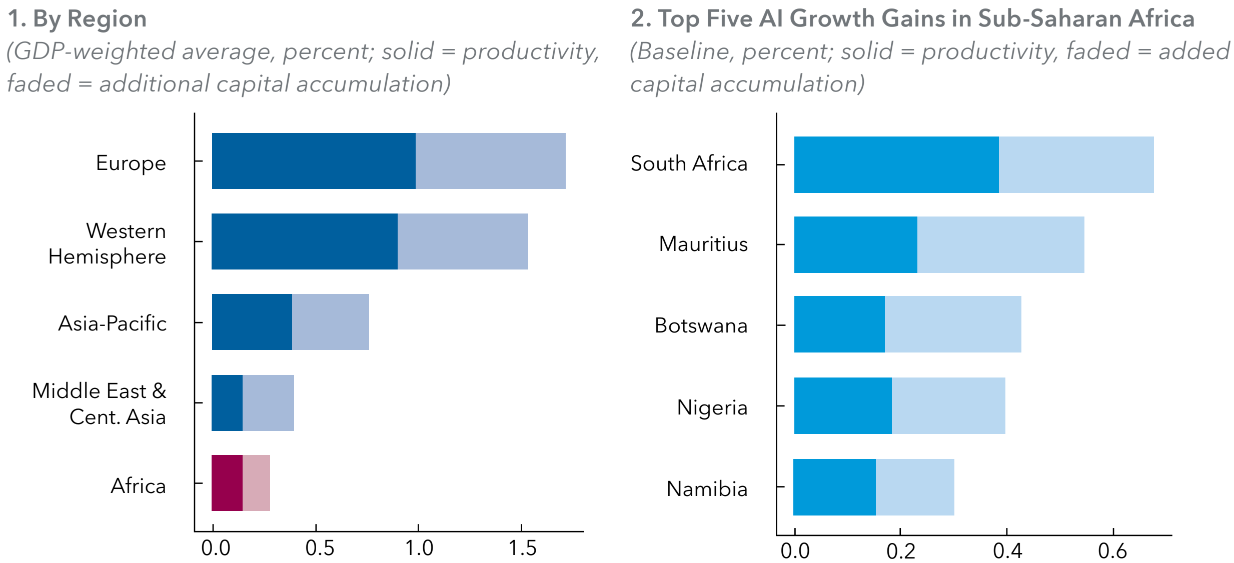


Source: IMF staff calculations.
Note: AI = artificial intelligence.

Combining the productivity gains from AI adoption with the contribution from associated AI-related capital accumulation provides an estimated total effect on GDP growth. In Acemoglu's (2024) framework, productivity gains from AI adoption are assumed to be accompanied by additional investment in AI-related capital, which accelerates capital deepening and further supports output growth. Assuming capital accumulation increases in proportion to projected productivity, the additional boost to GDP from AI through higher capital accumulation is estimated at 0.2 percent, with an overall cumulative growth effect of 0.4 percent over 10 years (Box 2 and Figure 11).

[4] Our estimates closely replicate the methodology and parametrization in Acemoglu (2024).

Figure 11. Potential Growth Effect of AI



Source: IMF staff calculations.
Note: AI = artificial intelligence.

Box 2. The Effect of Artificial Intelligence (AI) on Productivity and GDP

The task-based approach to quantify AI's effect on productivity and output is a widely used framework. In the Sub-Saharan African context, we introduce sector-specific assumptions on AI exposure, adoption, and task-level gains. This more granular calibration captures the region's significant cross-sector heterogeneity and also allows for additional, more forward-looking analysis, including the possibility that evolving AI capabilities may generate gains in sectors that have hitherto been considered as less exposed.

Productivity

Filippucci, Gal, and Schief (2024) show that, under standard assumptions, the aggregate gains from AI depend less on frontier capabilities per se than on three measurable margins:

AI exposure: the share of economically relevant tasks affected by AI
Adoption rate: the pace at which firms adopt the technology
Productivity gains: the magnitude of task-level cost savings

Accordingly, the effect of AI on total factor productivity (TFP) can be expressed as the product of exposure, adoption, and task-level productivity gains. To capture heterogeneity across sectors in Sub-Saharan Africa, we calibrate these parameters at the *sector level* and aggregate them for each country using each sector's share in total output. The cumulative change in aggregate TFP over the next decade can be written as:

$$\text{dlog TFP}_{\rightarrow 10\text{ years}} = \sum_{i \in I} \lambda_i \times [\text{AI Exposure}_i \times \text{Adoption Rate}_i \times \text{Productivity Gains}_i],$$

where dlog TFP represents the change in overall productivity over the next decade, and $\lambda_i = \frac{\text{Gross Output}_i}{\text{GDP}}$ is the so-called Domar weight, where $i \in$ {All sectors}.

Growth

To quantify the effect on GDP, Acemoglu (2024) allows for an additional expansion of AI-related investment, adding to the TFP effect. The contribution from higher investment assumes that capital accumulation grows proportionally with TFP and the economy's capital income share, so that:

$$\text{dlog GDP}_{\rightarrow 10\text{ years}} \approx \text{dlog TFP}_{\rightarrow 10\text{ years}} / (1\text{-}s_K),$$

where s_K represents the share of capital income in total income.

The Acemoglu (2024) results are intentionally conservative. They focus strictly on automation and task complementarity and abstract from more transformative channels, such as AI-driven innovation. Under the Acemoglu calibration, AI raises TFP in the United States by about 0.66 percent over 10 years (around 0.06 percent per year). The study argues that near-term gains are constrained by adjustment costs, limited diffusion, and the slower progress of AI on hard-to-learn tasks.

4. Why Are Current-Conditions Gains So Low? Barriers to AI Adoption

Under the task-based framework, AI's potential is highly sector specific and contingent on adoption rates within those sectors. The largest gains are expected in high-wage sectors with a high share of intellectual or information processing tasks, where AI acts primarily as a labor-augmenting technology. For sectors dominated by manual and elementary tasks, however, the assumption is that there is a more limited scope for cost savings, reflecting both lower AI exposure and fewer opportunities to substitute labor with technology. Given the sizable share of agriculture in Sub-Saharan African economies, this assumption materially dampens the effect of AI, as the current estimates for savings in agriculture are roughly three times lower than those in manufacturing, construction, and services. In this context, evidence from Microsoft Data (2025) shows that the adoption rate of AI for Sub-Saharan Africa is below 10 percent, about two to three times lower than in Europe or the Western Hemisphere.[5]

The modest estimates from the task-based framework are not without foundation and do not just apply to Sub-Saharan Africa. Even in advanced economies, estimated gains only reach 1 percentage point of GDP over 10 years; consistent with the fact that, at the economy level, AI-related productivity gains have so far proved elusive. Importantly, however, the framework we employ is static and calibrated to *existing* conditions—effectively baking today's adoption barriers into its estimates. Thus, the estimate for Sub-Saharan Africa is less a forecast of what AI *can* do for African economies but instead represents a snapshot of what current infrastructure, connectivity, and human capital barriers *permit* over the near term. Relax those barriers, and the same framework points toward a markedly different outcome. The following sections will outline the nature of the region's most pressing barriers to adoption and will then go on to discuss the potential future gains from AI if those barriers were to be addressed.

A. Reliable Access to Electricity

Around half of the region's population does not have reliable power (World Bank 2025). Worldwide, around 670 million people are without access to electricity, and an overwhelming proportion of these (85 percent) are in Sub-Saharan Africa. Access is expanding, to around 35 million people per year, but this is barely keeping pace with population growth, leaving a net gain of only 5 million per year.

Power supply disruptions can impose significant economic costs. Seventy-eight percent of firms in Sub-Saharan Africa report routine outages, with average losses of 8.4 percent of annual sales—well above the 5.2 percent global average (World Bank 2026b; Oseni 2021). For AI development in particular, these costs can be critical. Training and deploying AI models is highly energy intensive and requires centralized high-performance computing facilities that operate continuously. Similarly, applications such as digital payments, logistics platforms, tax systems, and health services require continuous operation of data centers to ensure uninterrupted service. Even short outages can disrupt training runs, increase latency, and generate significant financial losses.

[5] We use Microsoft Data (2025) on user access to AI through Windows devices as a proxy for general AI adoption.

Electricity reliability is therefore a central constraint under a high AI adoption scenario. As AI deployment expands, electricity demand will likely increase through two channels: the broader use of AI-enabled services across firms and public administration and growth in data center and cloud infrastructure. For example, data centers accounted for about 1.5 percent of global electricity consumption in 2024 and, under the International Energy Agency's base case, are projected to account for about 3 percent by 2030 (IEA 2025).

AI-related demand for power is currently muted, as the region currently hosts only a small share of global data center capacity. Existing facilities account for roughly 0.4 GW of capacity—less than 1 percent of the global total—and primarily support telecommunications and general cloud services rather than frontier-scale AI model training or inference. However, the medium-term investment pipeline suggests capacity could expand significantly over the next five years (Global Gateway 2025). Existing facilities can also be upgraded to support AI workloads through the installation of specialized accelerators.

Recent commitments underscore the scale of planned expansion. Microsoft and G42 have announced a US$1 billion investment in a 100-MW green data center campus in Kenya, powered by geothermal energy; Cassava Technologies and NVIDIA have partnered in a US$700 million deal to deploy 12,000 GPUs across facilities in South Africa, Nigeria, Kenya, Egypt, and Morocco; and the International Finance Corporation has committed US$100 million to expand data centers operated by the Raxio Group across several Sub-Saharan African markets, including Ethiopia, Angola, Mozambique, and Côte d'Ivoire, among others. Chinese technology firms are also scaling up, with Huawei committing over US$300 million to data center and cybersecurity infrastructure across the continent and Tencent announcing a US$2 billion cloud computing investment. Together with Western commitments, these flows underscore that Africa's AI infrastructure build-out is not only attracting diversified capital, offering greater choice and competitive pricing, but also raising data governance and strategic dependency considerations for policymakers.

Even a moderate expansion in AI infrastructure would increase electricity demand significantly. Under an expansion path where Sub-Saharan Africa's AI data center capacity share is still only 0.5 percent of global capacity by 2035, these AI data centers would generate additional electricity demand roughly equivalent to 10 percent of the region's 2023 installed generation capacity.[6] This remains modest relative to the much larger increase in generation, transmission, and distribution capacity that Sub-Saharan Africa will need over the next decade to expand electricity access, improve reliability, and meet rising household and industrial demand. In this context, the technical demands of AI operations are particularly challenging as power needs to be continuous, geographically concentrated, and sensitive to voltage stability and outage frequency.

But the close connection between the demand for compute and the need for electricity can work in both ways. Data centers, with their massive, predictable, and long-term energy requirements, can function as industrial anchor tenants whose demand makes large-scale power generation and grid expansion bankable for private investors—a dynamic that, if managed well, can extend electricity access to surrounding communities as a spillover benefit. The critical question is whether anchor demand catalyzes net additions to grid capacity or simply diverts existing supply—which depends on how power purchase agreements and grid extension mandates are structured.

For power grids under pressure, additional demand requires that generation and transmission capacity expand in parallel. The alternative is continued outages, and where grid reliability remains weak, firms often shift to costly self-generation. Indeed, evidence from the World Bank's Enterprise Surveys suggests that generator ownership is widespread in the three countries currently hosting the largest number of data centers—86 percent

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[6] This scenario assumes that around 0.5 percent of global AI data center capacity will be located in Sub-Saharan Africa by 2035. Based on the exponential growth model of the global AI data center capacity noted earlier, this would add to the region around 14 GW of power demand, which is equivalent to 9.9 percent of the 2023 power generation capacity in Sub-Saharan Africa (137 GW).

of Nigerian firms report owning or sharing a generator, whereas 65 percent and 63 percent do so in Kenya and South Africa, respectively. Generator-based electricity is typically more expensive and often relies on imported fuel, reducing total factor productivity relative to a reliable grid supply.

Insufficient electricity supply may also affect energy prices and public finances. AI-related demand can raise electricity prices in the medium term when electricity supply cannot expand sufficiently (Bogmans and others 2025). In the context of many Sub-Saharan African countries where tariffs are regulated or subsidized, increased demand may transmit primarily to public finances rather than to prices. In the three Sub-Saharan African economies with the largest data center presence, electricity subsidies were significant in 2022—exceeding 1 percent of GDP in South Africa and reaching approximately 0.2 percent and 0.05 percent of GDP in Nigeria and Kenya, respectively (Black and others 2023). Petroleum subsidies were also positive, reaching 0.8 percent of GDP in Nigeria and 0.1 percent in South Africa (Black and others 2023). Where marginal electricity generation relies on higher-cost fuel-based sources, additional demand can widen this subsidy burden.

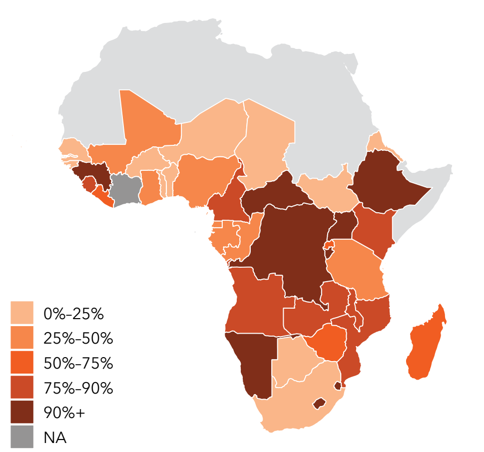
These pressures can propagate through several macroeconomic channels. Higher electricity prices reduce real disposable income for households and raise production costs for firms, weighing on profit margins, inflation dynamics, and external competitiveness. At the fiscal level, expanding subsidy burdens can crowd out public investment or weaken debt sustainability.

Electricity reliability, therefore, plays a critical role in determining whether faster AI adoption is feasible and at what costs for the rest of the economy. Where generation capacity, grid stability, and pricing frameworks adjust in parallel, AI-related electricity demand can be absorbed without macroeconomic strain. Where these adjustments lag, part of the projected productivity gains from AI-related capital deepening may be offset by higher operating costs and fiscal pressures.

B. The Potential Role of Renewables

Renewable energy expansion has begun to address electricity supply constraints (Figure 12). In 2024, renewable energy accounted for about 38.7 percent of installed electricity capacity across the continent (IRENA 2024), compared with about 46 percent globally or even higher numbers in some advanced economies (for example, 65 percent in Germany and over 50 percent in Spain). But country circumstances in Sub-Saharan Africa differ significantly. Hydropower-dominant systems such as Lesotho (100 percent renewable capacity), Ethiopia (96.9 percent), and Zambia (85.2 percent) rely primarily on renewables, whereas countries such as Botswana (1.3 percent) and Benin (12.0 percent) remain heavily fossil based.

Figure 12. Renewable Energy Share, 2023
(Percent of generation)



Source: IRENA.

Off-grid solar deployment has played a key role in the expansion of renewable capacity but is unlikely to be sufficient. Installed renewable capacity has doubled over the past decade, with off-grid solar playing a central role in extending access: Over 2020–22, 55 percent of new electricity connections in Sub-Saharan Africa were delivered through off-grid solar systems (World Bank 2024). And estimates suggest that off-grid solar is currently the lowest-cost option for providing access to almost half of the global population currently without power. But off-grid solar is unlikely, by itself, to provide the scale, continuity, and power quality required for large AI-related infrastructure such as data centers, which require continuous high-load electricity supply and have low tolerance for outages, voltage fluctuations, and service interruptions. As a result, off-grid and distributed renewable solutions can ease access constraints but are not a full substitute for reliable grid-based power systems in supporting AI-intensive activity.[7]

That said, the anchor-tenant model for AI data centers can strengthen the investment case for utility-scale renewables and downstream infrastructure. Kenya's experience is instructive: With over 90 percent of electricity generation derived from renewable sources, it is positioning its geothermal endowment as a competitive advantage for attracting green compute infrastructure. The Microsoft/G42 Naivasha campus draws power directly from geothermal generation, demonstrating that data center demand can make large-scale renewable projects financially viable in locations where dispersed household demand alone could not justify the investment. Initiatives such as the Africa Green Compute Coalition—a G7-endorsed program linking United Nations Development Programme, private sector, and African governments—are designed to institutionalize this link between renewable energy developers and digital infrastructure investors.

C. Digital Infrastructure and Affordability

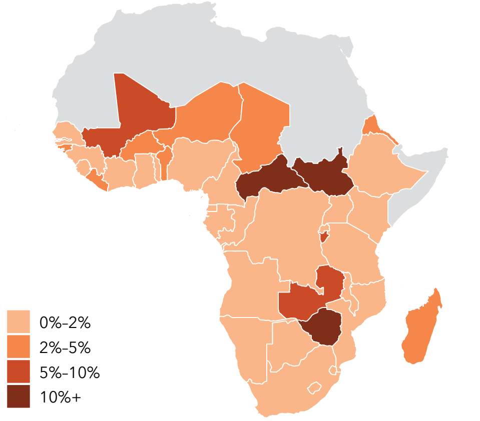
AI investment is strongly complementary to digital infrastructure and compute capacity. High-adoption scenarios implicitly assume high-capacity broadband networks and data center infrastructure, which together determine whether AI investment can scale efficiently across firms and sectors. Where complementary infrastructure is incomplete, the productivity effects of AI investment will be reduced. The mechanism is capital complementarity: AI investment raises productivity when combined with reliable electricity, high-capacity connectivity, and managerial adaptation (Acemoglu and Restrepo 2019). Where these complements remain constrained, capital deepening yields smaller gains.

Digital connectivity in Sub-Saharan Africa remains below global averages despite steady expansion in mobile networks. In 2024, 38 percent of the population in Africa used the internet, compared with 68 percent globally (International Telecommunication Union [ITU] 2024).[8] Mobile broadband subscriptions stand at about 52 per 100 people, roughly half the global average of 95 (ITU 2024; World Bank 2024). Although mobile network coverage covers an impressive 86 percent of the population, it remains uneven across regions and income groups, especially in rural areas (GSMA 2024). In addition, affordability remains a major barrier to digital adoption (Figure 13).

[7] In addition, installed renewable capacity does not automatically translate into reliable electricity supply. In several countries, a gap between installed capacity and realized output reflects grid bottlenecks, maintenance constraints, hydrological variability, and limited system flexibility.

[8] Internet use refers to the share of individuals who accessed the internet in the previous three months, following the International Telecommunication Union definition.

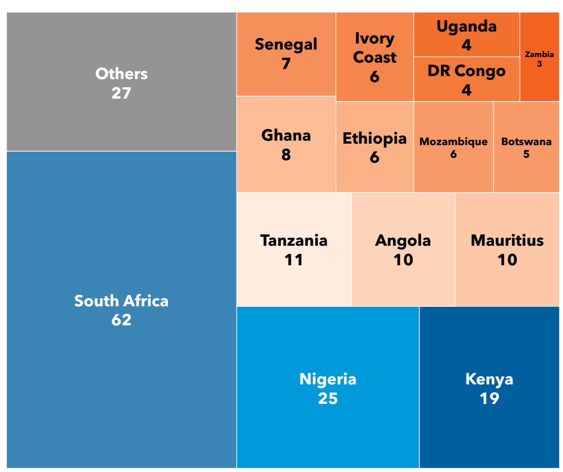
Figure 13. Affordability of 1 GB Mobile Data, 2023
(Percent monthly GNI per capita)



Sources: Cable.co.uk; and World Bank.
Note: GNI = gross national income; PPP = purchasing power parity.

Reliance on mobile networks has structural implications for digital capacity. A broad mobile coverage has helped develop a strong financial ecosystem in Sub-Saharan Africa, with Africa accounting for approximately 1.2 billion of the world's 2.1 billion registered mobile money accounts by the end of 2024 (GSMA 2025; Kakindé 2025). However, fixed broadband typically provides higher capacity, lower latency, and greater reliability than mobile infrastructure. Limited access to end-user devices further constrains digital adoption across Sub-Saharan Africa. Smartphone adoption also remains relatively low in Sub-Saharan Africa, at about 55 percent of mobile connections in 2023, compared with around 80 percent in East Asia and Pacific (GSMA 2024).

Figure 14. Data Centers in Sub-Saharan Africa
(Number of facilities)



Source: datacentermap.com.

AI infrastructure in Sub-Saharan Africa remains limited and heavily reliant on international investment. Although global technology firms are expanding cloud and AI infrastructure across the continent, compute capacity remains modest relative to global demand for AI infrastructure, with Africa hosting only about 160 data centers or about 5.5 percent of global installations (Kakindé 2025). Compute infrastructure is also geographically concentrated within the region, with nearly half of Sub-Saharan Africa's data centers located in South Africa, Nigeria, and Kenya (Patel, Nishball, and Ontiveros 2024; Pilz, Mahmood, and Heim 2025) (Figure 14).

D. Human Capital

Human capital constraints also limit the development and adoption of AI in the region. Fewer than 25 percent of higher-education students pursue science, technology, engineering, and mathematics disciplines, and tertiary enrollment remains low by global standards, at roughly 9 percent in Sub-Saharan Africa compared with about 40 percent globally (United Nations Educational, Scientific and Cultural Organisation [UNESCO] 2025). As a result, the pipeline of workers with advanced digital, engineering, and AI-relevant skills remains thin relative to the scale of future demand. The IMF AI Preparedness Index ranks Sub-Saharan Africa among the lowest globally in AI-related human capital readiness. In this regard, evidence suggests that AI-related productivity gains depend on complementarities between technology, skills, and organizational capabilities (Acemoglu and Restrepo 2019).

Brain drain compounds the AI skills deficit, driven in part by compute scarcity. Only 5 percent of Africa's AI talent has reliable access to the high-performance computing required for research (United Nations Development Programme [UNDP] 2024). And the result is striking: Although an AI practitioner in a G7 country can iterate on a model every 30 minutes during training, their African counterpart may wait up to six days for results from a single run (UNDP 2024). This "iteration gap" drives talent toward advanced economy markets where compute resources are more abundant. There exist, however, efforts to offset this trend. Research hubs like Carnegie Mellon University Africa in Kigali and grassroots communities like Masakhane (African-language natural language processing, with over 1,000 participants across 30 countries) and Deep Learning Indaba (a volunteer-led initiative that has become the largest AI research community on the continent) are building the ecosystems needed to retain talent locally. Nigeria's Three Million Technical Talent program, launched in late 2023, aims to train 3 million Nigerians in digital and technical skills. But without more local compute capacity, arresting the AI brain drain will remain a challenge.

Linguistic diversity adds complexity to AI development in Sub-Saharan Africa. Natural language processing systems require large digital corpora, yet many African languages remain underrepresented in digital data sets (Bender and others 2021). However, recent initiatives are beginning to expand language resources. Communities such as Masakhane have helped build open-source data sets and tools across multiple African languages (Nekoto and others 2020).

E. Investment Environment

AI deployment is capital-intensive and requires substantial upfront capital. The financing environment for AI ventures in Africa has tightened in recent years and remains concentrated. Total venture capital funding declined to approximately US$2.2 billion in 2024, with around 84 percent of flows directed to Egypt, Kenya, Nigeria, and South Africa (Kakindé 2025). Global AI investment is currently concentrated in advanced economies and a limited number of emerging markets with deeper capital markets, stronger infrastructure, and larger scale. In much of Sub-Saharan Africa, unreliable electricity supply, limited broadband capacity, smaller and more fragmented markets, and higher perceived risk weaken the investment case for large-scale AI infrastructure. Financing constraints may therefore affect both the pace and the distribution of AI adoption across the region. These dynamics echo a broader pattern in African development finance: Private capital is held back by a combination of sector-specific market failures and elevated project, macroeconomic, and exit risks and is unlikely to flow at scale without complementary public action (Eyraud and others 2021). Indeed, in the Sub-Saharan African infrastructure sectors that have attracted the most private participation, roughly half of all projects have relied on some form of public support—typically cofinancing and guarantees. AI is unlikely to prove an exception.

Digital industries tend to exhibit strong scale economies and network effects. Early-mover locations with stronger infrastructure and deeper capital markets are more likely to attract additional investment, reinforcing geographic concentration in AI-related activity. Although such concentration does not eliminate aggregate productivity gains, it affects their distribution across countries. Economies with weaker infrastructure and capital formation capacity may become increasingly dependent on externally hosted services. And for the region as a whole, AI-related value-added activities may tend to concentrate in a small set of digital hubs.

5. Surging Ahead versus Left Behind: Different Adoption Paths, Different Growth Paths

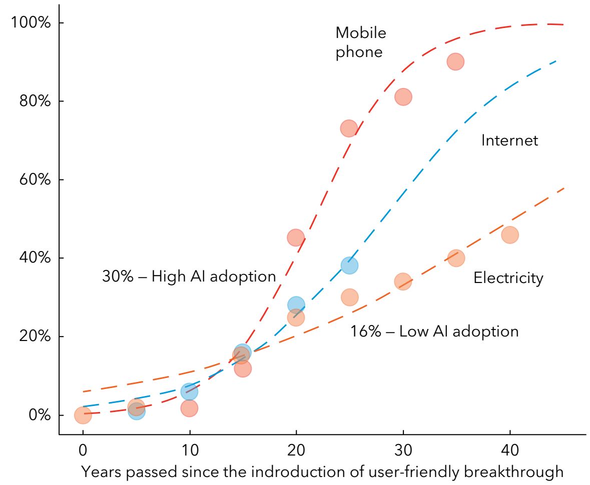
The barriers to AI adoption in Sub-Saharan Africa are real and represent binding constraints *at present*. But they are barriers, not boundaries—features of the current moment. Relax those assumptions, and the numbers could change substantially. This section explores what a high-adoption path might deliver, where the region's largest potential gains lie, and what the evidence from agriculture, health, and education is already starting to show.

A. Forward-Looking Assumptions

Backward-looking measures may not fully capture a future of transformative change. The framework estimates presented earlier are deliberately conservative, assuming a continuation of the region's subdued adoption trends, a modest reduction in labor costs, and no adoption in low-exposure sectors along with static exposure levels, resulting in only modest improvements in productivity and growth. But given the potentially transformative nature of AI, estimates of the technology's effect on future growth vary widely,[9] and estimated gains under the framework would be significantly larger under less conservative assumptions. For example, adoption is likely to increase in line with rising capabilities, including through cost-efficient AI-as-a-service models (that is, on-demand access to AI tools on a pay-per-use basis), which lower the fixed cost and technical barriers to entry, accelerate diffusion, and amplify the productivity compared with scenarios where only large, well-resourced firms adopt AI. Similarly, newer micro-level studies find substantially larger productivity improvements—with gains of almost 60 percent for programmers—suggesting that the commonly assumed saving of about 30 percent may be outdated. High-performing, open-source models—such as China's DeepSeek R1—are also lowering the capital threshold for adoption by delivering frontier-level capabilities at a fraction of proprietary costs (Quansah 2025). Bundled with affordable cloud services from providers such as Huawei, such models are already gaining traction among African developers, suggesting that cost barriers may fall faster than backward-looking measures imply.

[9] Aghion and Bunel (2024), for instance, revisit the Acemoglu (2024) approach and apply more optimistic assumptions on each component, arriving at significantly larger productivity gains for the United States—up to a 6 percent growth boost in total factor productivity (TFP) over 10 years, compared with Acemoglu's 0.7 percent. Similarly, the Penn Wharton Budget Model (2025) projects a cumulative GDP boost of about 1.5 percent for the United States by 2035. Analyzing the effect of AI in 56 advanced and emerging market economies and 16 sectors, the Bank for International Settlements (Aldasoro and others 2024) assumes a 1.5 percentage point boost to *annual* TFP growth, whereas the Organisation for Economic Co-operation and Development (Filippucci, Gal, and Schief 2024) lands at +0.25–0.6 percentage points to annual growth. Cerutti and others (2025) assume global TFP gains from AI of 0.8–2.4 percent over 10 years under low- and high-TFP growth scenarios, respectively, with the largest gains in AI-intensive sectors. Using similar methodology, AlHassan and others (2026) estimate that, for the regions of Middle East, North Africa, Afghanistan, and Pakistan and Caucasus and Central Asia, the low-TFP scenario implies modest gains after 10 years, ranging from 0.1 percent in low-income countries to 0.8 percent in the United Arab Emirates, whereas the high-TFP scenario yields gains of 0.3–2.2 percent.

Figure 15. Sub-Saharan Africa: Adoption Paths of Previous GPTs
(Usage rate, in percent)



Source: World Development Indicators database.
Note: AI = artificial intelligence; GPT = general-purpose technology.

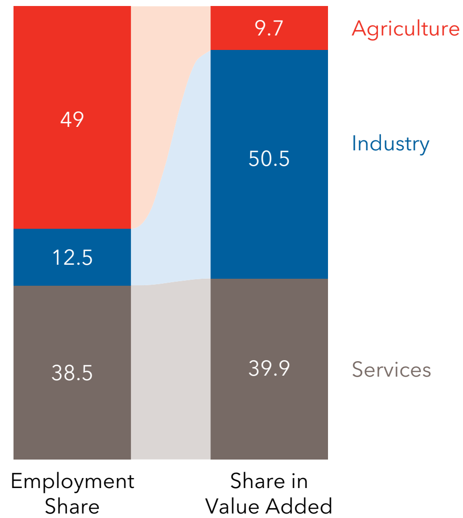
B. Pace of Adoption

Policies that increase adoption will be essential. Historically, the pace of adoption of new technologies in Sub-Saharan Africa has varied widely, from slow diffusion of technologies like electricity to rapid uptake of mobile phones and the internet, reflecting differences in the policy and business environment (Figure 15). With the arrival of AI, the need to foster the preconditions for integrating new technologies—such as improved digital infrastructure, enhanced skills, and a market-friendly business climate—has become even more urgent. If current adoption rates were lifted to levels observed in other emerging and advanced economies, productivity gains could more than double, increasing by an additional 0.8 percent over the next decade. Moreover, higher adoption would likely trigger complementary adjustments, such as increased AI-related investment and stronger human capital formation. These channels would amplify the direct productivity effects from AI exposure (Box 3).

C. Types of Exposed Sectors

Moreover, if AI were to filter into sectors traditionally viewed as "low exposure," the benefits for the region would be higher still. Agriculture, for example, has traditionally been one of the least productive sectors in Sub-Saharan Africa, employing roughly half of the workforce and characterized by large information gaps (Figure 16). Although agriculture is commonly classified as low exposure in task-based measures, targeted AI applications operate primarily through information and decision gaps rather than task substitution. As a result, there is scope for significant productivity gains when AI complements farmers' decision making, input use, and risk management. Generative and predictive AI tools, when adapted to local conditions, can provide real-time guidance on crop management, pest control, market conditions, and climate risks.

Figure 16. Sub-Saharan Africa: Employment versus Productivity
(Percent)

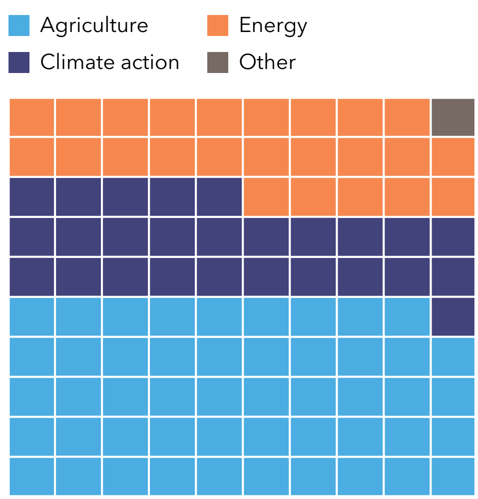


Source: World Development Indicators database.

D. Recent Successes in Agriculture

A gradual integration of AI, machine learning, and Internet of Things technologies is already helping a shift toward more data-driven and resilient agricultural systems in Africa. Although exact quantification varies, nearly half of the identified AI applications in Africa focus on agriculture, spanning mobile advisory platforms, supply-chain tools, and food security monitoring systems (African Centre for Technology Studies 2023) (Figure 17). This transformation draws support from a fast-growing regional agritech market (Boston Consulting Group 2025) that is addressing the reality that typical Sub-Saharan African crop yields hover at around 25–33 percent of potential (Ebeke and Ntsama Etoundi 2025). Notwithstanding this unexploited potential, examples of AI adoption in much of the region's agricultural sector are already numerous.

Figure 17. AI Applications by Sector
(Each square = 1%)



Source: GSMA 2024.
Note: AI = artificial intelligence.

For example, mobile- and short message service (SMS)-enabled solutions effectively reach remote farmers, broadening access where formal services lag. For instance, Farmerline's Darli AI (including its regenerative farming version) serves as an AI-powered companion for smallholders' decisions on planting and irrigation, using real-time weather data and supporting 27 languages, including 20 African ones; native-language delivery makes farmers 60 percent more likely to adopt techniques (World Economic Forum 2025). Similarly, FarmerChat (https://digitalgreen.org/farmer.chat/) is an AI-powered agricultural companion designed to help smallholder farmers make smarter decisions on planting, irrigation, and other essential tasks by leveraging real-time weather data. In addition, it serves as an educational tool providing climate and sustainability programs. These low-tech interfaces prove vital for smallholders who account for a dominant share of the sector (reaching over 80 percent) yet remain underserved by traditional extension services (Smart Africa 2023).

Advanced monitoring platforms enhance precision agriculture with local data. Kenya's Agricultural Observatory Platform leverages satellite geo-data for real-time advice to more than 700,000 farmers (CGIAR 2026). Similarly, FarmSpeak offers real-time poultry disease diagnosis for livestock monitoring (FarmSpeak 2024). Senegal's Tolbi employs machine learning for automated irrigation, cutting water use by up to 60 percent (We Are Tech Africa 2022). South Africa's Aerobotics uses AI drones to monitor crop health, achieving 15 percent yield gains and 15 percent pesticide reductions (Squatrito 2025).

Emerging evidence points to sizable productivity gains. Randomized trials across Nigeria, Ghana, Rwanda, Kenya, and Uganda show digital advisories lifting yields up to 15 percent, and 20–30 percent with complementary inputs (Brookings Institution 2025). In Ethiopia, customized fertilizer advice boosted wheat and maize yields by 15–30 percent (CGIAR/AICCRA 2024). A study by Aramburu-Merlos and others (2024) suggests that, under high-adoption scenarios combining improved agronomic practices, such as optimized cultivar selection, nutrient management, and enhanced pest and weed control, on-farm yields could roughly double, raising total maize production in Sub-Saharan Africa from about 80 million to nearly 170 million tons by 2050 on existing cropland, reflecting compounding productivity gains along the production chain. And Touza and others (2025) find that AI-enabled SMS advisory system led to a statistically significant 16.6 percent increase in crop yields and a 23 percent rise in agricultural income relative to a matched control group over one agricultural season. Productivity gains were driven by higher adoption of improved agronomic practices, with stronger effects for more intensive users of the service.

The potential of Africa's agribusiness has long been recognized—AI-based innovations have the potential to play a key role in realizing the vision of moving the region from a net food importer to a sustainable global leader through narrowing the yield gap (World Bank 2013).

E. Other Sectors

Beyond agriculture, AI is beginning to deliver meaningful gains in education and health care by augmenting scarce teachers and clinical staff, including in low-resource and rural settings. The effect, however, is not automatic: Effective deployment requires solutions tailored to local constraints—limited connectivity, basic devices, and low-bandwidth channels (including SMS, WhatsApp, and offline tools)—as well as integration into existing systems, with human oversight, local data, and strong monitoring and evaluation.

In education, AI-enabled tools are improving both access and learning outcomes through several scalable use cases. These include AI-supported tutoring and teacher-assistance tools, where general-purpose or specialized models provide curriculum-aligned practice and classroom support (for example, Nigeria's uLesson [https://blog.ulesson.com/embracing-the-future-ai-powered-homework-help-by-ulesson/] platform, chatbot-based tutoring in Nigeria, and virtual teaching assistants in Ghanaian higher education). Adaptive learning platforms (such as South Africa's Siyavula [https://www.siyavula.com/]) sequence practice and provide real-time feedback, and assessment dashboards (for example, Shule Direct [https://shuledirect.org/ai-teachers/] in Tanzania and tablet-based AI assessment tools [https://leadforghana.org/blog/ai-teachers-pilot-program] in Ghana) help teachers target remediation. Delivery models increasingly rely on low-connectivity channels, including SMS-based micro-lessons (for example, M-Shule in Kenya) and offline AI assistants (for example, Camara [https://camara.org/major-milestone-for-ai-in-education-in-ethiopia/] in Ethiopia), enabling access in underserved areas. These approaches are being complemented by national- and system-level initiatives—such as Rwanda's Smart Education Project, which connects schools to high-speed internet, deploys data centers, and supports digital skills training—and broader programs (ProFuturo-, Imagine Worldwide-, and KOICA-supported projects) combining infrastructure, teacher training, and digital content across countries including Liberia, Tanzania, and The Gambia. Evidence suggests sizable gains: A six-week chatbot-based tutoring program in Nigerian secondary schools generated learning improvements equivalent to roughly two years of schooling (De Simone and others 2025), whereas other evaluations report gains two to three times larger than those of peers in comparable schools.

In health care, AI applications are easing chronic capacity and access constraints across diagnostics, primary care, and system management. Diagnostic tools, including computer-aided detection for tuberculosis and computer vision systems for malaria, are among the most advanced use cases. AI-assisted decision support and triage tools, often deployed through mobile platforms, have shown measurable reductions in diagnostic and treatment errors in select African health care settings,[10] whereas telemedicine combined with algorithmic triage has been deployed at scale (for example, Rwanda), shifting patterns of health care utilization. AI is also supporting maternal and child health (for example, WhatsApp chatbots in Nigeria [https://www.gavi.org/vaccineswork/nigeria-ai-tools-are-already-changing-how-people-access-healthcare] and AI-enabled ultrasound tools in Zambia [https://www.dailytarheel.com/article/university-ai-pregnancy-research-20240910]), as well as supply chain and logistics systems, including AI-managed inventory platforms (for example, Viebeg Technologies in the Democratic Republic of the Congo, Kenya, and Rwanda) and drone-enabled delivery networks (for example, Rwanda and Ghana). At the system level, AI-enabled platforms are strengthening disease surveillance, outbreak detection, and health communication (for example, Ethiopia [https://www.afro.who.int/countries/ethiopia/news/ethiopia-digitalizes-and-modernizes-its-health-emergency-information-systems] and Rwanda [https://www.moh.gov.rw/news-detail/new-health-intelligence-center-to-drive-real-time-evidence-based-decisions]). AI also has the potential to strengthen epidemic preparedness and response through early warning, pathogen characterization, vaccine design, manufacturing, and deployment, although realizing these gains requires overcoming constraints in infrastructure, workforce capacity, and institutional frameworks (Standley and others 2025).

Across both sectors, scaling these gains will require investment in local data sets (including language and curriculum-specific content), improved infrastructure and connectivity, strengthened human capital, and robust governance frameworks to ensure privacy, safety, and equitable access.

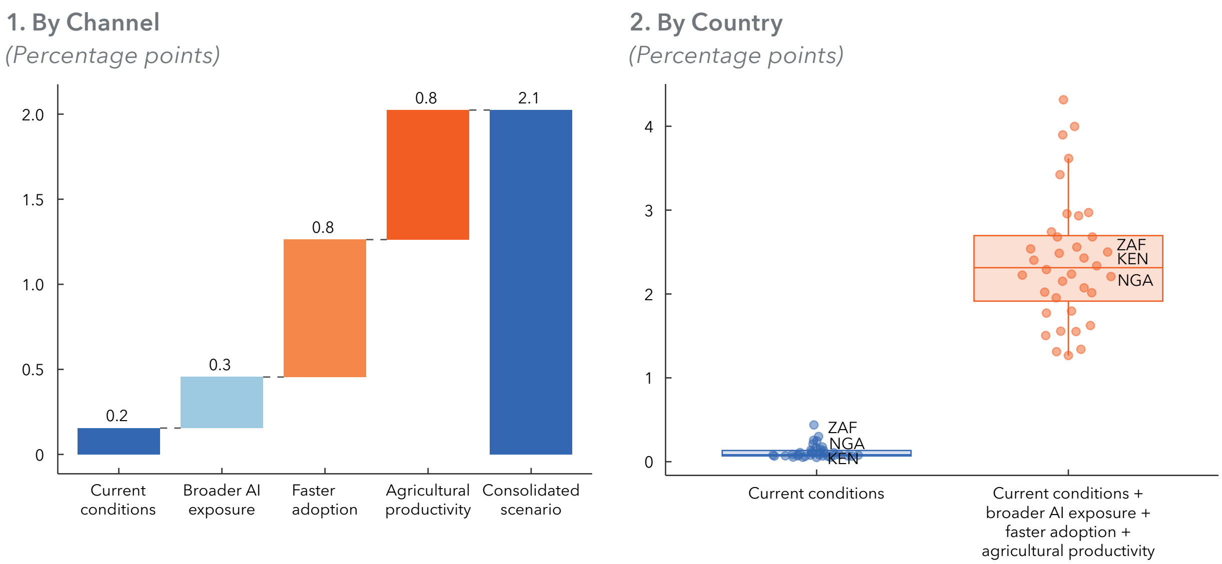
F. The AI Effect Could Be Significantly Higher

Assuming faster AI adoption generally, and a greater effect on agricultural productivity specifically, generates an increase in the estimated effect of AI in Sub-Saharan Africa by an order of magnitude compared with the current-conditions estimate. Recent evidence indicates that AI adoption has proceeded faster and across a broader range of sectors than assumed in early studies. Specifically, the adoption of generative AI has nearly doubled within a year, with around two-thirds of organizations covering all regions, industries, and sizes now using it in at least one business function (McKinsey and Company 2025). If adoption rates were to nearly double in Europe and the Western Hemisphere, reaching about 40 percent, overall productivity would improve by an additional 0.2 percentage point over the next decade, whereas for similar adoption

[10] One large-scale study in Kenya reported a 16 percent drop in diagnostic errors and 13 percent drop in treatment errors across nearly 40,000 patient visits (Korom and others 2025).

rates, the potential gains in Sub-Saharan Africa would be around 0.8 percentage point, reflecting the initial digital adoption gap. Moreover, extending AI adoption in Sub-Saharan Africa to agriculture and other sectors would add a further 0.8 and 0.3 percentage point, respectively, to productivity gains on average, significantly more than in other regions, owing to the sector's large employment share and the existing productivity gap. This would raise the median productivity effect more than 10-fold, from 0.2 to around 2.1 (Figure 18). The effect on GDP would be similarly amplified, rising to 4.0 percent over the coming decade, equivalent to adding nearly ½ percentage point of annual real GDP growth over the same time period—and potentially more if stronger human capital formation were to materialize (Box 3). Moreover, given the heterogeneity of the region, some countries could benefit substantially more than the regional average, largely reflecting greater gains from closing gaps associated with weaker initial conditions.

Figure 18. Sub-Saharan Africa: AI Productivity Effect



Source: IMF staff calculations.
Note: AI = artificial intelligence.

Achieving these additional effects will, however, require concerted policy efforts that provide the conditions conducive to broad-based AI adoption. The high-adoption scenario should therefore not be read as an automatic upside case. It is a policy-contingent scenario in which adoption accelerates because countries improve enabling conditions, expand exposed sectors, strengthen digital and energy infrastructure, and integrate AI into public and private workflows.

Even with these modified assumptions, the task-based framework, while simple, tractable, and widely used, may not fully capture all the additional nuances and uncertainties associated with such a fast-moving technology. That is, the framework still only identifies the direct, partial equilibrium effects of AI—the efficiency improvements within exposed tasks, assuming that factor prices and resource allocation are held constant. General equilibrium effects can either amplify or attenuate these effects (Baqaee and Farhi 2019), with the net effect an empirical question (Annex).

- On the *amplification* side, cost reductions in AI-adopting sectors can propagate through production networks, lowering intermediate input prices, raising real purchasing power, and stimulating downstream demand—effects that are particularly significant when adoption is concentrated in upstream or highly interconnected industries (Baqaee and Farhi 2019). Increasing returns to scale and cross-sector complementarities can reinforce these dynamics, generating aggregate productivity gains that exceed the sum of firm-level improvements.

- *Attenuating* forces include the reallocation of labor and capital toward AI-intensive activities, which may generate adjustment costs, skill mismatches, or diminishing returns in expanding sectors, partially offsetting the direct gains. Moreover, distortions and markup heterogeneity across production networks can cause the aggregate productivity response to diverge—in either direction—from what micro-level evidence alone would suggest (Baqaee and Farhi 2019). In this context, Baumol-type effects may further dampen aggregate productivity gains: Uneven AI-driven productivity growth can lower relative prices in high-productivity sectors and, through demand and wage effects, dilute overall gains. Similarly, AI-driven productivity gains may be dampened in cases where sectoral reallocation is constrained, and demand is relatively price inelastic, limiting employment and output growth despite higher productivity. In a separate analysis, we investigate the empirical importance of these general equilibrium effects in Sub-Saharan Africa and find them to be limited, on the order of about −0.1 percentage point annually, albeit with substantial cross-country variation (Kiendrebeogo 2026).

Box 3. Beyond Productivity: Other Channels of Artificial Intelligence's (AI's) Effect on Growth

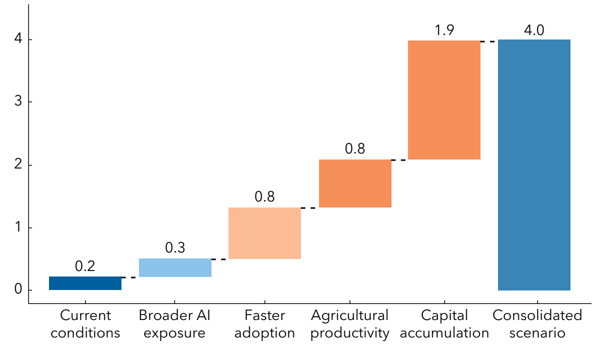
The effect of AI on growth is likely to extend beyond direct productivity effects. In particular, increased investment in AI-related capital provides an immediate boost to growth while expanding productive capacity over the medium term. In addition, AI adoption could accelerate human capital formation. And the effect may increase further if the creation of new tasks is taken into account, a feature that is often excluded from simple efficiency-focused models. Lastly, by accelerating scientific discovery and research and development, AI holds the potential for permanent growth effects rather than a simple onetime level shift in productivity. These channels could be especially important in Sub-Saharan Africa, where large investment shortfalls and development gaps imply substantial scope for catch-up and outsized gains from faster AI diffusion.

Accelerating investment in AI could raise the economy's productive capacity over the medium term. In addition to AI-related investment, a solid enabling environment for AI adoption would also improve the environment for investment more broadly.

But AI also has the potential to accelerate human capital formation by narrowing long-standing knowledge gaps between Sub-Saharan Africa and more advanced regions. Faster adoption can help workers and firms access and absorb information at significantly lower cost. This transformative channel, rooted in rapid skill acquisition, improved access to educational content, and more efficient knowledge transfer, could meaningfully raise the stock of effective labor. Although estimating the growth effect of AI-driven human capital accumulation is complicated by long lags, uneven educational infrastructure, and large differences in digital readiness across the region, its contribution to growth in Sub-Saharan Africa could be substantial, further amplifying AI's GDP effect over the coming decade.

Box Figure 3.1. Sub-Saharan Africa: Decomposition of GDP Effect

(GDP-weighted average, percentage point gain over 10 years)



Source: IMF staff calculations.

Note: AI = artificial intelligence.

6. Winners, Losers, and Risks

Removing barriers to adoption is necessary to benefit from the potential gains of AI but may not be sufficient. Even under the high-adoption scenario, the benefits are unlikely to be shared equally. The same forces that can raise productivity and improve service delivery can also widen inequalities, disrupt labor markets, concentrate market power, and amplify cyber and information risks, especially where institutions and infrastructure are weak. This section examines who stands to gain, who risks being left behind, and where the governance gaps are widest.

The distributional consequences of AI adoption in Sub-Saharan Africa are highly uncertain and will depend on the pace, pattern, and policy context of diffusion. AI will not affect all countries, sectors, or workers equally. Under some plausible paths, AI could be a powerful equalizer—raising agricultural productivity, expanding access to education and health care, and creating new opportunities for low-skill and informal workers. Under others, it could amplify existing inequalities. A central risk is that, absent deliberate policy action, rapid adoption reinforces rather than reduces structural disparities. Managing this risk requires

- protecting vulnerable workers and households during transitions, so that reform remains legitimate;
- preventing an outcome where AI's benefits accrue mostly to a small number of countries, firms, and skilled workers; and
- ensuring the rules of the game build trust around privacy, accountability, and cybersecurity.

A. Who Benefits, Who Is Left Behind?

The current-conditions estimate suggests that the region's current job structure should not only limit near-term labor market disruption but also constrain immediate economy-wide productivity gains. With employment concentrated in agriculture and informal services, sectors where AI exposure is generally low, any early effects are likely to be concentrated in narrower segments of the economy. The corollary is that, absent deliberate efforts to broaden adoption and build complementary inputs, AI's benefits may accrue primarily to a few firms, sectors, and locations, raising the risk that the region as a whole falls further behind frontier productivity growth.

Even so, AI could widen inequalities across workers, firms, and regions, both within and across countries. Job churn and wage polarization can still be significant, especially in urban formal segments where exposure is higher. AI may reduce demand for some tasks while increasing demand for complementary roles (for example, data-enabled extension workers, diagnostic assistants, and AI-supported compliance staff). The critical risk is a mismatch between the speed of task change and the pace of skills adjustment. Two features heighten the distributional stakes in the region: (1) the coming demographic wave, with a projected 15 million new labor force entrants each year, increasing the urgency of job creation and skills formation, and (2) the region's high degree of informality, limiting access to formal training, unemployment insurance, and other automatic stabilizers that can help smooth transitions.

Scale economies and network effects in digital industries favor geographic and commercial concentration. Venture financing and compute infrastructure are already concentrated in a handful of countries and hubs. This can translate into a pattern where value-added and high-skill jobs cluster in some areas, whereas others rely on externally provided services. This would lead to an uneven diffusion of productivity gains, the risk that dominant platforms may extract large profits, and strategic concerns about reliance on foreign providers.

Absent policy intervention, the near-term gains from AI are more likely to accrue to two groups, though outcomes will depend heavily on the adoption path and the policy choices that shape it. First, high-skill workers and firms in more formal, information processing intensive activities (such as finance, information and communications technology, and professional services), where AI is more readily deployed and can complement tasks. Second, early-mover economies and urban hubs with stronger electricity, connectivity, and compute capacity, and in particular those areas where data centers and cloud infrastructure are concentrated (currently South Africa, Nigeria, and Kenya).

Conversely, several groups face a greater risk of being left behind. First, workers in routine clerical and basic service roles that are more exposed to automation, especially where firms adopt AI to reduce costs and where reskilling pathways are limited. Second, small firms and informal enterprises that lack reliable power, affordable connectivity, devices, and managerial capacity to integrate AI tools; and this risks a widening productivity gap between frontier firms and the long tail. Third, rural communities and low-income households, for whom connectivity and affordability constraints remain binding (internet use remains below global averages and device access is limited), potentially reinforcing the already large spatial inequality. Finally, countries with weaker infrastructure and institutions, which may become more dependent on externally hosted services and imported solutions, with fewer domestic spillovers and weaker bargaining power over data, standards, and rents. But these outcomes are not predetermined: Targeted policies to broaden access, invest in skills, and extend infrastructure can significantly alter who benefits.

These distributional dynamics echo earlier waves of globalization and technological change: Although aggregate gains can be positive, political and social support hinges on how adjustment costs are managed and opportunities broadened. This underscores the need for complementary investments and active labor market measures. Past experience shows that redistributing aggregate gains to offset losses and compensate those losing out is difficult, requiring sustained political commitment.

B. The Need for New Regulation

Trust is the currency of the digital economy. Without credible governance, AI adoption can be slowed by legitimate concerns about privacy, misuse, bias, and surveillance, and where adoption proceeds anyway, weak governance can amplify harm. The region's governance starting point is uneven. Only a small number of countries have drafted national AI strategies; adoption and implementation are also still in progress.[11] Many countries have data protection laws, but enforcement capacity is inconsistent, reflecting fragmented regulation and limited institutional resources.[12] Four risk areas deserve emphasis.

Privacy and misuse of personal data. AI systems often rely on large data sets that can include sensitive personal and biometric information. In settings with weak safeguards, data can be used for commercial exploitation, political targeting, or discrimination, undermining trust and social cohesion.

Bias and exclusion. Limited availability of representative local data sets, including for low-resource languages, can reduce model performance and amplify bias, with real consequences in high-stakes domains such as credit decisions, hiring, and access to public programs.

[11] While concerted efforts are advancing, as of early 2026, only about a dozen Sub-Saharan African nations had drafted national AI strategies, with several others at varying stages of developing AI frameworks. (The OECD.AI Policy Navigator [https://oecd.ai/en/ The OECD Artificial Intelligence Policy Observatory - OECD.AI] provides detailed information.) And the average AI Preparedness Index score for Africa stands 13 points below the global average of 47.6, reflecting policy and regulatory gaps.

[12] A comparative analysis highlights this uneven capacity: While Kenya (Data Protection Act 2019) has achieved measurable progress in enforcement, Nigeria (Data Protection Act 2023) continues to face foundational organizational and enforcement issues.

Cross-border data and control trade-offs. Hosting data, compute, and critical digital infrastructure abroad can lower costs and provide resilience but may also create tensions around legal jurisdiction, access rights and control, and continuity of service during crises and conflicts. All these concerns are heightened when governance frameworks are incomplete.

Cybersecurity, fraud, and misinformation. AI lowers the cost of producing convincing content at scale that can be used for automated scams, deepfakes, impersonation, and disinformation, which poses risks to elections, social trust, and financial integrity. It can also be weaponized to identify vulnerabilities in digital systems. The risk is particularly acute where public systems are being digitized quickly, but security standards and incident response capabilities lag behind. And these threats can be macro-critical: Financial fraud can undermine confidence in digital payments; misinformation can hinder public health responses; and cyberattacks can disrupt critical infrastructure and public administration, with fiscal and growth costs. Managing these risks requires that AI adoption be accompanied by strong risk-based regulation, including timely updates to anti–money laundering/combating the financing of terrorism frameworks, effective risk-based supervision, enhanced due diligence and transaction monitoring, safeguards around digital identity, and closer coordination between financial supervisors and law enforcement authorities.

7. Addressing Barriers, Reducing Risks, Sharing the Gains

AI has the potential to boost productivity and welfare across sub-Saharan Africa: raising agricultural yields, improving health outcomes, expanding access to education, deepening financial inclusion, strengthening tax administration and public service delivery, and enhancing climate resilience. Translating this potential into broad-based gains requires a deliberate policy agenda. Building on the earlier distributional and risk considerations, this section sets out a pragmatic policy agenda that is sensitive to fiscal constraints and institutional capacity, focused on enabling adoption, expanding diffusion beyond early movers, and embedding safeguards through institutions and regulation.

A. Policy Approach and Sequencing

Realizing AI's potential requires a combination of economy-wide reforms and targeted complementary investments that enable adoption and diffusion across firms and the public sector, while supporting adaptation to local needs. This agenda has four operating principles:

- **Sequence for delivery**. Start with time-bound "quick wins" that demonstrate value and build implementation capability, while laying foundations for larger reforms in infrastructure, skills, and institutions.
- **Focus on complements and necessary conditions**. AI investment raises productivity when paired with reliable electricity, connectivity, data infrastructure, and organizational change.[13] Absent these, gains are smaller, and diffusion remains narrow and, in many cases, elusive, particularly where energy and digital infrastructure are weak. Broader structural reforms in the areas of trade integration, digital payment systems, public financial management, and investment climate are key complements and mutually synergetic with AI adoption.
- **Design for inclusion and scale**. Prioritize solutions that work under regional constraints, including low bandwidth, basic devices, and multiple languages. And enable scale through interoperability and regional integration.
- **Crowd in private capacity through public-private partnerships**. Pair public prioritization, data stewardship, and safeguards with private innovation and operations, using performance-based procurement and interoperability standards to scale proven pilots while limiting fiscal and lock-in risks. Mobilizing private finance for AI-related infrastructure will, in many cases, require a combination of risk mitigation (strengthening the business climate), targeted promotion (subsidies and guarantees), as well as possible compensation for those bearing the costs of reform—the three pillars set out in Eyraud and others (2021).

Near-term delivery priorities (quick wins). Governments can build momentum through low-cost use cases with clear service-delivery payoffs, implemented through time-bound pilots with measurable objectives and monitoring frameworks. In these pilots, the public sector should define priorities and service standards; provide enabling public goods (digital ID, core registries, administrative data, and connectivity for schools and clinics); integrate tools into frontline workflows; and set safeguards for privacy and cybersecurity, with stricter requirements for high-risk services. The private sector will then be able to develop, deploy, and operate solutions, providing maintenance and user support, and scale delivery once approaches are proven. Priority use cases include education (curriculum-aligned tutoring and teacher support); health (triage/

[13] See Cazzaniga and others (2024) and Bogmans and others (2025) on prerequisites for adoption, including energy, other infrastructure, and skills.

diagnostics support, scheduling, and logistics); and agriculture (advisory and predictive analytics that work under low-bandwidth conditions). Concrete early payoffs include last-mile logistics solutions in Rwanda and Ghana (for instance, drone deliveries of medical supplies), which can be strengthened further by AI-enabled inventory management and demand forecasting. Other near-term enablers include continued digitalization of core government functions, particularly revenue administration (Kenya's iTax) and customs modernization (Ghana's Integrated Customs Management System), to deliver fiscal dividends and build administrative data foundations for later AI use.[14]

B. Building the Foundations: Digital Infrastructure as a Binding Constraint

For many countries, the binding constraint is not the absence of AI tools but the high cost and limited reliability of the infrastructure needed to deploy them at scale. The priority is therefore to lower the cost and improve the reliability of digital services, especially outside major urban centers, so that AI does not remain confined to a few large firms or hubs.

Reliable, affordable electricity. Priorities include targeted grid investments and mini-grid solutions around high-demand nodes (schools, clinics, cooperatives, and local government offices) that can anchor local digital service hubs. Expanding renewables can support affordability and climate objectives; pilots such as solar-powered base stations and solar-powered data centers with battery storage can reduce outages and operating costs, particularly in remote areas. In this regard, strategic deployment of data centers can further strengthen the case for private investment in energy supply: a committed long-term power purchase agreement from a data center operator may provide the bankable demand that project financiers require. Policy frameworks should consider linking data center permits to grid extension commitments, ensuring that anchor demand catalyzes broad-based electrification rather than isolated enclaves.

Affordable broadband access and last-mile connectivity. Accelerate investment in fiber backbones and promote open-access wholesale markets to reduce unit costs and expand coverage (Oughton, Amaglobeli, and Moszoro 2023). Where commercial viability is limited (rural and peri-urban areas), use blended finance and improve universal service mechanisms to crowd in private participation and support community networks (Eyraud and others 2021).

Cloud infrastructure, data centers, and edge computing. Although falling model costs, open-source systems, and AI as a service can lower entry barriers, compute access may remain expensive, concentrated, and geopolitically fragmented, strengthening the case for regional compute facilities. Encourage regional data center development, pooled procurement, and transparent cloud contracts, supported by streamlined permitting and renewable energy procurement frameworks, to reduce latency and improve resilience. Promote content caching and edge computing in secondary cities to reduce bandwidth costs and improve user experience, enabling more AI-intensive applications under constrained networks (Cao and others 2024). Leverage data centers not merely as commercial facilities but also as strategic assets whose concentrated energy demand can anchor renewable energy projects—solar, wind, and geothermal—at the scale required for financial viability.

[14] See Alonso and others (2023) and Amaglobeli and others (2023) on digital public infrastructure building blocks; Nose and Mengistu (2023), Aslett, González, and Pecho (2024), and Betts (2022) on digital technologies in tax administration.

C. Developing Human Capital: Skills for Adoption, Innovation, and Governance

Sub-Saharan Africa's demographic dividend will depend on equipping workers and citizens with the skills to use, manage, and govern AI systems. Policy should prioritize measurable outcomes (enrollment, completion, and employability) and combine education system modernization with workforce upskilling and reskilling (Pizzinelli and others 2023).

Modernize education systems for an AI-augmented future. Address foundational learning gaps where binding, then integrate digital and AI literacy early in curricula (data basics, privacy, bias, and safe use of generative tools). At the tertiary level, expand capacity in computer science, statistics, data engineering, cybersecurity, and ethics through accreditation upgrades, faculty exchanges, and regional centers of excellence. Targeted incentives, such as research grants and innovation hubs, can help retain talent.

Scale workforce upskilling and modular training. Partner with employers and industry associations to deliver practical training in data labeling, prompt engineering, model evaluation, AI-augmented productivity tools, and basic maintenance. Establish national skills observatories to track demand for AI-complementary occupations and inform training procurement.

Embed inclusion by design. Use scholarships and stipends for women and marginalized groups—who lag in their usage of mobile and digital technologies, provide childcare and safe transport support, and facilitate recognition of prior learning with stackable credentials to lower barriers and facilitate transitions from informality to formal digital employment.

D. Fostering a Local AI Ecosystem: "Built in Africa, for Africa"

Although AI is a global phenomenon, maximizing its development effect requires solutions adapted to local contexts: languages, institutions, constraints, and sectoral priorities. Policies should support local innovators, strengthen the business environment, and attract investment while enabling safe experimentation and scale-up.

Support start-ups and small and medium enterprises. Time-bound tax credits or matching grants can help finance AI-related research and development, local data set creation, and model fine-tuning in priority sectors (Brollo and others 2024). To address the "valley of death" in financing—where promising projects languish as small-scale pilots without ever making the leap to broad-based adoption—governments can catalyze patient capital through public seed funds or first-loss guarantees that crowd in private investment. Where domestic fiscal space is constrained, multilateral and bilateral development partners can also amplify these instruments, drawing on a wider toolkit of blended finance and project preparation facilities (Eyraud and others 2021). Regulatory sandboxes, especially in fintech, agritech, and healthtech, can facilitate controlled testing while building regulatory learning and reducing bureaucratic hurdles (Bains and Wu 2023).

Create capability hubs and public-good digital assets. Support regional AI labs and innovation hubs connected to universities, hospitals, agricultural cooperatives, and municipalities. Encourage open-source communities (maintainer programs, training sprints, and mentorship) and run public data challenges using appropriately anonymized data sets linked to policy priorities, generating reusable code and models. In this context, the success of any effort to foster a local AI ecosystem will be closely linked to progress on local digital infrastructure. Without local compute, talent migrates; with compute, the possibility of a virtuous circle arises in which infrastructure unlocks talent, talent localizes solutions, and localized solutions generate growth that funds further infrastructure.

Invest in local data sets and accessibility. Expand interoperable digital ID systems and core registries, fund local-language data initiatives, and release anonymized public sector data sets (weather, traffic, and health statistics) to fuel innovation. Promote multimodal interfaces (voice, SMS, and Interactive Voice Response) to reduce barriers from literacy and device constraints.

Use regional integration to achieve scale. Fragmented national markets limit commercial viability. Leveraging the African Continental Free Trade Area to harmonize digital trade rules and data transfer policies can help firms scale across borders (African Union 2024). Pooling resources for regional high-performance computing centers can expand access for universities and researchers, whereas international research collaborations and diaspora networks can accelerate capacity building.

E. Embedding AI in the Public Sector: Productivity, Integrity, and Better Services

Economy-wide gains will hinge on successful adoption within the public sector, a major employer in much of the region. AI can increase the efficiency of government spending, improve targeting, strengthen monitoring and evaluation, and reduce opportunities for fraud and corruption. But all this is conditional on staff training, workflow redesign, and basic data readiness. A pragmatic approach should prioritize low-cost, high-impact applications that fit existing capacity, especially in frontline service delivery.

- **Education**. Deploy AI-enabled tutoring and adaptive learning tools aligned with curriculum, using low-bandwidth channels where needed. Pair deployment with teacher support and monitoring for accuracy and relevance.
- **Health**. Implement decision support and triage tools to augment scarce clinical capacity. Strengthen logistics with digital inventory systems and predictive analytics to reduce stockouts and wastage.
- **Revenue administration**. Build on digital tax foundations to adopt machine learning models for segmentation, anomaly detection, and audit prioritization. This will reduce burdens on compliant taxpayers while raising revenue and strengthening governance.
- **Support labor transitions through public systems**. Where automation affects tasks and occupations, strengthen social safety nets and expand targeted training and reskilling programs to help workers move into AI-complementary roles, including those created by adoption and digitization.

F. National AI Strategies and Regulatory Frameworks: Building Trust and Managing Risk

To implement this agenda coherently, countries need *credible national AI strategies* aligned with broader development goals. These strategies should identify priority sectors and use cases, assess constraints and comparative advantages, define investment needs in infrastructure and skills, and evaluate fiscal implications to ensure consistency with macro-fiscal stability. Where appropriate, they should outline public–private partnerships modalities that mobilize investment while protecting debt sustainability and public value. The usual instruments—guarantees, blended finance, project preparation facilities, and well-designed concessional support—can have meaningful multiplier effects on the quantity and quality of infrastructure delivery. But the appropriate mix depends on country circumstances and institutional capacity, with the strongest case for active mobilization in middle-income economies that already have market access (Eyraud and others 2021).

Strengthen data governance, privacy, and cybersecurity. Establish and operationalize comprehensive data protection laws aligned with global standards, alongside practical guidance for responsible data sharing within government and between public and private actors (Novelli, Taddeo, and Floridi 2023). Implement minimum security baselines for government systems (for instance, multifactor authentication, encryption, access logging, and incident response protocols) and strengthen resilience against digital fraud and AI-enabled threats through improved detection and response capacity (Barbosa and others 2024).

Adopt proportionate, risk-based regulation. Develop national AI ethics guidelines tailored to local institutions and cultures, emphasizing fairness and nondiscrimination. Apply tiered obligations, with stricter requirements for high-risk applications (for instance, those affecting rights or access to essential services) and lighter-touch approaches for low-risk productivity tools, to avoid stifling innovation while protecting citizens (Ebers 2024).

Build implementation capacity. Empower oversight bodies, such as independent data protection authorities, and strengthen coordination across government. Ensure that sectoral regulators (in particular, in telecom, competition, and financial services) have the expertise and tools to address AI-specific issues. Institutionalize stakeholder engagement with civil society, professional associations, consumer groups, and academia to strengthen legitimacy and improve design.

Leverage regional and global collaboration. Coordination through continental and regional bodies can support convergence on standards for AI safety, data governance, cybersecurity, accountability, and interoperability. It will both reduce fragmentation and enable peer learning. Develop secure, harmonized frameworks for cross-border data flows and mutual recognition of safeguards to enable regional public goods (including disease surveillance, disaster response, and trade facilitation) while protecting rights and trust.

G. A Pragmatic AI Agenda

The policy priority is to enable broad-based adoption by relaxing binding constraints in electricity, connectivity, computing, and skills, while building institutions that can govern AI credibly and support delivery. Governments can begin with "no-regrets" actions (high-impact pilots with strong monitoring and evaluation) while advancing deeper reforms in parallel—especially in energy and digital infrastructure, where long implementation lags make early action critical. With disciplined implementation and regional cooperation, Sub-Saharan Africa can harness AI to accelerate development and expand opportunity while safeguarding trust and inclusion.

8. Conclusion

AI-driven productivity gains are already shaping growth prospects globally. For Sub-Saharan Africa—where the effect has so far been muted—cumulative productivity gains over the next decade could range from 0.2 percent under current conditions to around 2.1 percent under a high-adoption scenario. The large range is the central policy message: The lower estimate is not a verdict on AI's potential but a diagnostic of today's constraints. Every additional year the region's preparedness gap persists, the growth divergence compounds—raising the cost of catching up and deepening dependence on external technologies. The costs of inaction are significant: growth forgone, unrealized efficiency gains in public services, and a widening technology dependence that will define the region's position in the global economy for the next decade.

A vital, though narrow, window of opportunity exists for the region to catch up through adoption, innovation, and decisive policy actions. The region's constraints—unreliable electricity, limited connectivity, scarce technical skills, and incomplete regulatory frameworks—are significant but not immutable: They are policy variables. Where governments and private actors have acted, progress has followed, including through national AI strategies, sectoral pilots, and emerging applications in agriculture, education, health, finance, and public administration. Accelerating AI adoption will require targeted reforms, strategic public investment, and clear prioritization of enabling infrastructure, human capital, and institutional capacity. AI adoption should therefore be seen not as a stand-alone technology agenda but as part of the broader structural reform agenda.

Critically, the challenge is collective. Fragmented national approaches will fall short of the scale required to sustain the infrastructure, training pipelines, or regulatory institutions that AI deployment at scale requires. Instead, regional coordination—including shared data centers, harmonized data governance, mutual recognition of qualifications and standards, and coordinated investment in connectivity corridors—offers a path to shared costs and scaled-up AI that few individual economies can achieve alone. Development partners and private investors have a key role to play, but their support must align with country-led priorities and move with urgency.

The choice is not whether Sub-Saharan Africa engages with AI, but how. Leveraging AI is not a luxury—it is a strategic necessity. Acting now, and acting together, will determine whether the region narrows the gap in a way that distributes the benefits broadly, or in a fragmented way that concentrates gains in a handful of hubs while leaving the rest of the region further behind.

Annex. General Equilibrium Channels Shaping the Macroeconomic Effect of Artificial Intelligence (AI)

This annex discusses selected general equilibrium mechanisms that affect the aggregate effect of AI adoption on aggregate productivity and growth beyond partial equilibrium models.

Using general equilibrium models with sectoral linkages and rigidities, Filippucci, Gal, and Schief (2024) and Baqaee and Farhi (2019) conclude that macroeconomic outcomes depend not only on micro-level productivity gains from AI but also on how these gains propagate through the economy through production networks, demand responses, and market frictions, highlighting that the aggregate effect of AI adoption may markedly differ from those based on partial equilibrium approaches. Following are the key channels:

- **Nonlinear propagation through production networks**

In multisector economies with input–output linkages, the aggregate effect of a sector-specific productivity shock depends not only on its Domar weight but also on how equilibrium sales shares and input intensities adjust endogenously. As shown by Baqaee and Farhi (2019), Hulten's theorem provides a first-order approximation that becomes inaccurate once shocks are sufficiently large or when elasticities of substitution depart from unity. AI adoption, by inducing heterogeneous and potentially large productivity gains across sectors, naturally operates in this nonlinear regime. Productivity improvements in upstream or highly central sectors generate amplified aggregate effects when downstream sectors rely on these inputs with low elasticities of substitution. Conversely, gains concentrated in weakly connected sectors propagate only limited spillovers. The resulting asymmetry implies that the macroeconomic effect of AI depends disproportionately on where in the production network AI adoption occurs, even when micro-level gains are comparable across sectors.

- **Sectoral reallocation and Baumol-type mechanisms**

When AI disproportionately raises productivity in a subset of sectors, relative prices adjust and induce reallocation of labor and capital. If expanding sectors face inelastic demand or if reallocation is incomplete, equilibrium value-added shares may shift toward sectors with lower productivity growth, generating a Baumol-type drag on aggregate productivity. AI-induced aggregate productivity gains may be muted if AI-intensive sectors remain relatively small or face highly elastic demand, whereas large service sectors with low productivity growth (such as health, education, and administration) continue to weigh on economy-wide averages. The Organisation for Economic Co-operation and Development framework (Filippucci, Gal, and Schief 2024) explicitly illustrates this mechanism in calibrated multisector general equilibrium models, showing that reallocation effects can materially reduce aggregate gains relative to first-order predictions, even when micro-level productivity improvements are substantial. Applying the Organisation for Economic Co-operation and Development framework on selected sub-Saharan Africa countries, we find that the Baumol-type effects are not large enough to offset the direct effect and input–output multiplier of AI. They reduce estimated productivity gains by around 0.1 percentage point per year, although the effect varies meaningfully across countries (Kiendrebeogo 2026).[15] In other words, the Baumol effect appears to trim the gains rather than overturn the main conclusion that AI can raise productivity.

[15] To isolate the Baumol effect from other channels, we assume AI adoption follows the pace observed for past general-purpose technologies. In the low-adoption scenario, adoption mirrors electricity; in the high-adoption scenario, it follows an average of mobile phones and the internet. These assumptions are intentionally conservative.

- **Labor and goods market frictions and adjustment dynamics**

Rigidities such as slow worker reallocation, skill mismatches, sticky wages, and hiring and training constraints can delay the movement of labor and capital toward high-productivity AI-adopting sectors, reducing realized gains and increasing transitional adjustment costs. The speed and extent of factor reallocation condition the realized aggregate gains from AI. Labor market frictions (such as skill specificity, mobility costs, and adjustment lags) limit the movement of workers toward AI-intensive sectors in the short to medium term. Capital adjustment frictions, particularly those related to intangible investments complementary to AI, further slow the transmission of productivity gains. In general equilibrium, such frictions interact with production complementarities to magnify transitional losses and delay long-term gains. Even when the long-term allocation converges toward a more productive configuration, adjustment dynamics can substantially lower realized productivity growth over empirically relevant horizons.

- **Demand elasticities and final-use responses**

Aggregate outcomes also depend on how final demand responds to AI-induced price and quality changes. When demand for AI-intensive goods and services is elastic, productivity gains translate into higher quantities and expanded sectoral output. When demand is inelastic, gains primarily appear as cost reductions with limited expansion of production, weakening spillovers to the rest of the economy. This mechanism interacts with production networks: Elastic demand in upstream sectors amplifies downstream gains, whereas inelastic demand can attenuate otherwise strong network effects. Consequently, demand elasticities constitute a key sufficient statistic shaping aggregate responses to AI-driven technological change.

- **Regulatory and institutional environment**

Legal clarity on data use, liability, and competition; effective labor market and education policies; and robust digital infrastructure and AI governance frameworks can either accelerate or constrain AI diffusion and complementarities with skills and capital, thereby shaping its ultimate effect on productivity and welfare.

Although these effects have been supported by theory, their size seems small and thus does not affect the main conclusion of our analysis (Kiendrebeogo 2026).

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