Overcoming the Automation Paradox: How Africa Can Build a Durable Advantage in AI-Enabled Services

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Abstract

African countries must generate hundreds of millions of decent jobs in coming decades as manufacturing's labor absorption wanes. This paper examines how AI-enabled services can serve as a major anchor within Africa's broader growth strategy.

We confront the paradox that some of the same AI capabilities that make services tradable may also make them automatable. We identify service production models built around human-AI complementarity — where human judgment, cultural knowledge, and quality assurance are structurally essential — as offering more durable competitive advantages than conventional augmentation. We argue that "cognitive capital" — institutional and organizational capabilities for embedding AI in workflows — is the binding constraint on deployment. These findings are situated within a portfolio approach to Africa's jobs challenge, where AI-enabled services complement — rather than replace — strategies in agriculture, manufacturing niches, and regional trade.

We propose a data-driven approach that targets countries' AI investments to sectors with the highest probability of export growth over a 2–5-year horizon ("progression network"), combined with an approach to identify bottlenecks and assets across the AI value chain. A Nigeria case study illustrates how AI capabilities could reinforce current service strengths and open adjacent export opportunities. The approach offers a practical framework for export-led, job-rich growth in Africa.

Keywords: Artificial Intelligence, Service Exports, Comparative Advantage, Industrial Policy, Africa, Digital Trade, Economic Development

JEL Codes: O33, F63, O25, L86, O55

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1 Introduction: A Different AI Path for a Different Demographic Reality

Africa faces a stark challenge: it must create hundreds of millions of new jobs in the coming decades. More than 500 million people are projected to enter the African labor force by mid-century—possibly the largest workforce expansion in history (Kendall (2025); Ahmed et al. (2014); Cardona et al. (2020)). Without a rapid rise in labor demand, the continent risks that its demographic dividend becomes a "demographic markdown" of mass underemployment, diminished human-capital investment, and political strain Hosan (2022).

Manufacturing, the traditional route to large-scale employment, will not deliver enough jobs in most African countries. Global manufacturing is automating, decarbonizing, and regionalizing, offering fewer opportunities for labor-intensive, export-led growth (Rodrik, 2016; Diao et al., 2025; Rodrik and Sandhu, 2025). Many African economies are already experiencing premature deindustrialization, accelerated by high unit labor costs, fragile logistics and energy systems, and an inability to compete in value chains that are increasingly capital- and skill-intensive (Rodrik, 2016). As industrial employment stalls, workers are shifting into low-productivity urban services and informal activities with limited prospects for sustained income growth.

Yet services represent a major and underexplored opportunity within a comprehensive growth strategy alongside infrastructure, agriculture, manufacturing niches, and regional integration. Figure 1 shows services already account for the bulk of net labor absorption across the continent, and Figure 2 shows that globally, their share of trade is rising while manufacturing's share shrinks. Not all services are alike: traditional services remain locally anchored and low productivity, but modern services — Information and Communications Technology (ICT), finance, logistics, creative industries, business process outsourcing — are often digitally tradable, higher-wage, and feature positive feedback loops between technology adoption and specialization Mishra et al. (2011); Loungani et al. (2017). We focus on these because they are the most neglected relative to their potential and because AI is reshaping them most dramatically.

Artificial intelligence is now reshaping this landscape. The global AI race has been dominated by a few hyperscale firms and jurisdictions capable of training frontier foundational AI models, an arena that most countries — including those in Africa — cannot feasibly compete in Franco et al. (2025). But the most important opportunities lie not in building massive models but in applying AI at the deployment layer. Small and specialized models are proliferating, inference costs have collapsed by over 99% since the launch of GPT-3 (Figure 3). Diffusion is far more global than in earlier technology waves Brynjolfsson et al. (2019); Baldwin and Forslid (2020). This shift opens the door for resource-constrained economies to embed AI in everyday workflows and services without frontier-scale infrastructure.

But the opportunity comes with an inherent tension. The same AI capabilities that make services more tradable — language translation, quality standardization, compliance automation — also make them more automatable. A strategy that simply bets on conventional service exports like BPO or basic coding is betting on a shrinking competitive window. Evidence increasingly shows AI's potential to enhance tradability, lower coordination costs, and augment rather than displace lower-skilled workers Acemoglu and Restrepo (2019); Berg and et al. (2025); Brynjolfsson et al. (2018); Loungani et al. (2017); Mishra et al. (2023); Henn et al. (2013); Lederman and Maloney (2012) — but these gains may prove transitional for services where the human role is routine. The resolution lies not in avoiding services but in identifying production models where human contributions — judgment, cultural knowledge, quality assurance — remain structurally essential.

The argument of this paper is that African countries should not pursue AI in the abstract or chase unrealistic goals like frontier model dominance. AI is best understood as a tool within a larger jobs-and-exports strategy. We propose a data-driven approach that targets countries' AI investments to sectors with the highest probability of export growth, combined with methods to identify bottlenecks and assets across the AI value chain.

Section 2 and 3 document five stylized facts on services, AI costs, infrastructure, and labor-market impacts. Section 4 explores how AI can be integrated into an industrial strategy, illustrated through a Nigeria case study. Section 5 sets out policy recommendations and the need for more data-driven policy approaches.

2 Services as the New Engine of Structural Transformation

Africa's demographic moment coincides with another global inflection point: the rapid transformation of the global services sector driven partly by digital transformation. This section starts with an observation on the value of shifting from a supply-side focus to thinking in terms of demand creation in labor markets, then presents five interlinked stylized facts that set the stage for the rest of this paper.

Stop Trying to Push Labor Supply and Focus on Creating Labor Demand Instead.

The conventional international development approach still leans on supply-side fixes—job boards, training, "digital readiness"—but the binding constraint is labor demand. Jobs create skills more than skills create jobs. Africa needs sectors that actually hire Maclay (2025). Viewed through the "non-consumption" lens Christensen et al. (2019), the continent faces non-consumption of its labor, especially by global markets—so the priority is building tradable, high-value sectors that make African labor globally valuable.

2.1 Fact 1. Industrial Labor Absorption is Stalling, While Services Are Rising as Drivers of Jobs and Growth

Figure 1 reveals Africa's structural shift from agriculture to services. In net terms, roughly four-fifths of the labor released from agriculture since 2000 has been absorbed by services, not industry.[1] The right panel underscores that much of this absorption is *informal*: informality rates exceed 90% in several West African economies (e.g., Benin and Chad at 96.9%), far above a non–Sub-Saharan-Africa (SSA) average near 54%; only South Africa (33.7%) and Seychelles (16.1%) sit well below that benchmark.[2]

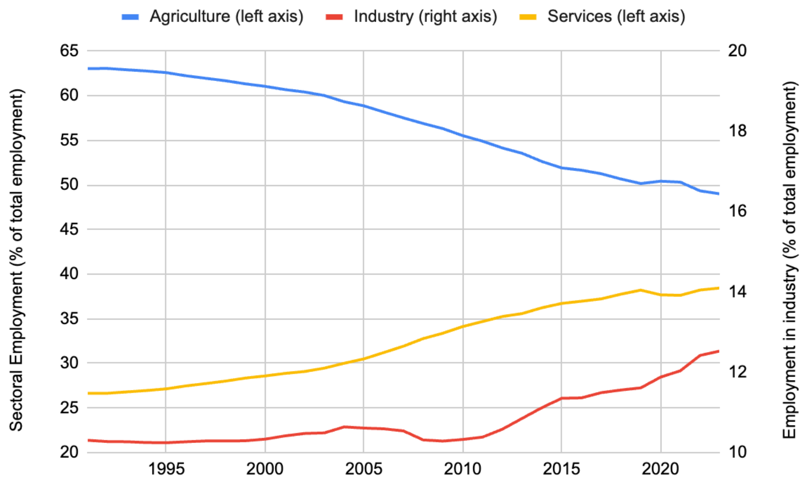
The fact that services absorb most net labor is necessary but not sufficient for a services-led strategy. Most of this absorption is into low-productivity informal activities, and a classical view of growth policy would interpret Africa's structural shift toward services as a sign of weakness—evidence of deindustrialization and stalled transformation. The strategic question is whether higher-productivity, tradable services can be scaled fast enough to absorb a meaningful share of new entrants — and whether AI changes the calculus.

Within the broader services expansion, higher-productivity "modern" services—including ICT, finance, logistics, and business support—are growing rapidly, even if they still account for only a modest share of total employment. These activities are augmented by

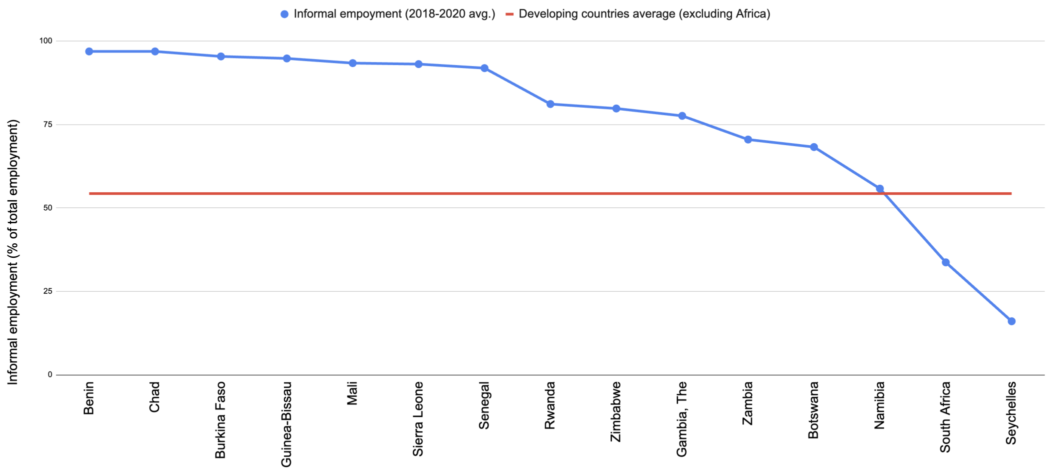
[1] Between 2000 and 2023, Africa's employment structure shifted decisively toward services (Figure 1). Services rose from 28.6% to 38.5% of total employment (+9.86 pp, ~0.43 pp/year, a 34% relative increase), while agriculture fell from 61.1% to 49.0% (−12.05 pp, ~0.52 pp/year). Industry (plotted on the *right* axis because its level is much lower) edged up only from 10.34% to 12.53% (+2.20 pp, ~0.10 pp/year).

[2] Informality figures reflect ILO model-based estimates; values shown are 2018–2020 averages for the listed countries. See also ILO (2018) *Women and Men in the Informal Economy.*

technology, often tradable, and better positioned to absorb labor at rising productivity levels. Thus, modern services should be viewed not as a dead end but as a viable pillar within serious job-creation strategies for Africa. [3]



Panel A: Employment Shares



Panel B: Rate of Informality in Select Countries

Figure 1: Employment Shares Reveal Lagging Industrial Absorption. Informality is High Across Sub-Saharan Africa.

Source: Authors' calculation using World Development Indicators; International Labor Organization model estimates; Elgin, C., M. A. Kose, F. Ohnsorge, and S. Yu. (2021), "Understanding Informality," *CEPR Discussion Paper 16497*, Centre for Economic Policy Research, London.
Notes: Panel A: Services are taking over from agriculture, while manufacturing is marginal. Panel B: Africa has the lowest share of formal industrial employment among developing regions.

[3]This argument is consistent with research showing that modern services can contribute materially to growth and job absorption when they scale and trade (Mishra et al., 2011; Loungani et al., 2017)

2.2 Fact 2. Service Exports Are Converging

Not all services are the same. **Traditional services**—such as hospitality, retail, and personal care—typically require face-to-face interaction, exhibit low productivity growth, and remain anchored to place (and thus un-tradable). But **modern services**, including finance, ICT, logistics, creative industries, tourism, and outsourcing of business processes, can be delivered remotely, across borders, and often have higher wages with greater scope for technology-driven productivity growth.

Figure 2 shows how developing economies have been catching up in services trade, especially modern services. Panel A (index 1990=1) shows developing countries' service exports growing much faster than those of advanced economies (developing countries growing nearly 19-fold compared to 11-fold in advanced economies). Panel B tracks shares of world service exports: developing countries' share has roughly doubled since 1990 while the advanced-economy share declined (the share of developing countries in global service exports has doubled from 10% to 20%, while advanced economies' share has declined steadily over the same period). Panel C separates by type of services: the catch-up is led by digitally tradable *modern* services (solid lines) from developing countries, not by *traditional* services (dotted lines).

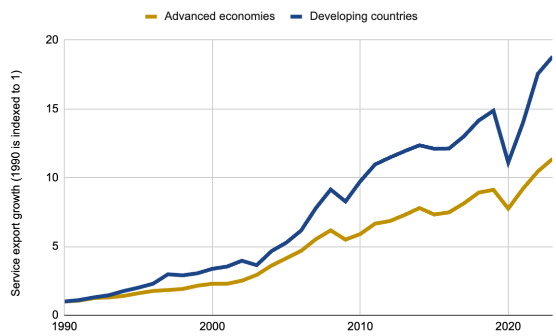
This convergence story is encouraging but must be read carefully. Much of the developing-country catch-up is driven by a handful of countries — notably India and the Philippines — with specific preconditions (English language, large IT talent pools, early-mover advantages in BPO). Whether other developing countries, including in Africa, can replicate this path is an open question. It's also an open question if this trend will continue as AI continues to make gains in automating tasks associate with these sectors.

We think the pattern of growing modern services trade reflects two fundamental trends. Starting in the early-2000s, and driven in some large part by digitization and global outsourcing which lowers costs to deliver services across borders, what we call the ***First Services Revolution*** (Mishra et al. (2011); Mishra and Tiwari (2020); Kharas and Ghani (2010); Ghani (2010)) has spurred an increasing share of global trade in services against a backdrop of declining or plateauing share of trade in goods Baldwin et al. (2023). India and the Philippines have successfully taken advantage of this trend to enter global markets without factories.

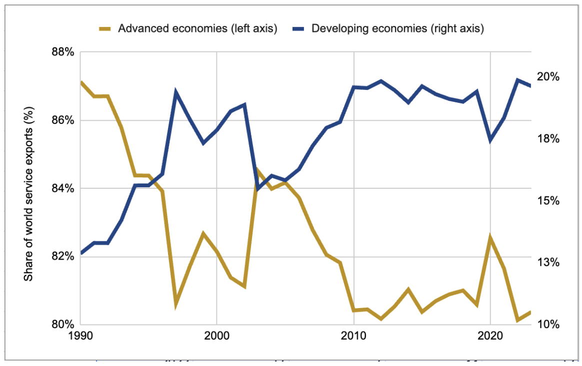
As we show in Section 3.1, new evidence suggests AI potentially lowers language, search, and compliance frictions; upgrades service quality; facilitates compliance and other forms of local adaptation, and allows mixed human–AI teams to serve global clients at competitive price–quality points.

AI may enable a second shift (a **Second Services Evolution**?), but *what kind of shift* matters enormously. If AI simply makes existing service tasks cheaper and faster, those tasks will eventually be automated entirely. If instead AI enables new production models

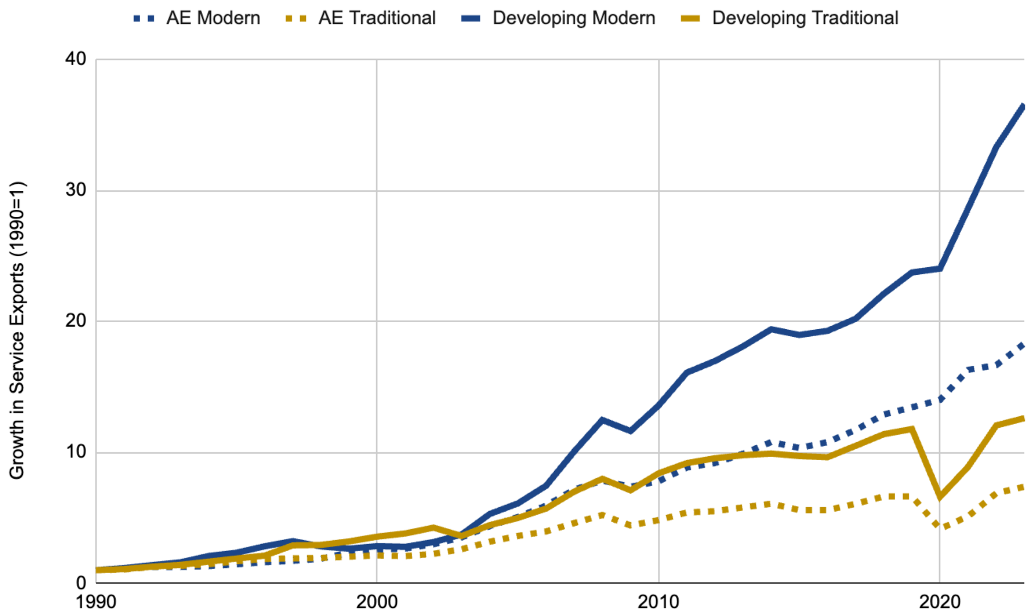
— where human workers supervise, validate, extend, and contextualize AI outputs — then a more durable form of competitive advantage becomes possible. This distinction, which we develop in Section 3, is central to whether the services opportunity is transitional or structural.



Panel A: Service Export Growth (1990 = 1). Developing countries have grown faster than advanced economies in service exports, indicating convergence over time.



Panel B: Share of World Service Exports (%). Developing countries' share of global service exports has steadily risen, while advanced economies' share has declined.



Panel C: Growth in Modern vs Traditional Service Exports (1990 = 1). Convergence is driven by modern services, particularly in developing countries, which have shown rapid expansion in digitally tradable services.

Figure 2: Convergence in Service Export Performance Between Advanced and Developing Countries.
Source: authors' calculation using IMF Balance of Payments Manual 6, 2025.

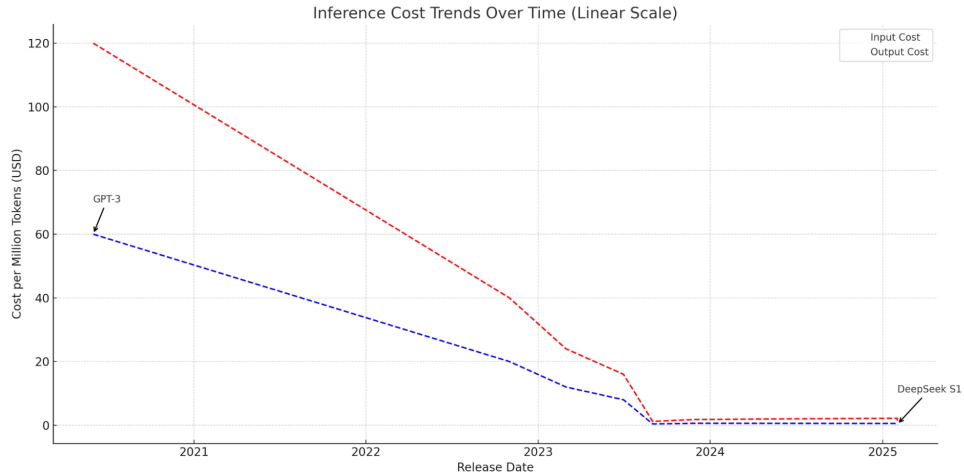
3 AI as a Force Multiplier for Services

3.1 Fact 3. AI Training Costs Soar, Inference Costs Collapse, and Diffusion Globalizes

Two divergent paths. On the one hand, frontier **training** is a scale game where a handful of labs (mostly in the US and China) push ever-larger runs with dramatically increasing compute, capital, and energy costs (Figure 3 Panel B). On the other hand, the costs of **using** AI in applications is dropping dramatically. As (Figure 3 Panel A) shows **inference costs** (the price to *run* models in production) keep falling due to a variety of forces. The center of gravity is thus shifting from "who can train the biggest model" to "who can deploy capable systems cheaply, reliably, and at scale."

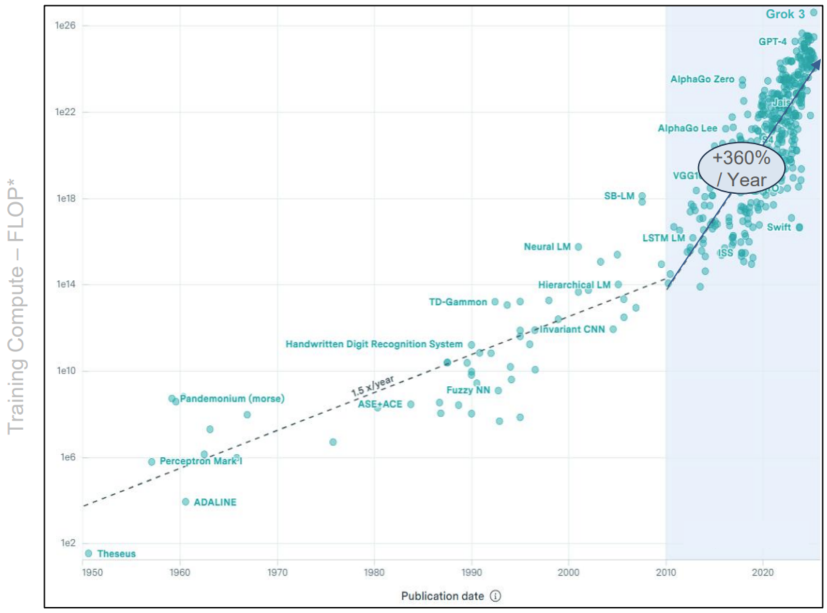
Sources: OpenAI, Google, Anthropic, Together AI, Fireworks AI, vLLM Blog.

Diffusion globalization: AI adoption is spreading faster and more globally than the early internet. Another trend that bodes well for African AI deployment is the fact that adoption is already spreading much more evenly across regions than the early internet (see Figure 4). The diffusion of AI appears much more globally balanced than previous waves of innovation, suggesting that Africa may not be left behind if policies are well-crafted.



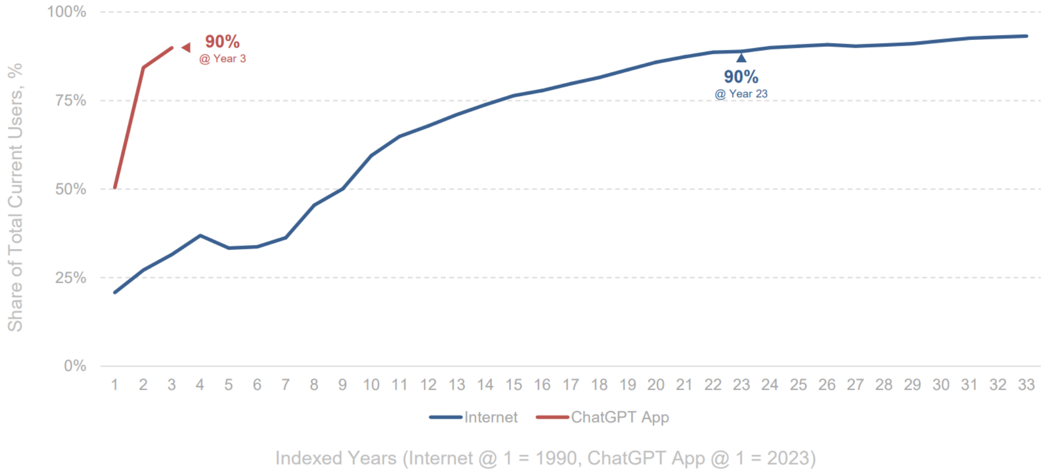
Panel A: Inference costs have fallen 99.9% since the introduction of GPT-3.

(a) Falling inference costs (input+output tokens) unlock real-world deployment in cost-sensitive settings.



Panel B: Training Compute (FLOP) for Key AI Models – 1950–2025. Graph from Meeker (2025). A FLOP (floating point operation) is a basic unit of computation used to measure processing power, representing a single arithmetic calculation involving decimal numbers. In AI, total FLOPs are often used to estimate the computational cost of training or running a model. *Note:* Only language models shown (per Epoch AI, includes state of the art improvement on a recognized benchmark, >1K citations, historically relevant, with significant use). Source: Epoch AI (5/25).

Figure 3: Model training is bifurcating: small models are getting very good and cheap, while frontier training requires skyrocketing compute and capital.



Internet vs. ChatGPT Users – Percent Outside North America (1990–2025). Graph from Meeker (2025). *Note:* Year 1 for Internet = 1990; year 33 = 2022. Year 1 for ChatGPT app = 5/23; year 3 for ChatGPT app = 5/25. ChatGPT app monthly active users (MAUs) shown. ChatGPT is not available in China, Russia and select other countries as of 5/25. China data may be subject to informational limitations due to government restrictions. Includes only Android, iPhone & iPad users. Figures may understate the true ChatGPT user base (e.g., desktop or mobile webpage users). Regions per United Nations definitions. Figures show % of total current users in that year – note that as year 3 for ChatGPT has not yet finished, percentages could move in coming months. Data for standalone ChatGPT app only. Country-level data may be missing for select years, as per ITU. **Source:** Graph from Meeker (2025), United Nations / International Telecommunications Union (3/25), Sensor Tower (5/25).

Figure 4: The growth in AI adoption outside the US.

3.2 Fact 4. Cognitive Capital and Enabling Infrastructure — Expanding, If Slowly

Deploying AI in economically meaningful use-cases requires more than cheap inference and internet access. It requires what some authors call *cognitive capital*: the stock of institutional and organizational capabilities and infrastructure that allow AI to be embedded in real workflows (Mishra and Rao, 2025; Odeh and Mishra, 2025). This includes standardized data schema and digital public infrastructure (identity, payments, data exchange); interoperable systems and open APIs; regulatory frameworks that accommodate experimentation; domain expertise within firms and government agencies; and organizational routines for absorbing new technologies.[4]

A country can have adequate broadband and cloud computing access yet still fail to deploy AI productively if its data is fragmented, its regulatory environment cannot accommodate new service models, or its firms lack the capabilities to integrate AI into service delivery. This reframes the infrastructure question: the binding constraint on AI deployment in most African contexts is not compute or connectivity per se, but the institutional capacity to use them. Investments in cognitive capital—data quality, DPI adoption, regulatory adaptability, organizational capacity-building in target sectors—may yield higher returns than investments in hardware and should be prioritized accordingly.

Physical and digital infrastructure is expanding. African countries are already laying groundwork for AI adoption. Procurement data from Taiyō.AI (Mishra et al., 2024) show rising investments in broadband, digital education, and smart grids. Public tenders increasingly target AI enablers—connectivity, energy, and skills—extending beyond capitals into secondary cities (Figure 5). Budgets for digital infrastructure have grown steadily over two decades, signaling that the transition is underway.

Yet major gaps persist. Limited power, connectivity, and digital skills still exclude much of the population. As Figures 6 and 5 show, the project landscape remains fragmented—driven by external actors, multilaterals, and private investors with weak coordination and few spillovers.

Priorities for building cognitive capital. Rather than top-down master plans to build data centres, countries should prioritize the institutional foundations for AI integration. There are a number of interoperable, open building blocks across the Digital Public Infrastructure "stack"—ID, payments, and data exchange—using proven modules widely supported in the international development ecosystem.[5]

Second, build talent pipelines—diaspora fellowships or joint labs—linked directly to private-sector employers, echoing how China's AI rise leveraged overseas–domestic links (Lee, 2018; Zhang et al., 2021; Mishra and Wang, 2021). Third, pair this with open observatories and regulatory sandboxes so regulators, providers, and researchers can see deployments, test integrations, and share playbooks. The net effect: Cognitive Capital ties physical infrastructure to human and institutional networks—lowering unit costs, speeding diffusion, and channelling investment toward exportable, AI-ready services rather than siloed vanity projects (Mishra and Rao, 2025; Mishra et al., 2025).

Box 1 illustrates these trade-offs in the case of subsidizing local GPU farms. The issue is not that compute infrastructure is unimportant per se: local cloud capacity may support data sovereignty, lower latency, and ecosystem development. Rather, the risk is that poorly designed subsidies can lock scarce public resources into fast-aging, power-hungry assets without solving the more binding institutional and organizational constraints. Where governments do choose to support cloud compute, they should

[4] This concept is related to "absorptive capacity" in the technology adoption literature and to diffusion speed and adoption lags in macroeconomics.

[5] Examples: Mojaloop for low-cost, interoperable retail payments; MOSIP for modular digital ID; and DHIS2 / OpenHIE (via Digital Square) for health data platforms - or their private sector equivalents.

generally do so with strong private-sector participation, and ideally in partnership with frontier global providers. This can help preserve commercial discipline, reduce the risk of simply sheltering local incumbents, and create channels for technology transfer, operational know-how, and access to the technological frontier.

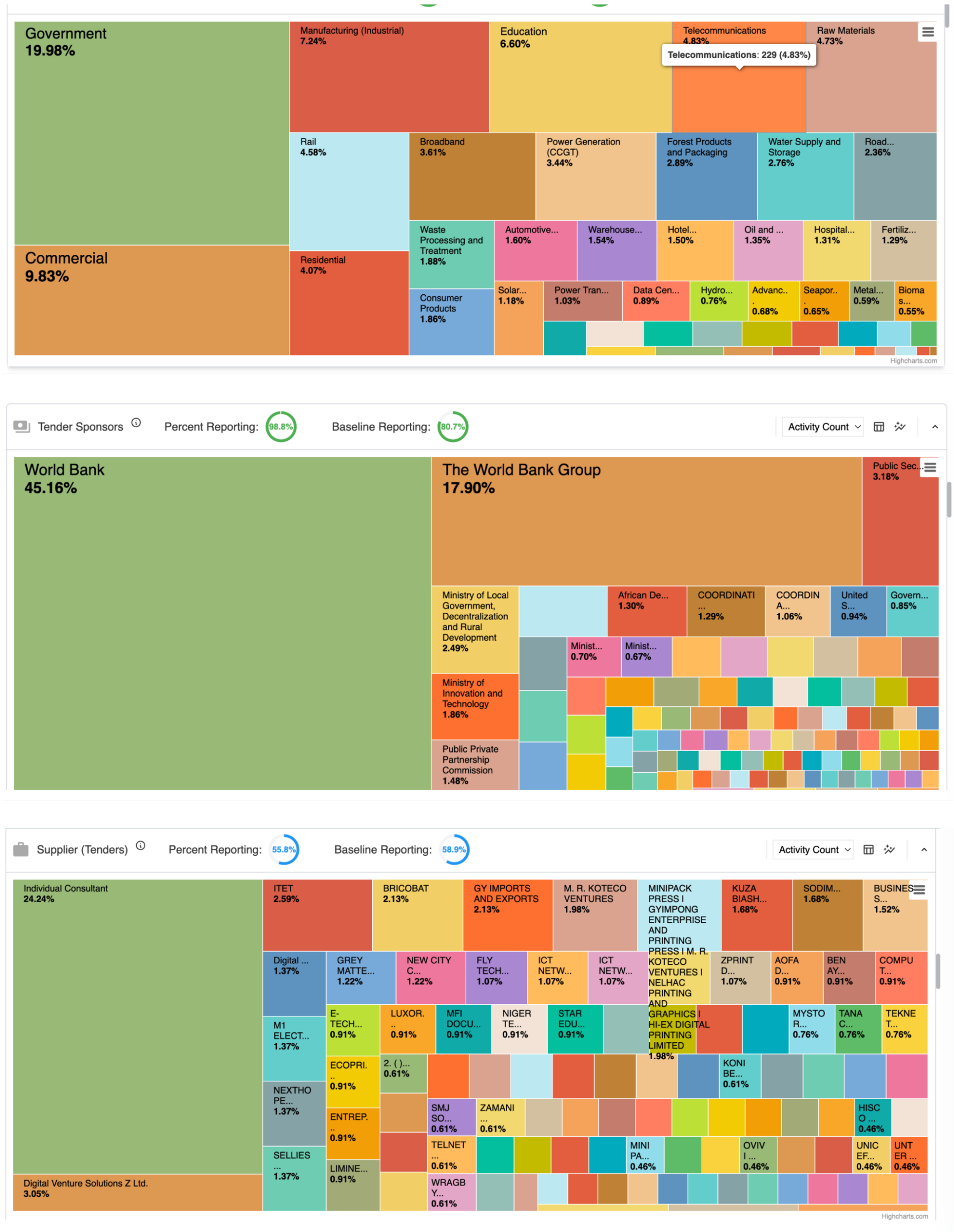


Figure 5: Digital and AI-Linked Sectoral Procurement across Sub-Saharan Africa, Government and Multilateral Procurement in Africa. Top treemap shows sectoral distribution, the second treemap shows the government agencies, and the third treemap shows suppliers awarded contracts

Source: Taiyō.AI, based on aggregation of various public procurement records.

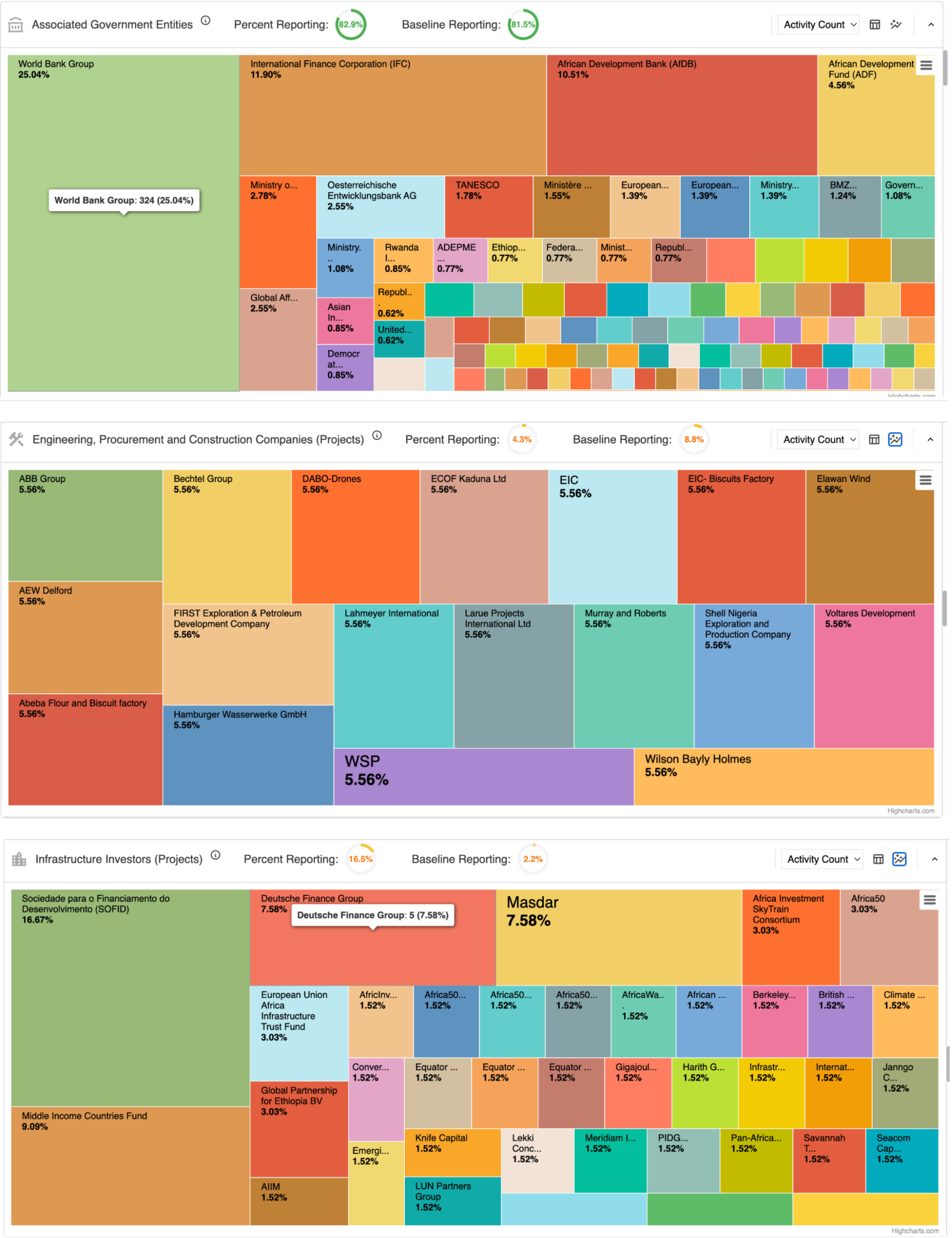


Figure 6: Leading Entities in AI-Linked Infrastructure Projects in Africa. Multilaterals, EPCs, and government agencies are already operating in this space.

Source: Taiyō.AI, based on aggregation of various public procurement records.

Box 1. Should African Governments Support Local GPU Clouds?

Calls to "build local compute" are increasingly common, but public support is easiest to justify when two conditions hold: (1) **Clear need** — local capacity is important for data residency, resilience, or very low-latency use cases; and (2) **Market failure** — private actors are unlikely to provide it at adequate scale or on acceptable terms. Absent these conditions, scarce public funds may be tied up in fast-aging, power-hungry assets that should have been left to the private sector. In many contexts, firms can access offshore compute with manageable frictions, while the case for strict data on-shoring is often narrower than policy debates imply.

Potential benefits (examples). Lower data-sovereignty and continuity risks; faster response for real-time workloads (fraud, telco core); catalytic effects on data-center build-out and skilled jobs; policy leverage to support priority sectors.

Key risks / trade-offs. Grid and water constraints; hardware obsolescence within short refresh cycles; performance and tooling gaps versus hyperscaler providers; high opportunity cost relative to investments in power, fiber, data systems, and skills.

If proceeding, design for discipline.

- Secure **anchor tenants** (government, telcos, banks) before investing.
- Prefer **Joint Ventures with hyperscalers or frontier providers** to share refresh cycles, expertise, and technology transfer.
- Require international partners to **hire/contract local** to build capabilities.
- Tie access/subsidies to **export performance** or other clear metrics of commercial success.

Note: This is a qualitative guide; costs and benefits are context-specific.

3.3 Fact 5. AI Shows Potential to Increase Services Tradability and Augment Labor

Though the evidence is still relatively nascent, there are a growing number of studies that relate to how AI interacts with labor markets and changes the tradability and productivity within services.
Early evidence speaks to AI's impact on tradability. AI is not only boosting productivity—it also has potential to change what can be traded. Evidence points to at least three channels:

- **Language & search frictions fall.** LLMs reduce "location-bound" barriers. For example, eBay's auto-translate lifted U.S.–LatAm exports by 17–21% (Brynjolfsson et al. (2018)); newer evidence finds AI features can *triple* cross-border use of digital services, with localization rules clawing back about half Sun and Trefler (2025).
- **Localization costs drop.** Fine-tuned LLMs draft contracts, specs, and compliant copy to local norms. Across 76 countries, AI/data patents correlate with higher service-export shares and modular scale economies in finance, design, and professional services Wang et al. (2025).
- **Regulatory fit gets cheaper.** AI ingests jurisdictional rules and rewrites outputs to comply. Interoperable legal-tech standards cut fixed entry costs across systems Ghoshal (2025); AI shifts barriers from "thick" (idiosyncratic) to "thin" (codifiable) Goldfarb and Trefler (2018).

These channels push the **tradability frontier outward**, turning previously immobile services into exportable digital products. At the same time, these same channels lower barriers for *all* providers, including automated ones, reinforcing the need to focus on complementarity rather than just tradability.

Augmentation may be a transitional state for routine services, but it can only be a long-run advantage for services designed around human-AI complementarity.

Evidence on displacement vs. augmentation is cautiously optimistic. Outcomes hinge on design and policy.

- **Bigger gains for lower-skilled workers.** In call centers, software teams, and consulting, AI disproportionately boosts initially lower-skilled workers Brynjolfsson et al. (2018), potentially easing entry for less experienced African workers into global service markets.
- **Augmentation often outweighs displacement.** ILO analysis of task-level susceptibility to AI suggests more jobs gain from augmentation than are at risk of replacement, especially in developing economies Berg and et al. (2025).
- **Policy is pivotal.** Steering toward augmentation—tools that leverage human judgment, cultural knowledge, and relationships—can raise productivity and create new roles. Policy can nudge firms toward these designs.

3.4 The Automation Paradox and Human–AI Complementarity

The collapse in AI costs and growth in capabilities creates a strategic tension for developing countries considering services-led growth. The same capabilities that enable an African firm to offer AI-augmented customer service or software development to global markets also enable a client firm to deploy fully automated versions internally. In short: AI makes services tradable *and* automatable, often in the same domains. Because the evidence remains early and capabilities are moving quickly, what follows should be read as a provisional framework for identifying more durable labor-demand opportunities, not a settled taxonomy of "automation-proof" jobs.

The services most commonly proposed as entry points for developing-country workers — BPO, call centers, data entry, basic coding, content moderation — are precisely the services with the highest exposure to AI automation (Berg and et al. (2025)). A study of Africa's BPO sector found that 40% of tasks could be automated by 2030, with only 10% fully resilient; entry-level jobs, comprising 68% of the workforce, are most exposed (Caribou Digital et al., 2025). Countries that bet exclusively on these services are building on a foundation that may quickly erode. For long-run viability policy makers will have to focus in areas where human contributions will remain structurally valuable even as AI gets better.

We suggest that more durable advantage is likelier in **human–AI complementarity models**: service architectures in which AI handles routine information processing and content generation while humans resolve ambiguity, provide contextual knowledge, manage relationships, perform quality assurance, and carry responsibility for outcomes. AI capabilities are evolving at unprecedented speeds, as are the business models and usage patterns around them, which jointly shape how jobs will change. Nevertheless, several characteristics appear—provisionally—to predict greater durability:

1. **Irreducible ambiguity and the demand for human accountability.** In some domains, ambiguity is structural—arising from conflicting objectives, incomplete information, or moral weight—not merely from complexity that more data will solve. (Dell'Acqua et al., 2023) show that AI sits on a "jagged technological frontier": it improves performance strongly on some tasks but makes workers 19 percentage points less likely to solve others correctly. Beyond capability limits, many decisions also require a human who can be held responsible and to whom affected parties can appeal—in judicial, medical, financial, and other high-stakes settings (Salatino et al., 2025).
2. **Low-frequency but high-cost errors.** Where mistakes are rare but extremely costly, full automation may remain unattractive even as average AI accuracy improves. In such settings, the

relevant margin is not mean performance but tail risk, liability, and the institutional need for a responsible human in the loop.

3. **Essential cultural, relational, or institutional knowledge.** Some services depend on embeddedness in specific linguistic, social, or market contexts—knowledge expressed through trust, emotion, accent, informal norms, and institutional memory, not just codified information. Even in customer experience work, human oversight is often still needed where accents, emotions, and cultural nuance matter (Caribou Digital et al., 2025). The key test is simple: would the service be materially worse without locally embedded judgment or human relationships?

4. **Tacit or rapidly evolving domain expertise.** Some knowledge is embodied and intuitive, or changes too quickly for historical training data to remain reliable. (Brynjolfsson et al., 2025) find that AI produces the largest gains for less experienced workers, while the most experienced workers see little benefit and sometimes small declines in quality—suggesting that frontier expertise is harder to codify and that complementarity is strongest where tacit judgment still matters. At the same time, heavy reliance on AI may erode the learning processes that generate such expertise in the first place.

5. **Expanding demand (Jevons effects).** In some sectors, productivity gains may expand the total market rather than shrink the workforce, especially where demand is highly elastic and large needs remain unmet. This is more plausible in healthcare, legal services, education, and agricultural advisory than in routine outsourcing, where buyer demand is more bounded and substitution into internal automation is easier (Caribou Digital et al., 2025).

The criteria above suggest a provisional set of production models where Africa has existing strengths and where human contributions may be more structurally durable than merely transitional:

- **AI-augmented creative industries.** Nollywood, Afrobeats, and Africa's growing design and gaming sectors already serve global audiences. AI handles production, VFX, localization, and distribution; humans provide creative vision and cultural specificity that *constitute* the product. Nigeria hosted its first AI film festival (NAIFF) in 2025. Creative output tends to expand as production costs fall—a Jevons effect already demonstrated by Nollywood's video revolution.
- **AI-augmented financial and logistics services.** Africa's fintech ecosystem (M-Pesa, Flutterwave, Moniepoint) demonstrates competitive advantage at scale. AI extends this into areas such as credit analytics and fraud detection; humans handle relationship management and judgment in data-sparse informal markets where trust is interpersonal and contextual knowledge is irreducible. Vast unmet demand for financial inclusion makes long-run expansion likely.
- **AI-augmented agricultural advisory.** In agriculture, AI can process satellite imagery, weather, and market data; while human extension agents interpret these signals for local conditions, navigate cultural farming practices, and maintain farmer trust. Agriculture employs roughly half of Africa's workforce, and most smallholders receive no professional guidance—creating enormous scope for demand expansion. This model bridges the services and agricultural sectors.
- **Expert data curation and AI quality assurance.** Demand for domain-specific evaluation of AI outputs may grow with global AI deployment. It appears more durable at the expert end of the spectrum—for example in African-language NLP, tropical medicine, or local agronomic knowledge—than in basic labeling, where synthetic data may close the window more quickly.
- **Bespoke digital micro-enterprise.** As AI collapses the fixed costs of starting service businesses, it may erode the position of some large SaaS firms while enabling small teams to provide bespoke solutions in software, legal, accounting, and related services. Here the durable human value lies less in

coding alone (done mostly by AI) than in client relationships, understanding need, and tacit domain knowledge. Individual firms may remain small, but the sector could be very large, matching Africa's existing entrepreneurial structure.

These examples exhibit combined durability and labor-absorption potential—creative industries, agricultural services, fintech, and bespoke micro-enterprise. All build on areas where African firms already show capabilities and where demand could still expand. They imply a different bet from conventional BPO: not competing mainly on cost in services that AI is rapidly standardizing, but on human contributions that remain harder to commodify. Further work will be needed to test which of these models prove most durable in practice, and under what policy and market conditions.

4 Building AI-Enabled, Services-Led Growth Strategies

The landscape of stylized facts we lay out above suggests that African countries' AI development strategies should ignore the race to produce frontier models and instead focus on applied innovation anchored primarily in the modern services sector.

4.1 Portfolio Approach to Sectoral Transformation with a Services Anchor

No single sector or strategy can absorb Africa's full workforce expansion. Agriculture remains the largest employer and upgrading agricultural productivity is essential. Manufacturing niches — particularly in agro-processing, light assembly, and construction materials — retain potential where infrastructure and logistics permit. Regional trade integration expands domestic market scale. This paper focuses on AI-enabled services not as the sole answer, but as a *major anchor* within this portfolio — one that has been systematically neglected in development policy and that AI is making dramatically more viable." Within the services component, we argue for the addition of a specific approach: targeting production models built around human-AI complementarity, using data-driven methods to identify sectors and sub-sectors with the highest potential.

4.2 A Data-Driven, Country-Specific Approach to AI Strategy

Here we set out a data-led way to pick priority sectors from a country's existing structure and assets. Recent work shows how capital inflows that fund AI technologies can spill into tradable output. Mishra et al. (2023) links time-stamped investments across 29 AI subfields to later export performance in dozens of goods and services. The core question is simple: if a country specializes in an AI area (X) at time (t), which exports tend to grow a few years later? The answer is a probability matrix and a directed network from today's AI activity to the goods and tradable services most likely to follow.[6] Figure 8 sketches the idea: specialization in, say, logistics/route-optimization AI today can lift transport and warehousing services as the technology is adapted.

This yields two complementary development paths, anchored in an AI-driven progression model:

1. **Enhance what exists:** raise competitiveness in current goods, services, or AI niches by deploying targeted AI sub-areas in those sectors.
2. **Find the next-door wins:** step into adjacent or higher-value specializations by leveraging linkages across AI, goods, and services.

[6] The paper uses time-series methods to establish causality. These help rule out some spurious links but have known limits; treat results as suggestive.

A related paper Franco et al. (2025) assesses measures of *bottlenecks* and *assets* along the AI value chain—useful for directing interventions that raise deployment. Used together with related research, these results could support a practical, export-led jobs workflow:

1. **Diagnose.** Use the composite scoreboard to locate binding constraints (e.g., data/process digitization—e-procurement, licensing, customs, clinical encounters—plus open standards/APIs, skills, public investment) and to spot active AI sub-fields.
2. **Target.** Compute country Revealed Comparative Advantage (RCA) in AI sub-sectors and in goods/services, then use the global progression network to shortlist sectors—the goods and tradable services with the highest conditional probability of following from today's AI basket over a 2–5 year horizon.
3. **Act & learn.** Convert the shortlist into export-oriented policy: sponsor applied-AI projects and data standards in those use cases; align procurement and regulatory sandboxes; track exports, employment, and wages; iterate as the sector evolves.

This keeps attention on *labor-demand creation* in tradable services and adjacent light-industry or agricultural niches—avoiding generic "AI everywhere"—and is explicitly data-driven, country-specific, and iterative. It also connects to *cognitive capital*: the stock of codified information assets and organizational routines that let institutions absorb and operationalize AI (Mishra and Rao, 2025; Mishra et al., 2025; Odeh and Mishra, 2025).[7] Policymakers should pair sector bets with investments that accelerate this "cognitive capital" in priority sectors—better data quality, standardization, DPI, and institutional absorptive capacity—to make AI deployment faster, lower-risk, and more productive. See also DFS Lab's investor and macro policy POVs for complementary theses.

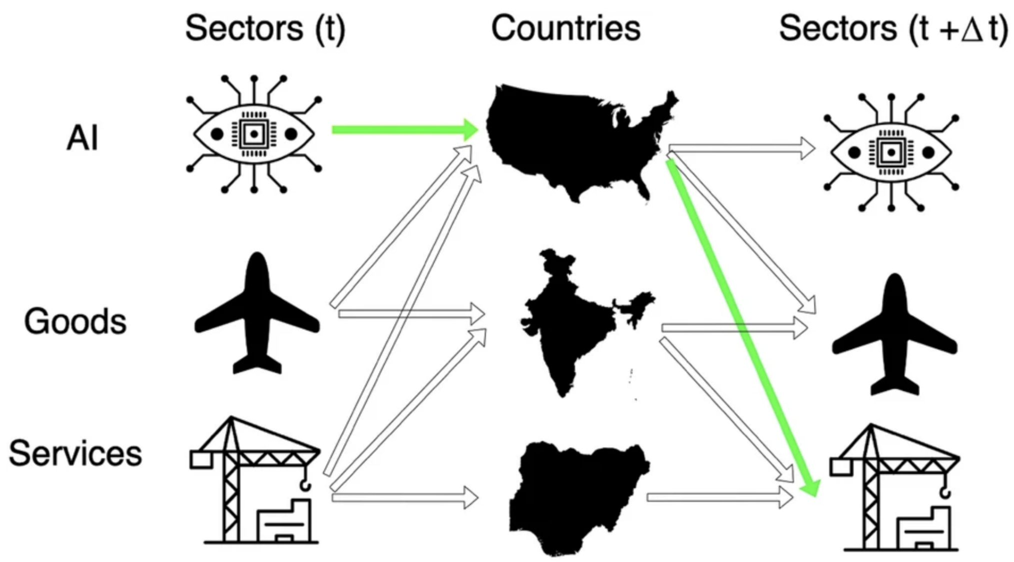


Figure 8: Schematic representation of the *Progression Network*, showing how specialization in AI, goods, and services evolves over time through countries' revealed comparative advantages. Green arrows illustrate dynamic spillovers: for example, a country specializing in computer vision (AI) at time t may specialize in construction services at time $t + \Delta t$. Source: Adapted from Mishra et al. (2023).

[7]Related to "absorptive capacity" in technology adoption and to diffusion speed/adoption lags in macroeconomics.

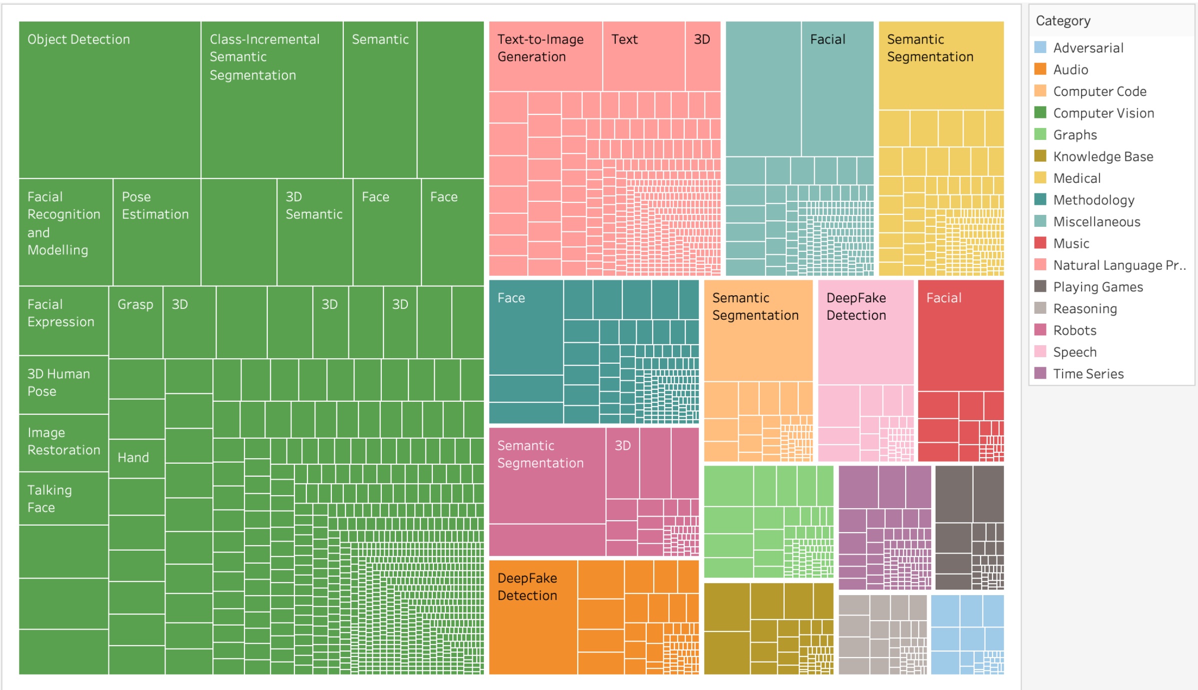


Figure 7: The Evolving Topology of AI Tasks and Domains.

Source: authors' calculations using data from PapersWithCode (2025). **Notes:** This treemap visualizes the layered architecture of AI development, based on benchmark data from the PapersWithCode platform. Each color corresponds to a top-level domain such as Computer Vision, Natural Language Processing, or Robotics, while the nested boxes represent subdomains and specific tasks within each. For example, Computer Vision spans areas like 3D recognition, video analysis, and facial detection, while Natural Language Processing includes tasks such as sentiment classification and entity recognition. Robotics, as another example, encompasses trajectory planning and grasp estimation. The size and density of each segment reflect both the volume of research activity and the diversity of benchmarks, emphasizing that AI is not a singular capability but an expanding ecosystem of specialized, interrelated functions. This figure complements insights in Mishra et al. (2025) and Kerry and Mishra (2025), who emphasize the strategic and governance implications of this expanding task frontier.

4.3 Deep Dive: Using AI–goods–services linkages to target strategy

Figures 9–10 are from Mishra et al. (2023) which uses a progression network methodology to map time-directed links from *investments* in AI sub-sectors to *exports* of goods and services in which countries subsequently develop trade specialization. For each country we compute revealed comparative advantage (RCA) in AI, goods, and services—how much activity or exports in a category exceed the global average—then estimate the conditional probability that specialization in an AI node at time t precedes specialization in a connected good/service at $t + \Delta$. Thicker edges indicate higher probabilities. Left-side nodes are AI (29 sub-sectors, proxied by private investment); right-side nodes are 35 goods and 12 services export categories. The network identifies which AI sub-sectors most often translate into later competitiveness in specific tradable activities.

Figure 9 shows sector-specific subgraphs. Panel A links Wi-Fi/Home-tech AI to downstream consumer electronics, home appliances, and related services, illustrating spillovers from home-networking capabilities. Panel B connects Energy-related AI to fuel distribution, solar-equipment manufacturing, and maintenance/business services, capturing diffusion from energy analytics and control systems. Panel C ties specialization in Home-and-Office goods to later AI activity in computing-adjacent areas (e.g., AR/VR) and to restaurant/food-service and real-estate applications. These patterns are not anecdotes but repeated, time-lagged co-specializations observed across countries.

Figure 10 provides a second example: robotic (process) automation sits at a hub with dense forward links to real-economy activities. Validated edges include a pathway from robotic process automation to Home-and-Office products and a cross-sector link to offshore oil rigs, consistent with tele-operation, inspection, and preventive maintenance use cases. Read the panel as a lookup map: given current specialization in a focal AI node, the thickest validated edges indicate the goods/services where growth most often emerges next, informing near-term (2–5 year) targeting and policy sequencing.

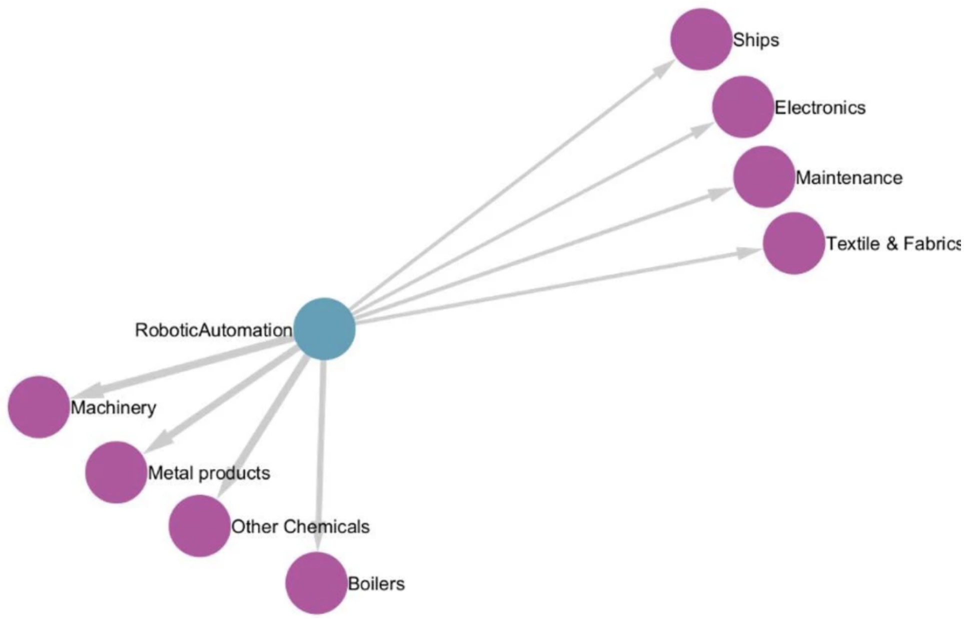
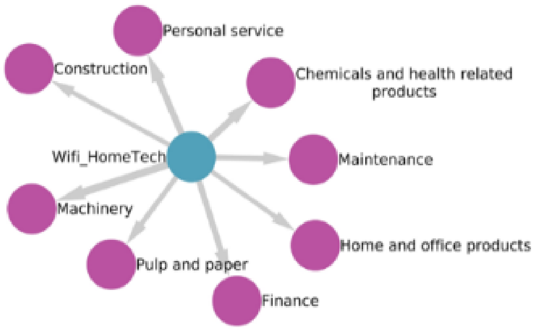
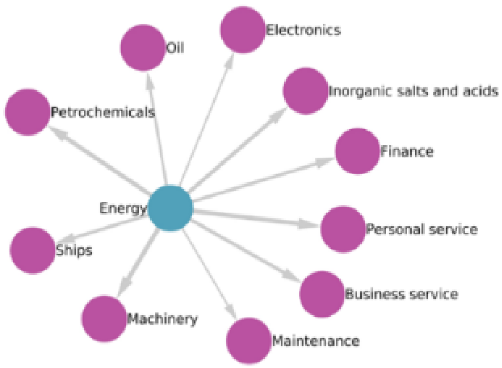


Figure 10: AI in Robotic Automation is strongly linked to manufacturing industries from textiles to machinery and shipbuilding. Thicker arrows denote stronger, statistically significant linkages.

Notes: Graph shows sectors with the strongest direct progression links to the AI sub-field *Robotic Automation*. Link weights are derived from a time-directed "progression network" that tracks revealed specialization co-evolution between AI sub-sectors and trade specializations in goods/services.
Source: Authors' elaboration using the progression-network methodology in Mishra et al. (2023).



(a) Wi-Fi/Home Technology



(b) Energy

(c) Home and Office

Figure 9: AI–Goods–Services Linkages and Pathways for Economic Diversification. Subgraphs of AI Investments and their linkages to goods and services specialization. The first graph demonstrates how Wi-Fi/Home Technology–related AI investments connect to downstream specializations in consumer electronics, home appliances, and related service offerings. The second graph depicts Energy-related AI investments and their spillovers into goods and services such as fuel distribution, solar equipment manufacturing, and maintenance services. The third graph illustrates how specialization in home and office products (goods) are related to subsequent specialization in AI-related investments in AR-VR, restaurant and food services, or real estate related AI investments. Together, these graphs highlight time-delayed linkages: an AI specialization in a specific domain (e.g., Wi-Fi/home tech AI investment or any goods or service) can pave the way for a country or firm to expand into new goods or services or AI specialization, given the nature of prior capabilities (as measured by comparative advantage in sub-areas of AI investment or goods or services).

Source: Mishra et al. (2023)

4.4 Case Study: Nigeria's Applied AI Sectoral Integration and Export Potential

Nigeria illustrates the approach outlined above. As shown in Figure 11, the country's AI specialization is strongest (measured by Revealed Comparative Advantage or RCA) in *Money and Personal Finance* and *Business Management*, reflecting its regional leadership in fintech and administrative services (examples being fintech startups Flutterwave and Moniepoint - both of whom are valued over $1Bn). On the services side, finance and transport are Nigeria's top export specializations, while its goods exports remain concentrated in oil, followed at a distance by agricultural products (cotton, rice, soybeans and others), tropical tree crops and flowers and leather.

This tight clustering offers a strategic advantage. Nigerian companies aren't building AI in the abstract—they are building AI that serves specific, high-impact use cases: credit scoring, mobile payments, logistics optimization, and supply chain intelligence. These AI capabilities reinforce current service strengths and could unlock growth in adjacent sectors.

AI	RCA
Money and Personal Finance	18.1
Business Management	11.7

Goods	RCA
Oil	18.5
Cotton, rice, soy beans and others	2.6
Tropical treecrops and flowers	2.5
Leather	1.7
Processed minerals	0.9
Agrochemicals	0.7

Services	RCA
Finance	7.4
Transport	2.5
Construction	1.5
Travel	1.3
Government	1.0

Figure 11: Nigeria's AI–Goods–Services Specialization Matrix in 2019. The table highlights a starting point to document for a given country their relative top sectors of specialization or revealed comparative advantage (RCA) in AI investment (Money and personal finance or business management), Goods (Oil, Cotton, rice, etc...) as well as service exports (Finance, Transport, etc..) This is a first-step stock taking for any given country to identify top sectors and thereafter determine specializations linkages to inform how and which type of AI can help existing strengths in goods and services with specific business use cases and offer strategic diversification paths going forward.

Source: Mishra et al. (2023)

4.5 Discovering Adjacent Opportunities

Another important principle is to invest in new sectors that build on strengths developed through existing sectors. Figure 12 highlights "adjacent" sectors that could become future export strengths based on current AI capabilities.

One example: *Travel services*, where Nigeria shows specialization, is closely related to the AI subdomain of Money and Personal Finance. By investing in digital payments, fraud protection, and customer analytics tailored to the travel sector, Nigeria could make its tourism industry more competitive and expand service exports.

Another example: *Fish and Seafood* - not yet a specialization - could become one, given its links to AI related to fintech and logistics. Similarly, *Processed minerals* could see value addition if combined with AI for quality control, logistics optimization, and trade facilitation.

4.6 Summary: Initial Policy Prescriptions

The argument developed in this paper does not imply a single-sector development model, nor does it suggest that AI-enabled services should displace other priorities such as agriculture, selective

Top Sectors	Density	Related AI Sectors	Specialization	Application
Travel	0.49	Money and Personal Finance	Emerging	Enhance emerging specialization
Fish & Seafood	0.38	Money and Personal Finance	Absent	Discover new specialization
Processed minerals	0.36	Business Management, Money and Personal Finance	Absent	Discover new specialization
Milk & cheese	0.22	Business Management	Absent	Discover new specialization
Animal Fibers	0.22	Money and Personal Finance	Absent	Discover new specialization

Figure 12: Strongest linkages from Nigeria's AI specialization portfolio to goods and services.

manufacturing, or regional trade integration. Rather, it points toward a broader policy orientation in which AI-enabled services form a major pillar within a more diversified growth strategy. For many African countries, these services may represent one of the most scalable and labor-absorbing opportunities available, but they are best understood as part of a portfolio approach rather than a stand-alone blueprint.

A first policy task is therefore strategic orientation: deciding what kinds of AI-linked growth opportunities to pursue. Governments should treat AI-enabled services as a major anchor of future industrial strategy, while continuing to invest in agricultural upgrading, selective industrial niches, and regionally integrated markets. Within services, the emphasis should not be on generic automation or a simple expansion of conventional BPO, but on production models organized around human–AI complementarity. The most promising opportunities are likely to be those in which human judgment, cultural knowledge, relational capacity, and quality assurance remain central to the value proposition even as AI handles routine processing and content generation. Sector choice should also be more disciplined than the now-common tendency toward "AI everywhere" strategies. The progression-network logic developed above offers a more credible basis for identifying specific sub-sectors and adjacent opportunities where AI capabilities are plausibly linked to existing or near-adjacent comparative advantages.

A second task is to build enabling conditions. In many settings, the more binding constraint is not frontier compute but what might be called cognitive capital: the institutional, organizational, and data foundations that allow firms and public agencies to absorb and deploy AI effectively. This includes investment in data standards, interoperable digital public infrastructure, regulatory sandboxes, and the managerial and organizational capabilities needed to integrate AI into production. Talent strategies should likewise be tied to concrete sources of demand rather than framed as generic "digital skills" agendas. More promising approaches include diaspora fellowships, joint university–industry labs, and apprenticeship pipelines linked to target sectors and real firms. Public procurement can also play a more strategic role, not only as a channel for adopting AI-enabled services in government, but as a way of creating domestic demand, building local implementation capability, and helping firms develop the cognitive capital needed to compete. Support for local GPU or cloud infrastructure may be justified in some contexts, but as argued in Box 1, it should be approached selectively and with strong commercial discipline, ideally alongside private-sector participation and partnerships with frontier providers.

A third task is execution discipline. Public support should be conditional, time-bound, and tied to performance. One useful principle is export discipline: governments may help coordinate investment and de-risk entry into promising sectors, but firms that fail to demonstrate competitiveness in external or otherwise disciplined markets should not receive indefinite support. This logic, associated with the experience of the East Asian industrializers, is especially important in AI-related sectors where hype can easily outrun commercial viability. Policy should also work with large incumbent firms and established sector leaders, not only startups. Startups are important sources of experimentation, but scaling often depends on organizational capacity, distribution channels, regulatory credibility, and sectoral reach that incumbents are more likely to possess. Because conditions in AI are changing rapidly, policy frameworks should also be explicitly iterative. Governments should define review cycles in advance, monitor outcomes, and be willing to redirect resources as technologies, markets, and comparative advantages evolve.

5 Conclusion: Next Steps and What's at Stake

5.1 The need for further research and exploration

The policy framework outlined above is necessarily exploratory: evidence is new and therefore suggestive; and there is no strong academic consensus or long historical precedent for comparable strategies. However, given the pace of the AI wave and the urgency of generating jobs for Africa's 500 million new workers in coming decades, waiting for perfect evidence would be riskier than acting with adaptive, evidence-guided policies.

Industrial policy has always involved uncertainty—governments must make bets on sectors that may later falter due to shifts in global demand or technology. Extending such strategies to emerging service sectors, where there is little precedent, requires especially careful design and learning-by-doing.

Rapid technological change compounds this challenge. Trends in AI pricing, model architectures, and training economics evolve faster than most policy processes can track. Policymakers will need to decide amid constant flux, relying on close monitoring rather than fixed blueprints.

These realities call for ambition tempered by discipline: policies anchored in data, continuous feedback, and humility to adjust course as conditions change. A central priority will be building the data framework needed to support that adaptive, evidence-based approach.

5.2 The Stakes

Africa needs to create half a billion decent jobs in one generation. AI will not magically deliver them, nor inevitably destroy them. Its impact will hinge on how quickly governments, firms, and universities measure the right signals and move resources toward the most promising capability corridors. A data-driven policy agenda that is context-specific, adaptive, and inclusive is the urgent next step. Done right, it can ensure that African workers, companies, and countries not only keep pace with global technological change, but shape it—turning comparative disadvantage into comparative advantage, and uncertainty into opportunity.

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