OVERVIEW

STRENGTHENING AI FOUNDATIONS

WORLD BANK GROUP

Digital Progress and Trends Report 2025

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Digital Progress and Trends Report 2025

Strengthening AI Foundations

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Foreword

Artificial intelligence (AI) is advancing at an extraordinary speed, reshaping how people learn, work, and live. Its ability to unlock access to knowledge, boost productivity, and open new markets holds immense potential to accelerate development—creating jobs, new industries, and economic transformation.

Expanding digital access will be one of the greatest drivers of future employment: 10 of the 15 fastest growing jobs globally are now in technology or technology-enabled roles. In addition, AI-related job postings are now rising faster in middle-income economies—up 16 percent in upper-middle-income and 11 percent in lower-middle-income countries—compared to just 2 percent in high-income countries.

This report, *Strengthening AI Foundations,* is the second in the *Digital Progress and Trends Report* series, providing a comprehensive, data-driven snapshot of the global AI landscape. It highlights a stark divide: Most innovations remain concentrated in high-income countries. Yet, a promising trend is emerging, as low- and middle-income countries are actively adopting "small AI" solutions. While these immediate, localized impacts are crucial, continued investment in strengthening the broader AI foundations is needed to embrace AI at scale over time.

To seize this opportunity and facilitate the growth of small AI, governments need to prioritize investment in what we call the foundational "4Cs":

- *Connectivity,* encompassing reliable digital infrastructure, energy, and device access, is the indispensable baseline.
- *Compute,* covering AI chips, servers, data centers, and cloud services, is increasingly becoming the "new electricity" of the AI era.
- *Context,* or locally relevant data and content, is essential to build trusted, inclusive, and effective AI systems.
- *Competency* is the set of robust digital skills that are indispensable for adopting, adapting, and innovating with AI.

Governments have a pivotal role to play in building and strengthening these critical foundations so that AI can take root and flourish in developing countries. The World Bank Group is committed to helping countries harness AI for inclusive and sustainable development, including supporting the 4Cs, strengthening data governance, championing regulatory and institutional reforms, and investing in the human capital essential to thrive in today's digital era.

Our new World Bank Group digital strategy includes AI readiness as a core pillar. It also emphasizes the importance of having dynamic local innovation ecosystems and ensuring that AI tools are aligned with local realities and priorities. Policies that promote competition and equitable distribution of AI gains will be critical for mitigating risks and ensuring broad-based benefits.

As the AI era accelerates, developing countries need to be prepared to leap forward. Small AI offers a unique opportunity to bypass traditional development barriers and spark homegrown innovation and inclusive growth.

This report is a call for collective and strategic action. To ensure that AI becomes a force for shared prosperity—rather than a new source of inequality—we must work together to expand access, close skill gaps, manage risks, and shape a future where the transformative power of AI truly benefits everyone.

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Acknowledgments

Overview

Introduction

Artificial intelligence (AI) refers to the capability of machines or computer systems to simulate human intelligence. Although AI as a concept traces back to the 1950s, recent advances—driven by access to vast data, algorithmic innovation, and more powerful computing—have demonstrated its transformative potential.

Unlike prior general-purpose technologies (GPTs), modern AI systems learn and adapt autonomously, creating unique economic and ethical considerations. The emergence of generative AI (GenAI), powered by large language models (LLMs), represents a further transformative leap, generating original content and enabling unprecedented human-machine collaboration through natural language. In some scenarios, GenAI's performance now exceeds average human benchmarks. This evolution complements traditional AI systems and expands their scope, pushing the boundaries of what machines can achieve and ushering in an era of general-purpose capabilities that reimagine technological possibilities.

The rapid evolution of AI has outpaced society's ability to fully grasp its implications. Unlike technological shifts that have unfolded over decades, AI's integration is accelerating at an unprecedented speed and scale. Along with its immense opportunities come new responsibilities—especially regarding ethical deployment, accountability, and alignment with human values—that have few precedents in previous technological revolutions. In response, the *Digital Progress and Trends Report 2025 (DPTR)*, the second in this series, examines recent trends in AI development. Focusing on low- and middle-income countries (LICs and MICs), the report proposes a 4Cs framework of foundations for AI readiness (refer to figure O.1): connectivity (infrastructure), compute (processing power), context (training data, algorithms, and applications), and competency (digital skills).

This report provides a data-driven snapshot of the global AI divide, identifying systemic market failures and prioritizing investment and policy actions. It emphasizes the need for global coordination and targeted interventions to close widening AI gaps between developed and developing countries, where resource constraints threaten to exacerbate inequality. The *DPTR* 2025 uses the 4Cs as a lens to assess the foundations for AI readiness and inform the *World Development Report 2026,* which will provide a more comprehensive, in-depth exploration of AI's long-term development impacts and policy directions.

FIGURE O.1 **The 4Cs of AI foundations**

Source: Original figure for this publication.

Note: The "coordination and responsible AI governance" topic is covered in a companion publication (World Bank 2024, https://hdl.handle
.net/10986/42500). AI = artificial intelligence.

The modern AI ecosystem is a vast, rapidly evolving landscape. It is underpinned by foundational infrastructure like energy grids and telecommunications networks. The compute layer (specialized AI chips, servers, storage, and data centers) forms the physical backbone supporting AI workloads, with cloud computing platforms offering scalable access to integrated AI services. The training data layer aggregates information from digital devices, sensors, platforms, business transactions, and public data sets, which are collected, labeled, and preprocessed to ensure accuracy before use in model training. The algorithm and model layer houses AI development tools that build and train models, and the application layer fine-tunes tasks for specific use cases and devices, embedding AI capabilities for local operation. The boundaries between these layers are fluid, and many companies operate across multiple segments within the ecosystem.

New frontiers in AI capabilities include multimodality, advanced reasoning, agentic AI, and physical AI:

- *Multimodality* systems process and synthesize information from diverse data types—text, images, video, and audio—for richer understanding and more natural interactions.

- *Advanced reasoning* moves beyond pattern recognition to multistep problem-solving that involves logical deduction, planning, and creative strategizing to tackle complex challenges.

- *Agentic AI* pushes autonomy further, enabling systems to set subgoals, resolve conflicts, adapt strategies, and orchestrate workflows, all while continuously learning from new environments. This promise, however, raises challenges around reliability, accountability, trust, and bias.

- *Physical AI* captures data directly from the real world via sensors and Internet of Things devices, with applications in autonomous vehicles, robotics, and industrial automation.

These evolving capabilities fuel a wide divergence of expert perspectives on AI's future pace and impact. Some researchers and technology entrepreneurs foresee artificial general intelligence (AGI) within 5–20 years (Hinton 2023; Kurzweil 2024). Although AGI could substantially boost output, it would also require a fundamental rethinking of labor, income distribution, education, and the

meaning of work (Korinek 2024). Prominent figures such as Sam Altman, Geoffrey Hinton, Elon Musk, and Mustafa Suleyman highlight AI's superhuman potential while warning of existential risks. In contrast, skeptical analysts such as Jim Covello of Goldman Sachs question whether the technology can truly solve the problems commensurate with its huge cost (Mickle 2024). Critics like Gary Marcus deem current LLMs powering GenAI as flawed and not transformative (Zinn 2025), while Arvind Narayanan and Sayash Kapoor contend that current benchmarks miss real-world utility, suggesting gradual economic impact over decades as complementary innovations and institutional adaptations emerge.

Global trends are uneven for AI innovation, adaptation, and adoption

AI innovation remains concentrated in high-income countries (HICs), with China and India catching up. Just as with many other technologies, AI development is dominated by a handful of nations (refer to figure O.2). HICs account for 85 percent of AI start-ups, 91 percent of venture capital (VC) funding, and 54 percent of global AI publications (2000–24). A notable shift since 2022 is the rise of corporate power, with 80 percent of notable AI models emerging from private labs, sidelining academia's role. Patent trends reflect a similar concentration—China holds 66 percent of GenAI patent filings (2014–23, a ninefold growth since 2017), whereas India shows the highest growth (56 percent annually), and LICs are largely absent from AI innovation and adaptation.

FIGURE O.2 **Contribution to AI innovation and adaptation activities, by country income group**

Sources: Original figure for this publication based on analysis of various indicators from Epoch (https://epoch.ai/), OECD.AI (https://oecd .ai/en/), and WIPO (https://www.wipo.int/en/web/ip-statistics).

Note: For models with multiple contributors, only the nationality of the first or leading contributor is counted. AI = artificial intelligence; GDP = gross domestic product; GenAI = generative artificial intelligence; HICs = high-income countries; LICs = low-income countries; LMICs = lower-middle-income countries; UMICs = upper-middle-income countries; US = United States.

The rapid pace and concentration of AI innovation presents a challenge for developing countries: the need for continuous adaptation. Unlike past technological breakthroughs such as electricity or automobiles—which required limited adaptation—AI requires continuous technical and cultural refinement to remain relevant and effective, rather than relying on one-time developments. Countries that do not innovate or adapt global AI solutions risk becoming passive consumers, missing out on value creation—such as cultivating local AI ecosystems and expanding high-value job markets—and being excluded from shaping global standards on ethics, interoperability, and governance.

Moreover, the risks of dependence extend beyond economic disparities. Systems that influence hiring, health care, loan approvals, or judicial decisions may perpetuate biases—from gender discrimination to racial profiling. AI's reliance on vast data sets raises security and sovereignty vulnerabilities: Sensitive data (for example, biometrics and health records) processed by foreign AI providers could be exploited for surveillance or manipulation. Culturally and politically, AI's influence over media and public discourse—via recommendation algorithms or deepfakes—can transform it into a tool for propaganda and social engineering, potentially undermining local governance.

Open-source models offer a pathway to mitigate these threats. They enable nations to tailor AI to local languages, cultures, and needs without reinventing foundational technologies from scratch. By fostering local adaptation, open-source AI can prioritize equitable access to AI tools while safeguarding cultural and political autonomy.

AI adoption started with rapid uptake, but this growth masks shallow usage and stark disparities. The global uptake of GenAI tools among individuals has been unprecedented, with platforms such as ChatGPT reaching 100 million users within 2 months, far outpacing the diffusion rates of earlier technologies. The momentum is strongest in countries with robust digital infrastructure, skilled workforces, and large youth populations. HICs and MICs drive more than 99 percent of ChatGPT traffic in mid-2025, and LICs account for less than 1 percent (refer to figure O.3, panel a).

Even in MICs, usage intensity remains low. While many MICs show impressive total traffic (refer to map O.1, panel a), each internet user engages with tools such as ChatGPT below 0.4 times monthly, compared with nearly three times in HICs (refer to map O.1, panel b). Despite GenAI's reach across 209 economies, its daily traffic remains below 2 percent of Google's traffic, highlighting its still-niche role in global digital activity. Even where it has been adopted, it is skewed demographically toward young, college-educated men (refer to figure O.3, panel b).

Beyond individual use, AI adoption by businesses and governments is in its nascent stages, characterized by a slow and uneven process hindered by localization challenges and fragmented capabilities. Even in advanced economies, corporate uptake lags; only 8 percent of OECD firms adopt AI on average in 2024 (refer to figure O.4), primarily concentrated among large enterprises in information technology, finance, and professional services. Meanwhile, adoption in sectors critical to equitable development, such as agriculture, education, and health care, remains limited.

Low AI adoption stems not from limited usefulness but systemic barriers that demand policy intervention. Coordination challenges prevent small firms and farmers from achieving the scale needed for collective AI investment, and information asymmetries, particularly in LICs, limit awareness of AI's applicability or access to localized models. Left unaddressed, these market failures will concentrate AI's benefits among advanced nations, large corporations, and high-skilled workers, thereby widening global inequality and preventing technology from reaching its wide and socially optimal potential.

FIGURE O.3 ChatGPT and GenAI traffic over time, by income level and country

a. ChatGPT traffic, by income level

b. GenAI uptake, by user characteristics, March 2024

Sources: Liu, Huang, and Wang 2025; Liu and Wang 2024.
Note: GenAI = generative artificial intelligence; GPT = general-purpose technology; HICs = high-income countries; LICs = low-income countries; LMICs = lower-middle-income countries; MICs = middle-income countries; UMICs = upper-middle-income countries.

MAP O.1 ChatGPT traffic by country, March 2024

a. Total traffic, March 2024

(Continued)

MAP O.1 **ChatGPT traffic by country, March 2024 (*Continued*)**

b. Traffic per internet user, March 2024

Traffic per user:
visits per person

- 2.66
- 2.00
- 1.60
- 1.20
- 0.80
- 0.40
- 0

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Source: Liu and Wang 2024.
Note: GPT = general-purpose technology.

FIGURE O.4 **AI adoption, by firms across OECD countries, 2024**

All firms (%)   Large firms (%)

□ All (10+ employees)   ● Large (250+ employees)

Source: Original figure for this publication using data from OECD 2024 (https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/05/oecd-digital-economy-outlook-2024-volume-1_d30a04c9/a1689dc5-en.pdf).
Note: For a list of country codes, refer to https://www.iso.org/obp/ui/#search. AI = artificial intelligence; OECD = Organisation for Economic Co-operation and Development.

Realizing the potential of AI hinges on the 4Cs, the foundation of AI readiness

This report underscores the critical need to strengthen the foundational 4Cs that form the bedrock of a country's capacity to adopt, adapt, and innovate with AI: connectivity, compute, context, and competency. These four pillars are the essential enablers of an inclusive and effective AI ecosystem.

Connectivity

Connectivity is the gateway to AI participation. AI systems rely on networked infrastructure to access data sets, perform distributed computing tasks, and enable real-time inference through application programming interfaces and remote servers. Without reliable internet or data links, users cannot upload data, download models, or integrate with collaborative platforms or cloud services. Furthermore, edge AI devices often require periodic synchronization with central servers for updates, security patches, and enhanced processing,[1] rendering isolated systems obsolete or ineffective in dynamic AI ecosystems.

Internet access continues to expand, with satellites offering new possibilities of closing the remaining gaps. Mobile networks now cover more than 98 percent of the global population. Advanced networks are spreading rapidly, with 5G already the dominant technology in HICs and upper-middle-income countries (UMICs) and expanding fastest in LMICs, where coverage rose from 6 percent to 35 percent between 2022 and 2024.

Nonterrestrial networks, especially satellites, have risen sharply as a complementary pathway to bridge remaining gaps. Since 2015, the number of commercial satellites in orbit has grown more than 14-fold. Low Earth orbit systems constitute 90 percent of these deployments, driving higher speeds and lower latency and extending connectivity to remote and underserved regions (refer to figure O.5). New business models and price points are increasing the adoption of satellite communications services globally. As connectivity expands, adoption continues to rise, with internet penetration now reaching 68 percent of the global population. This growth has brought 400 million new users online, nearly half of whom are from LMICs. About 170 million people worldwide still live without any mobile signal, most of them living in LICs, where only 4 percent of the population has 5G coverage, leaving most users reliant on slower 3G and 4G networks (refer to figure O.6).

Despite progress in access, stark disparities in affordability, speed, and data usage persist between richer and poorer countries, leaving large parts of the developing world offline and unable to participate fully in the AI economy. Near-universal mobile coverage has not translated into universal participation, with gaps remaining severe, particularly in developing economies. In 2024, one-third of the global population remains offline, including 1.8 billion in rural areas and 800 million in urban areas. Although internet penetration has nearly saturated HICs, only about one-quarter of the population is online in LICs.

- Affordability has improved but remains a critical constraint in LICs. Broadband prices have fallen but are still prohibitive in many economies. For instance, in 2024 a 5-gigabyte fixed broadband plan consumed 29 percent of monthly income in LICs, compared with less than 3 percent in HICs and UMICs. These costs force families to ration internet use, often relying on shared broadband subscriptions.

- Speed gaps have widened. HICs and UMICs saw a 50-percent increase in internet speeds between 2023 and 2024, reaching 143 megabits per second (mbps) and 74 mbps, respectively;

the median speed in LMICs and LICs stagnated below 25 mbps, underscoring a persistent quality deficit (refer to figure O.7).

• Gaps in data use are widening, with HICs leaving others further behind. In 2023, average data traffic per capita reached 1,400 gigabytes in HICs, 400 gigabytes in UMICs, 100 gigabytes in LMICs, and only 5–6 gigabytes in LICs. Limited traffic reduces demand for digital services, constrains firms' ability to scale, and narrows the markets in which AI applications can generate value.

FIGURE O.5 Growth in commercial communications satellite constellations, by orbital positioning, 2015–23

Source: Original figure for this publication using data from Union of Concerned Scientists (https://www.ucs.org/resources/satellite-database).
Note: GEO = geostationary Earth orbit; LEO = low Earth orbit; MEO = medium Earth orbit.

FIGURE O.6 Mobile network coverage, by country income group, 2022 and 2024

Source: Original figure for this publication using data from GSMA (https://www.gsmaintelligence.com/).
Note: HICs = high-income countries; LICs = low-income countries; LMICs = lower-middle-income countries; UMICs = upper-middle-income countries.

FIGURE O.7 **Median fixed and mobile download speed, by country income group, 2023 and 2024**

Broadband speed (mbps)

Legend: ☐ Fixed 2023 ☐ Fixed 2024 ○ Mobile 2023 △ Mobile 2024

Sources: Original figure for this publication calculated using data from Ookla (https://www.speedtest.net/global-index).
Note: HICs = high-income countries; LICs = low-income countries; LMICs = lower-middle-income countries; mbps = megabits per second; UMICs = upper-middle-income countries.

Telecommunications markets in LICs and MICs exhibit clear market failures. High fixed costs to build fiber optic cables and cell towers deter competition, resulting in high prices, poor service, and limited choice. This market structure deepens the digital divide because private firms often lack the incentives to extend networks to less profitable rural areas, which in turn slows economic growth and human development. Conversely, the positive externalities of digital connectivity, such as network effects that drive productivity gains and spur innovation and commerce, are vast. However, these transformative benefits are constrained by chronic underinvestment in "last-mile" connectivity, limiting the very data required for AI applications to scale.

Furthermore, the entire digital ecosystem is critically dependent on energy. Unstable power supply is a significant negative externality, because unreliable grids and frequent outages can render even the most-advanced digital and AI infrastructure useless. This issue underscores why foundational investments in the energy sector are inseparable from digital development goals. Therefore, ensuring affordable energy pricing, robust grid resilience, and the successful integration of renewables are fundamental to building a sustainable and functional digital future.

A cohesive policy approach is essential to expand affordable connectivity. This work requires integrating governance across multiple domains. For example, the dialogue between nongeosynchronous orbit satellite deployment and terrestrial networks presents opportunities to extend coverage and lower costs, but it demands careful policy design to manage spectrum and ensure interoperability. Similarly, because AI readiness depends on both digital infrastructure and reliable power, governments must align energy, connectivity, and data policies.

Governments can attract, retain, and expand private sector investment in telecommunications infrastructure by liberalizing foreign investment, ensuring fair competition, and creating stable regulatory frameworks to reduce investor uncertainty. Reducing network deployment costs is critical and can be achieved by streamlining permitting and rights-of-way processes and promoting infrastructure sharing through co-investment mandates and financial incentives. To close remaining

gaps, governments should open markets to satellite providers for remote areas and directly address affordability through targeted subsidies, shared access points, lower taxes on digital devices, and innovative financing mechanisms.

Compute

In the AI era, compute is the "new electricity." The transformative power of AI is fundamentally reliant on compute—encompassing AI chips, data centers, high-performance computing (HPC) systems, and cloud services. This layer of the AI ecosystem is the engine that stores, processes, and transfers data at scale, required for training and deploying AI models. The demand for computational power has been exponentially increasing: Before the deep-learning revolution began around 2010, the compute required for training doubled roughly every 24 months. Since 2010, the compute required has been doubling every 6 months ("The Race Is on to Control the Global Supply Chain for AI Chips" 2024).

The compute supply chain is highly concentrated with a few firms deciding how computational power is manufactured and priced. The processor chips market, projected to expand 10-fold over the next decade, is led by NVIDIA, which holds 70–95 percent of the market for AI chips and 92-percent market share in the data center graphics processing unit (GPU) segment as of 2023 ("NVIDIA Dominates the AI Chip Market, but There's More Competition Than Ever" 2024). This dominance is rooted in its first-mover advantage and its robust, optimized software ecosystem, Compute Unified Device Architecture, which has become the industry standard for GPU-accelerated computing. Although competitors are emerging, the high barriers to entry mean that, for the near future, access to cutting-edge AI hardware is filtered through a narrow bottleneck.

A similar pattern of concentration unfolds in the public cloud computing sector, which allows organizations to access powerful compute resources without massive upfront capital investment. This market is dominated by a handful of "hyperscalers," with Amazon Web Services, Google Cloud, and Microsoft Azure collectively commanding two-thirds of the global market share (Richter 2025). The cloud market is projected to expand at a 22-percent annual growth rate, reaching a value of US$2 trillion by 2030 (Goldman Sachs 2024). This concentration is driven by immense economies of scale, network effects, and high entry barriers. Although these large providers offer sophisticated, secure, and efficient services, their dominance raises significant concerns about vendor lock-in, reduced competition, and systemic risks as entire sectors of the economy become dependent on a few private entities.

The concentration of compute supply translates directly into a severe global divide in compute capacity, leaving developing nations profoundly disadvantaged.

- *AI chips and servers.* In 2024, the United States hosted half of the world's secure internet servers (refer to figure O.8, panel a). Other HICs account for another 41 percent, leaving only 9 percent for the rest of the world. On a per capita basis, the United States has 200 times more servers than a typical MIC and 20,000 times more than a typical LIC.
- *HPC.* These supercomputing systems are essential for frontier AI research. As of June 2025, HICs host 86 percent of the world's top 500 HPC systems and command 97 percent of their total capacity (refer to figure O.8, panel b). In stark contrast, MICs (excluding China and India) host only 3 percent of these systems and account for a mere 1 percent of capacity, despite representing 15 percent of global gross domestic product and 48 percent of the world's population.
- *Data centers.* The physical homes for compute show the same pattern. As of June 2025, HICs accounted for 77 percent of global colocation data center capacity (measured in megawatts). UMICs held 18 percent; LMICs, 5 percent; and LICs, less than 0.1 percent.

FIGURE O.8 **Compute capacity, by country income group and region**

Share of global total (%)

Sources: Original figure for this publication using data from World Development Indicators, World Bank (https://databank.worldbank.org/source/world-development-indicators).
Note: GDP = gross domestic product; HICs = high-income countries; HPC = high-performance computing; LICs = low-income countries; LMICs = lower-middle-income countries; MICs = middle-income countries; UMICs = upper-middle-income countries; US = United States.

Because compute is highly tradable, many countries rely on importing services via the cloud. International broadband connectivity and cloud computing offer partial alternatives to domestic data centers. The trade-offs depend on the technical design of compute resources and applications, as well as factors such as internet latency, data transmission costs, privacy, and data sovereignty. This dynamic means some countries rely on imports of cloud services rather than building extensive domestic data center capacity, even as design choices and network conditions shape the cost-benefit balance.

However, this trade is highly imbalanced. The United States leads in global cloud computing and data storage markets, accounting for about 87 percent of global exports during 2016–21. China's exports share has jumped from 1 percent in 2016 to 6 percent in 2021, whereas Germany's share has declined from 10 percent to 6 percent. Excluding these three countries, all other countries combined have contributed only 1 percent (Stojkoski et al. 2024).

Of US exports, 84 percent flow to HICs, with UMICs and LMICs receiving 14 percent and 2 percent, respectively, leaving LICs with virtually none (refer to figure O.9, panel a). France, Germany, and the United Kingdom alone import nearly as much as all developing nations combined. Within the developing markets, Latin America and the Caribbean stands out as the leading destination for US cloud computing exports (refer to figure O.9, panel b), fueled by geographical proximity and demand from Brazil and Mexico (accounting for 33 percent of developing world imports). China, reliant on domestic providers, imports just 2 percent of US cloud services.

FIGURE O.9 **US cloud computing exports, by destination country income group and region, 2019–23**

a. Income group

b. Region, excluding HICs

Source: Original figures for this publication using data from World Trade Organization statistics (https://stats.wto.org/).
Note: The sum of exports by income group is below US total cloud computing exports, as bilateral exports below certain value thresholds are not reported. EAP = East Asia and Pacific; ECA = Europe and Central Asia; HICs = high-income countries; LAC = Latin America and the Caribbean; LMICs = lower-middle-income countries; MENAAP = Middle East, North Africa, Afghanistan, and Pakistan; SAR = South Asia; SSA = Sub-Saharan Africa; UMICs = upper-middle-income countries; US = United States.

The compute market is characterized by significant market failures and externalities. High entry costs for data centers and AI hardware, coupled with poor energy and digital infrastructure, are prohibitive for most firms in developing countries. Positive externalities, such as cross-sector productivity gains from AI applications, are underinvested because private actors cannot capture all benefits.

Conversely, negative externalities, such as data centers' environmental impact (energy use and e-waste) and geopolitical risks (data sovereignty), are not priced into private markets, leading to systemic underinvestment and insufficient mitigation of harms. Coordination failures also precent large-scale, socially optimal investments, like regional data centers. This is worsened by a shortage of local cloud expertise and regulatory uncertainty about data governance, creating a vicious cycle of low adoption. Therefore, carefully tailored government action is essential to create an enabling environment for compute access.

A key strategic decision for governments is whether to focus on building domestic compute capacity (for example, data centers) or securing affordable access to international cloud services. Promoting domestic infrastructure can spur local economic development, job creation, and sovereignty, but it requires affordable energy, robust grids, and sufficient local demand—conditions often lacking in LICs or MICs.

Cloud imports could provide scalability, cost-efficiency, and rapid AI deployment with access to cutting-edge infrastructure, yet they entail risks of dependency, longer latency, data sovereignty concerns, and national security vulnerabilities. China's reliance on domestic providers (for example, Alibaba Cloud) contrasts with Latin America's dependence on US exports. Smaller or less-developed economies must weigh embracing cloud-enabled growth against developing domestic capabilities.

Regardless of the path chosen, governments can deploy a range of targeted interventions:

- *Public funding and public-private partnerships*. To overcome high entry costs, governments can cofund regional data centers (for example, African Union initiatives); provide compute subsidies or vouchers for small and medium enterprises (SMEs), start-ups, and researchers (for example, the Republic of Korea's credits); and partner with technology firms to deploy affordable GPUs, potentially through regional collaborations that can create economies of scale.

- *Reduce regulatory risks and environmental externalities*. Governments can attract private investment by ensuring regulatory certainty on data governance, privacy, and cross-border data flows. Clear policies can reduce vendor lock-in, while promoting renewable energy for data centers can help mitigate negative environmental externalities.

- *Fostering local demand and expertise*. Public initiatives can raise awareness and boost adoption by promoting digital literacy, investing in training programs for cloud and AI expertise, and supporting the development of local AI applications that drive demand for compute resources.

A hybrid approach—strategic domestic investments combined with regulated global cloud integration—is essential. Governments must upgrade energy grids, foster expertise, and negotiate fair cloud access to ensure inclusive AI development.

Context

AI's capabilities, at their core, hinge on three critical aspects of their training data—quantity, quality, and diversity. *Quantity* refers to the scale of data that allows the model to learn broad patterns and reduce overfitting. *Quality* refers to the accuracy, completeness, timeliness, granularity, and fairness of the data, which minimize errors and bias while preserving useful information. *Diversity* captures representativeness across social, economic, institutional, cultural, and linguistic dimensions, making the model robust and adaptable to different contexts. Together, these three aspects determine AI's real-world effectiveness and explain why gaps in any of them can cripple a model's performance in certain regions or sectors.

High-quality AI training data moves through a comprehensive data production chain with five key stages: sourcing, collection, processing, brokerage, and usage (refer to figure O.10). The process begins with sourcing data (open-source, commercialized, or private) and collecting it via methods like crawling or purchasing. The raw data then undergo processing, where they are cleaned, filtered, deduplicated, formatted, and sometimes labeled to enhance quality and meet the requirements of AI models, a task developers can perform in-house or outsource to data brokers. During the final usage phase, data are refined by AI developers to fit specific AI models, creating a feedback loop that continuously improves the production chain. The entire process embodies both technical challenges, like data cleaning and labeling, and governance challenges related to privacy, consent, copyright, and ethical data use, making responsible data essential for trustworthy AI.

FIGURE O.10 **Production chain for training data**

Data sourcing	Data collection	Data processing	Data brokerage	Data usage
• Open-source data • Commercialized data • Private data	• Crawling • Purchase	• Cleaning: filtering, deduplication, formatting, etc. • Information extraction • Labeling	• Monetize • Aggregate • Customized analysis	• Refining • Debias • Feedback • Add value

Source: Original figure for this publication.

The AI training data industry is growing rapidly, with its value projected to grow from about US$2.26 billion in 2023 to US$17 billion by 2032, reflecting a compound annual growth rate of 22 percent ("AI Training Dataset Market Size" 2025). This boom is fueled by robust investor appetite, with private capital investment reaching US$32 billion between 2012 and 2023. However, this investment is highly concentrated, raising important equity concerns. From 2014 to 2023, the United States received 56 percent of cumulative AI training data VC funding, followed by China (17 percent) and the European Union (15 percent). The rest of the world, excluding India, received just 6 percent, exacerbating gaps in language representation and AI utility for diverse cultures (refer to figure O.11).

Although English dominates AI training data, nontext formats such as video can unlock opportunities for LICs and MICs. Spoken by roughly 19 percent of the global population, English dominates high-quality text data—accounting for 45 percent of global URLs, 56 percent of open-source data sets on Hugging Face (refer to figure O.12), and an overwhelming 98 percent of scientific papers. In contrast, the language distribution in nontext modalities is more diverse, opening doors for non-English-speaking communities to contribute and benefit from AI technologies. For example, only about 21 percent of YouTube videos are in English; 7.6 percent are in Hindi, and 6.7 percent are in Spanish. These trends indicate that multimodal data sources—such as images, audio, video, and integrated data sets—may offer pathways for broader participation and value creation by developing countries. Harnessing multimodal data could democratize AI's cultural relevance and mitigate bias.

FIGURE O.11 **Training AI in a data desert: VC investments in training data, by country and region**

a. Number of start-ups, 2024

- United States, 40%
- EU, 21%
- Other HICs, 17%
- United Kingdom, 9%
- China, 6%
- Other UMICs, 5%
- India, 2%
- Other LMICs, 1%

b. VC funding, 2014–23

- United States, 56%
- China, 17%
- EU, 15%
- Others, 6%
- India, 3%
- United Kingdom, 2%

Sources: Original figures for this publication using calculations from OECD.AI (https://oecd.ai/en/data?selectedArea=investments-in-ai-and -data&selectedVisualization=vc-investments-in-data-start-ups-by-country) and CB Insights (https://www.cbinsights.com/); data extracted in September 2024.
Note: Start-ups in the training data sector were selected because the keywords *data management, data collection,* or *data tracking* were present in their company descriptions. EU = European Union; HICs = high-income countries; LMICs = lower-middle-income countries; UMICs = upper-middle-income countries; VC = venture capital.

FIGURE O.12 **Predominance of English in online content**

a. Distribution of leading languages, 2025

Leading languages

English	4.8	14.0
Mandarin Chinese	12.2	2.4
Hindi	4.3	3.3
Spanish	6.0	0.9

Percentage of global population

■ Native speakers ■ Other speakers

b. Global URLs, by language, 2025

Other languages, 21%
Unknown, 3.02%
French, 4.12%
Spanish, 4.21%
Japanese, 5%
Chinese, 5%
German, 6%   Russian, 6%
English, 45%

c. Open-source data sets from Hugging Face, by language, 2024

Other languages, 30.0%
Russian, 2.4%
Spanish, 2.8%
French, 3.4%
Chinese, 5.1%
English, 56.3%

d. YouTube videos, by language, 2022

English, 21.4%
Hindi, 7.6%
Spanish, 6.7%
Portuguese, 5.0%
Russian, 4.5%
Arabic, 3.2%
Other languages, 51.6%

Sources: Original figures for this publication based on calculations using Ethonologue 2025 data (https://www.ethnologue.com/); CommonCrawl data accessed in July 2025 (https://commoncrawl.org/); OECD.AI data updated on April 22, 2024 (https://oecd.ai/en/); and Figure 18 in McGrady et al. 2023.
Note: AI = artificial intelligence.

Although private firms have been pioneers in data generation, and synthetic data solutions have begun to fill some gaps, several market failures distort incentives and limit the sharing and reuse of data. Positive spillovers from data reuse (for example, open data sets for pandemic modeling), and the difficulty of capturing these benefits in private valuations, mean that data owners underinvest in data creation and sharing. Property rights (for example, user data versus platform rights) with respect to data are often vague, especially when data are scraped from the web or assembled from mixed sources, which discourages licensing and sharing.

Valuing data remains challenging, complicating pricing, trading, and investment planning. Privacy and security concerns further dampen willingness to share sensitive data, particularly across borders or in regulated sectors. Taken together, these market failures create underinvestment in high-quality, diverse data and undersharing across entities, underscoring a clear role for public policy and governance to address these externalities and foster more inclusive AI development.

Governments can consider a suite of measures to enhance data accessibility and governance and unlock AI's potential for all populations:

- *Public data commons.* Governments can create public data commons, curating and publishing data assets as public goods or federated resources for AI training. Examples like the UK Data Service demonstrates how this reduces entry barriers for researchers and firms, accelerating AI development. Digitizing nondigital records will further unlock valuable data.

- *Enhancing data governance and interoperability.* Robust frameworks, privacy-preserving technologies, and data trusts can enable secure collaboration. Promoting interoperable data formats and taxonomies will lower costs, streamline integration, and improve data quality, fostering an accountable digital ecosystem where data can be aggregated and reused for AI.

- *Financial support for data access.* Financial incentives, such as subsidies and vouchers, can help SMEs access high-quality AI training data and tools. Programs such as the European Union's Horizon 2020 and Korea's data vouchers illustrate how such incentives support a competitive and innovative AI environment.

Developing countries are navigating AI adoption of open-source and proprietary models. For many developing countries, the primary challenge in AI adoption extends beyond acquiring large, high-quality data; it involves effectively adapting models to their unique economic, cultural, and institutional contexts. The AI model landscape comprises both open-source and closed-source (proprietary) approaches. Open-source models, exemplified by Meta's Llama 3.1 or Stability AI's Stable Diffusion, make their underlying code or parameters publicly accessible, fostering collaboration, transparency, and cost-effectiveness, although the degree of openness varies, with some projects sharing comprehensive components and others restricting access to key elements. Proprietary models such as Google's Gemini or OpenAI's GPT-4 offer optimized performance and integrated security but maintain confidential code. Although *open source* implies full accessibility, the degree of openness varies.

Both approaches present trade-offs. Open-source solutions offer customization and transparency but often demand substantial technical expertise and carry security risks, while proprietary systems deliver high performance, and tailored support, but risk dependency and limited adaptability. Open-source AI presents a crucial development pathway for developing countries, offering a lower-cost, customizable alternative that addresses issues such as model misalignment, high licensing fees, and resource-intensive adaptation. This enables localized AI solutions (or "small AI," as discussed later) without prohibitive expenses, especially as open-source models increasingly narrow the performance gap with proprietary systems. A more level playing field is emerging.

However, successful open-source adoption requires substantial technical resources, data curation, and sustained capacity-building. Therefore, a tailored approach is essential, blending open-source strengths with targeted investments in local data ecosystems, regulatory clarity, and technical expertise. Governments must balance these approaches, prioritizing responsible use over restrictive policies to foster innovation. Regulatory frameworks should promote competition and innovation through adaptive standards, enabling developing economies to customize solutions while mitigating risks such as vendor lock-in. By encouraging open-source development through investments in digital

infrastructure, AI education, and collaborative ecosystems—and leveraging proprietary partnerships where appropriate—nations can harness AI's potential without compromising sovereignty or inclusivity, ensuring technologies align with local priorities and constraints.

Competency

The past decade has witnessed near-universal digitalization across occupations, making digital skills a prerequisite for jobs. While high-skill roles consistently utilize more digital technologies and tools (as shown by the O*NET database), mid- and low-skill occupations have experienced the largest increases in digital integration (refer to figure O.13). By 2024, professionals used more than 60 percent of digital tools and 90 percent of digital technologies. The growing incorporation of AI into these digital tools has further transformed daily workflows by simplifying tasks and broadening applications.
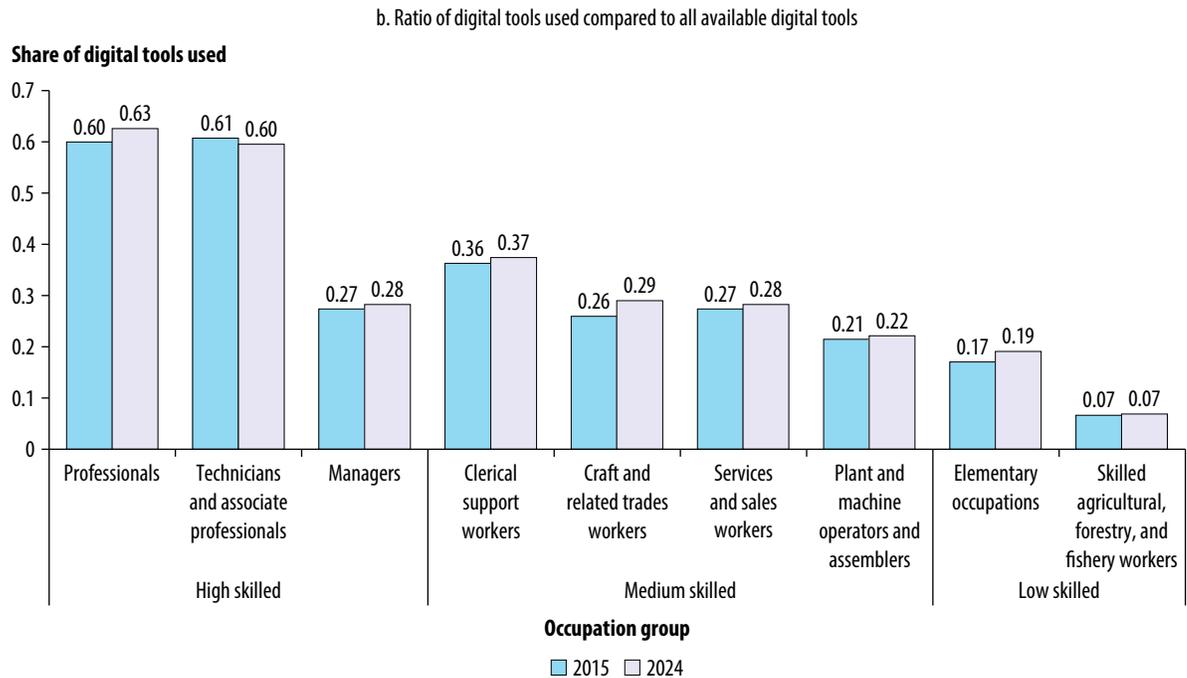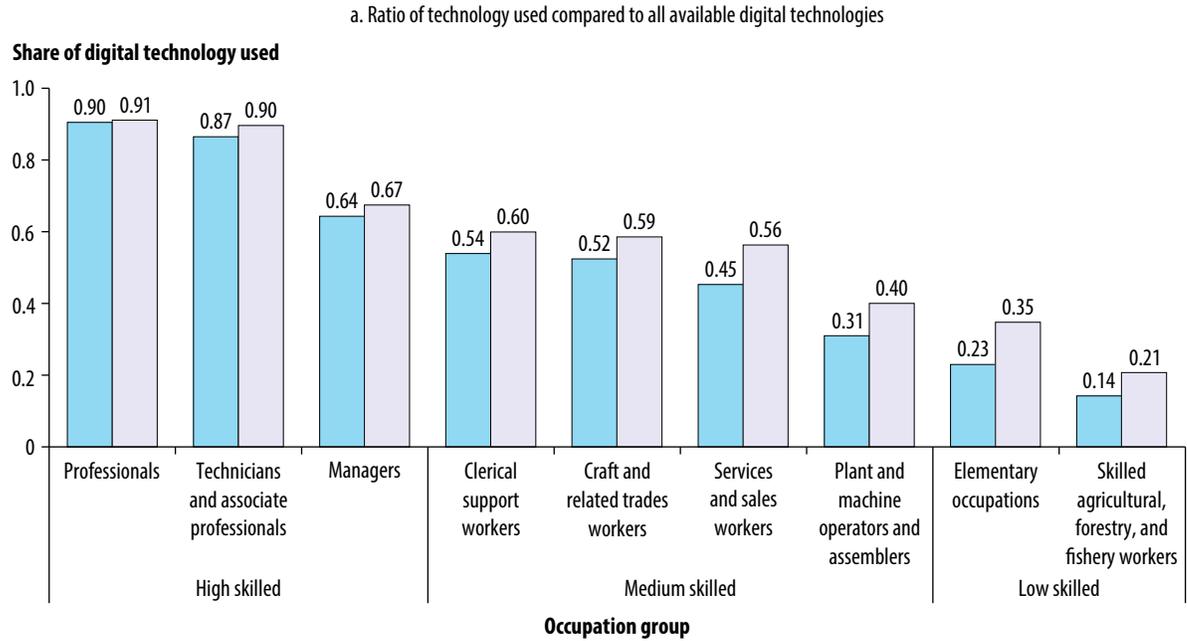
The rapid advancement of AI is reshaping global labor markets, creating pronounced and uneven skill gaps. In 2024, more than 70 percent of AI-related job postings were concentrated in HICs, reflecting a stark geographic disparity in AI readiness. Globally, GenAI vacancies surged ninefold from 2021 to 2024, but they still represented only 0.2 percent of all online vacancies. Before public GenAI tools, demand in HICs focused on model development; afterward, it shifted toward integration and usage skills. By 2024, GenAI-skilled vacancies reached nearly 300,000 globally (refer to figure O.14, panel a), with the United States and France accounting for about half.[2]

Encouragingly, the number of job vacancies requiring AI skills is rising faster in MICs than in HICs. From 2021 to 2024, AI-related job postings rose 16 percent in UMICs, 11 percent in LMICs, and only 2 percent in HICs. Specific examples include a tripling of AI vacancies in Brazil, Indonesia, and Malaysia, a doubling in Colombia, the Arab Republic of Egypt, Mexico, Pakistan, the Philippines, and Viet Nam, and a fivefold increase in Kenya (albeit from a low base). In China, demand for natural language processing surged by 111 percent in the first half of 2024 compared with the same period in 2023, followed by a 76-percent growth in AI for robotics, a 61-percent growth in deep learning, and a 49-percent growth in autonomous driving ("Research on the Potential Impact of AI Big Models on My Country's Labor Market Released" 2024). These data signal the potential for developing countries to strengthen AI competency and build a growing AI workforce.

Although information and communication technology (ICT) professions dominate AI demand across all income groups, GenAI skills are expanding into diverse fields, such as content creation, marketing, research and development, education, and health care. In HICs, more than 40 percent of all GenAI vacancies in 2024 were for ICT professionals (refer to figure O.14, panel b), with their role in customizing solutions across sectors. Other occupations like teaching and health show notable GenAI integration. In contrast, ICT professionals account for around 60 percent of all GenAI vacancies in MICs, with GenAI roles in occupations like education and health care being nearly absent. This highlights both a significant opportunity for MICs to build their core AI workforce and a need for broader GenAI integration into development-relevant sectors.

Challenges to meeting AI demand include supply shortages and brain drain. Despite consistent growth in ICT program enrollment across all income groups since 2010, universities are struggling to meet the accelerating demand for AI skills. In Canada and the United States, the number of computer science graduates has tripled (from about 18,000 in 2010 to 52,000 in 2022), with the number of bachelor's-degree graduates rising from 9,000 to 36,000 and master's-degree graduates rising from 7,000 to 14,000; the number of PhDs saw only marginal growth, increasing from 1,800 to 2,100 (Thormundsson 2025), yet supply remains significantly short.

FIGURE O.13 Exposure to digitization through use of technologies and IT tools, by occupation

a. Ratio of technology used compared to all available digital technologies

b. Ratio of digital tools used compared to all available digital tools

☐ 2015 ☐ 2024

Source: Original figures for this publication using calculations based on O*NET data (https://www.onetonline.org/).
Note: IT = information technology.

FIGURE O.14 Trends in AI and GenAI skills demand across country income groups, 2021–24

a. GenAI vacancies, by income group

b. Distribution of GenAI vacancies, by 2-digit occupation and income group

Source: Original figures for this publication using computations based on Lightcast data (https://lightcast.io/).
Note: Data for UMICs is severely underestimated due to extremely limited coverage in China. AI = artificial intelligence; GenAI = generative artificial intelligence; HICs = high-income countries; ICT = information and communication technology; LMICs = lower-middle-income countries; UMICs = upper-middle-income countries.

Scaling ICT programs faces considerable hurdles, including the difficulty of recruiting qualified faculty due to more financially rewarding industry offers and the substantial, slow-to-scale infrastructure investments required (for example, dormitories, classrooms, and labs). Moreover, many universities struggle with curriculum relevance; a survey of African universities revealed 40 percent had not updated ICT curricula in more than 5 years, creating a critical mismatch between graduate skills and employer needs.

The global supply of ICT specialists remains highly concentrated—with China at 21 percent, the United States at 21 percent, and India at 15 percent leading, whereas LICs account for less than 1 percent. This concentration highlights a severe digital skills gap in LICs and MICs, where less than 5 percent and 20–40 percent of the population possess basic and intermediate digital skills, respectively, further exacerbated by pronounced gender and urban–rural disparities (refer to figure O.15).

Moreover, digital talents in LICs and MICs increasingly are migrating to HICs, exacerbating brain drain. For example, 26 percent of top AI researchers originate from China and 8 percent originate from India, with most working in the United States. This migration diminishes origin countries' innovation capacity and widens global skills divides, as well as reinforces the United States' formidable ability to attract and retain top global AI talent, a key factor in maintaining its technological leadership and economic competitiveness.

FIGURE O.15   Supply of digital skills, 2023

a. Share of population, by digital skill level, 2023

b. Gender and urban-rural gap in digital skills, 2023

Source: Original figures for this publication using data from the International Telecommunication-Union (https://datahub.itu.int/).
Note: For panel a, data include 5 countries in LICs, 16 in LMICs, 31 in UMICs, and 49 in HICs. For panel b, gender gap data include 11 countries for LMICs, 27 for UMICs, and 46 for HICs; for the urban-rural gap, data include 11 countries for LMICs, 20 for UMICs, and 23 for HICs. Bars indicate min and max of distribution; dots are outliers. For a list of country codes, refer to https://www.iso.org/obp/ui/#search. HICs = high-income countries; LICs = low-income countries; LMICs = lower-middle-income countries; UMICs = upper-middle-income countries.

Developing countries face significant market failures and systemic barriers in building and retaining digital talent, hindering their participation in the digital economy. Limited access to high-speed internet, modern computing infrastructure, and AI labs restricts hands-on learning opportunities. A critical challenge is the lack of quality, industry-aligned education and training programs, often because of poor coordination between academia and the private sector. High training costs and credit constraints further prevent many from acquiring digital skills, and firms underinvest in employee training because of poaching fears. Compounding these issues, brain drain remains a persistent issue, as skilled professionals seek better opportunities abroad. These interconnected barriers create a vicious cycle: A shortage of skilled workers discourages investment in the digital sector, which, in turn, further limits talent development and retention.

Bridging the skills gap and safeguarding workers requires a complex, multifaceted policy approach tailored to a country's readiness level. Low-readiness countries can focus on foundational elements: device access; digital literacy; and embedding basic AI skills in compulsory schooling, emphasizing critical thinking. Middle-readiness countries could expand affordable digital training for SMEs, address instructor shortages, and foster robust industry-education partnerships with regular curriculum updates, drawing inspiration from models such as Korea's Meister schools and Singapore's SkillsFuture. Ensuring quality assurance for AI tools in education and building frameworks for ongoing diagnostic needs are also vital.

For high-readiness countries, priorities shift to improving access to AI infrastructure and data for universities and start-ups, funding advanced AI education and research, and implementing talent retention and recruitment measures. This includes competitive public sector salaries, grants and targeted incentives, and streamlined visas or digital nomad programs.

Across all readiness levels, the overarching goals are lifelong learning, robust digital infrastructure, and inclusive policies to reduce brain drain and promote equitable, sustainable AI-enabled growth.

Small AI offers an accessible, affordable way for developing countries to embrace AI

In the rapidly evolving AI landscape, the distinction between "big AI" and "small AI" is becoming increasingly relevant, especially in resource-constrained environments. *Big AI* relies on LLMs that are resource intensive to build and operate, requiring enormous data sets and computing power that make them prohibitively expensive for many developing countries.

Small AI, in contrast, leverages specialized models to perform a narrow range of repetitive tasks, such as AI tutors in Nigeria or diagnostic apps for nurses in South Sudan. As an emerging concept, it is defined by shared traits that make it a strategic tool for innovation in low-resource settings. Small AI thrives on minimal data and power, often running on consumer-grade devices such as laptops or smartphones. The following core characteristics enable targeted, context-relevant outcomes (Kim and Qiang, 2025):

- *Scope of application.* Domain or context specific, tailored to address local needs;
- *Data needs.* Reliance on specialized, smaller data sets;
- *Adaptability.* Operable on edge devices,[3] functional offline, and able to leverage existing infrastructure;
- *Model adaptation.* Customization of pretrained open-source or proprietary models to fit specific needs or tasks; and
- *Cost-efficiency.* Minimized infrastructure and operational costs by reduced dependencies on data, compute, and cloud services.

Small AI addresses development challenges at the local level, where its application in agriculture, health, and education shows patterns of practical, ground-up innovation.

Agriculture: Cultivating resilience and productivity

In agriculture, small AI empowers farmers with targeted, localized solutions that boost smallholder productivity and climate resilience:

- *Precision advisory services.* These services deliver timely insights. For example, a Ghanaian start-up provides hyperlocal weather short message service alerts via tropical-specific algorithms helping farmers decide when to plant, irrigate, and harvest—all on basic devices. In Senegal, an agricultural technology firm uses digital farmer profiles and crop data for mobile-based advice on disease management, yield forecasts, and water needs.
- *Vision-based diagnostics.* Computer vision tools transform low-connectivity farming. India's Maharashtra systems offer AI soil health diagnostics, and Kenya's Nuru app identifies crop diseases from photos. These edge computing applications run offline, putting tools directly in farmers' hands.
- *Infrastructure alignment.* Small AI builds on existing systems. Colombia's Agrosavia has developed AI irrigation tools for coffee farms. India's Agristack portal has created a federated farmer registry, enabling layering of AI tools for credit, markets, and personalized advice—a model Bangladesh is adopting.

Health: Expanding access and strengthening systems

In health care, small AI provides robust, low-bandwidth tool diagnostics and triage in low-connectivity areas, tailored to frontline workers and local needs.

- *Edge diagnostics.* In India, AI screens for tuberculosis and diabetic retinopathy. In the Pacific Islands, tools test maternal care diagnostics in remote areas, trained on smaller, relevant datasets and running offline.

- *Low-bandwidth communication and surveillance.* Chatbots handle screenings and inquiries in local languages, using minimal data and processing power. Mobile platforms use machine learning to collect symptoms for outbreak warnings. These capabilities were accelerated by COVID-19 lessons.

- *Culturally relevant care.* Recognizing health care's local nature, small AI adapts to community contexts. A Peruvian firm offers voice-based diagnostics with native language translation, blending technology with Indigenous systems to build community trust and adoption.

Education: Bridging gaps and personalizing learning

In education, small AI delivers inclusive, mobile-first tools that prove impactful without full-scale LLM development, targeting underserved learners in resource-limited settings:

- *Inclusive tutoring.* Tailored experiences have been provided in Costa Rica, the Dominican Republic, and Mexico. AI tutoring systems reach remote and Indigenous communities. Ghana's Rori, a WhatsApp-based math tutor trained on 500 microlessons, costs only $5 per student annually and yields an extra year of learning gains through personalized practice.

- *Mobile-first, offline delivery.* Personalized platforms like Diksha (India) and Shikkhok (Bangladesh) integrate AI into mobile apps that function offline or on limited bandwidth, supporting multilingual engagement in remote areas.

- *Teacher support.* Small AI also eases educator workloads. A Chilean nonprofit organization develops AI lesson planners for student-centered teaching, while Uruguay Ceibal uses AI for routine queries and reminders, freeing teachers to focus on core instruction.

Key lessons

Across agriculture, health, and education, key strategic lessons emerge:

- *Focus on hyperlocal problems.* Small AI excels when tackling specific, well-defined needs like crop disease, linguistic barriers, or prevalent health issues. This context-specific approach ensures relevance and drives adoption.

- *Leverage existing infrastructure.* Initiatives succeed by building on existing platforms such as WhatsApp (in Ghana), national farmer registries (India's Agristack), or health worker networks. This dramatically lowers entry barriers.

- *Prioritize mobile-first, offline functionality.* With smartphones as the digital gateway in developing countries, offline designs of mobile-native solutions are essential for achieving scale and impact.

- *Embrace public-private partnerships.* These examples demonstrate synergy among government infrastructure (for example, digital public infrastructure), nonprofit organizations, and private sector innovation, creating ecosystems for AI solutions.

Although big AI captures headlines, small AI is quietly delivering value on the ground. Evidence shows it is powerful and economical for key sectors, offering a pragmatic, affordable path for developing countries to deploy tailored AI solutions at a fraction of big AI's cost (Belcak et al. 2025). Although less accurate and scalable, it helps tackle everyday issues, leapfrog traditional barriers, and build crucial local capacity and AI literacy. This paves the way for societies to adopt more advanced systems as they emerge, creating a natural progression toward AI readiness.

There is no time to delay urgent strategic investment tailored to each country's AI readiness level

The rise of AI presents a defining moment for the global development landscape. For developing countries, the opportunity to leapfrog is tangible, and the risk of being left behind is real. AI's rapid evolution demands strategic foresight and anticipatory governance. Overlooking AI's long-term transformative potential in favor of immediate development needs would be a short-sighted miscalculation. Delaying engagement risks exacerbating global divides, as advanced economies accelerate AI adoption, reaping substantial productivity gains. Without proactive strategies, developing countries could face a bifurcated global economy, where AI-empowered nations surge ahead, leaving others struggling with stalled progress, and potentially exacerbating international inequality. Governments must recognize AI's inevitability and invest strategically to mitigate disruptions, fostering resilience and opening opportunities through early preparation.

Embracing AI is essential to maintain competitiveness and open new opportunities in today's digital marketplace. To capture substantial benefits, developing countries, especially those with greater digital maturity, should strive to localize and customize AI models for local demand, evolving into producers and innovators in specific AI niches rather than merely consumers of off-the-shelf solutions.

Prioritizing the 4Cs is a no-regret investment strategy. Governments face the challenge of balancing the risks of inaction against those of misallocated investment. Given AI's growing economic significance, early strategic action is crucial; first-movers gain significant advantages, while laggards risk permanent setbacks. The investment strategy should prioritize the 4Cs—connectivity, compute, context, and competency—tailored to each country's context (refer to box O.1). These foundational elements are essential not only for harnessing AI's potential but also for driving broader digital transformation, sustainable economic growth, and social progress.

Priorities must be tailored to each country's unique circumstances and its AI readiness level (refer to table O.1). Low-readiness countries should center priorities on foundational capabilities, such as universal access to electricity and affordable broadband connectivity. For computing, these countries primarily rely on international cloud services. In terms of context, they largely use existing or translated AI models, focusing on improving government data collection and forming partnerships to gather local data. Workforce development at this stage is to improve basic and intermediate digital literacy.
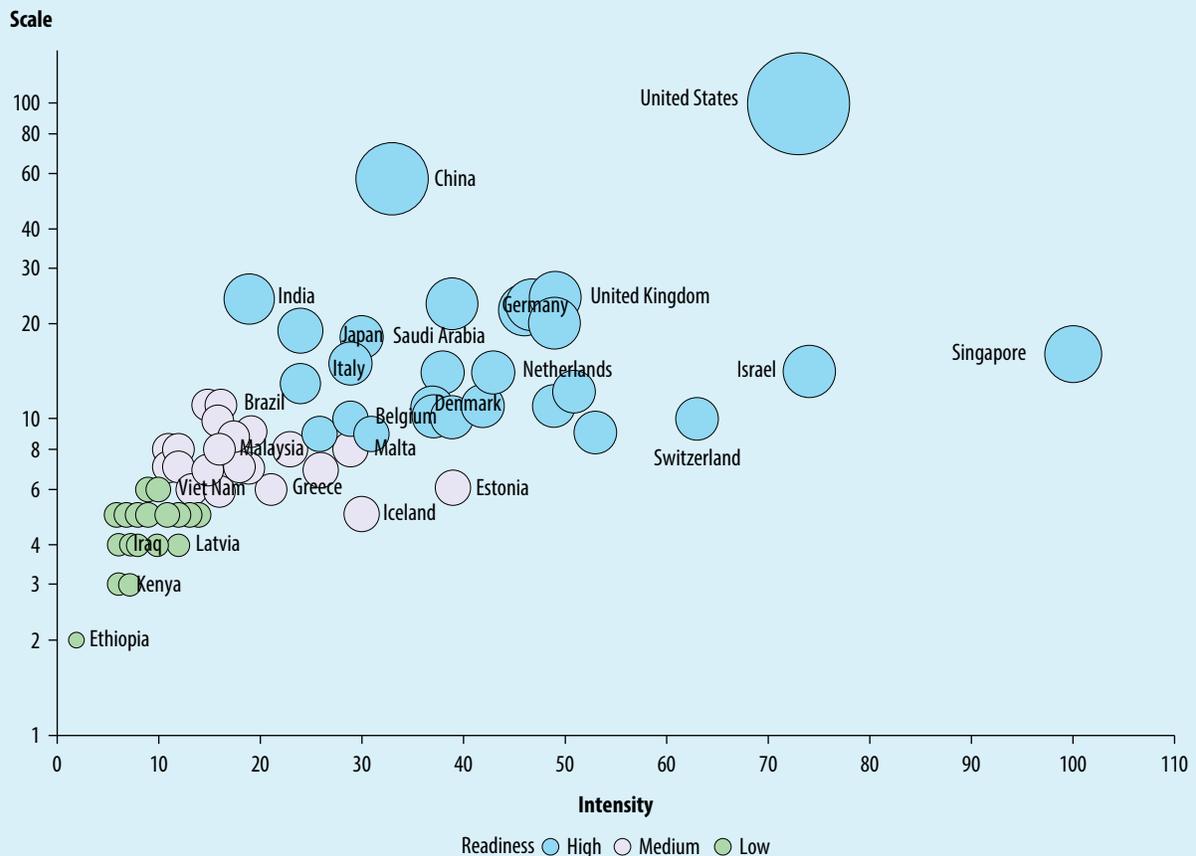
Medium-readiness countries should shift their focus to AI adoption and adaptation. They can upgrade their broadband infrastructure and invest in domestic data centers, as well as form strategic partnerships with foreign technology providers for localized experimentation. These nations can adapt AI for local needs by creating specific data sets, customizing open-source models, and developing applications for niche markets. Their competency focus shifts to fostering more advanced digital skills and implementing strategies for talent attraction and retention.

BOX O.1 Scale and intensity are drivers of AI readiness

In the digital and artificial intelligence (AI) age, a country's size, manifested as a vast, integrated domestic market, provides a significant edge through economies of scale and scope. Digital technologies and AI platforms deploy at near-zero marginal cost, with value amplifying via network effects that favor large user bases. This fosters "winner-takes-most" dynamics, enabling firms in large markets to rapidly scale, iterate products, and gather the vast, diverse data sets crucial for training AI models without facing regulatory or linguistic barriers. Furthermore, significant market size justifies concentrated, sustained investments in expensive research and development and compute infrastructure, attracting talent and fostering self-reinforcing innovation cycles. This dynamic explains the dominant influence of AI in nations such as China and the United States, while smaller, fragmented economies risk perpetual dependence on foreign AI solutions, limiting their role to that of consumers rather than innovators.

Although market scale drives AI innovation, AI intensity—measured per capita in the 4Cs (connectivity, compute, context, and competency)—is essential for widespread adoption and societal penetration, fostering inclusive productivity and resilience. High intensity ensures AI integration into public services, small businesses, and daily workflows, leading to broader productivity gains and enhanced national resilience. Ultimately, a country's position in the global AI value chain is determined by the interplay of both scale and intensity. Large-scale countries lead in foundational AI innovation, and smaller ones can thrive by focusing on niche AI adoption and customization (refer to figure BO1.1). This dual perspective highlights diverse pathways to build AI readiness, underscoring the need for strategic investments in the 4Cs.

FIGURE BO1.1 Country AI readiness level, 2024

Source: Original figure for this publication using calculations from the Tortoise Media's Global AI Index (https://www.tortoisemedia.com/data/global-ai).
Note: AI = artificial intelligence.

Finally, high-readiness countries can move to rapid deployment, innovation leadership, and advanced talent development. These countries can support their advanced digital ecosystem by developing or purchasing cutting-edge AI chips and building HPC systems and AI data centers. They can create custom domestic AI models trained on extensive local data, supported by strong data governance. Their workforce strategy can focus on cultivating top-tier AI researchers and advanced AI skills, ensuring they can attract and retain the best talent.

The promise of AI can be realized only through proactive, self-aware policy making. By understanding their unique contexts and advantages, developing countries can move from being passive consumers of foreign technology to active shapers of their own digital destiny (Pitt et al. 2025). The goal is to strategically harness AI to solve their most-pressing challenges, connect their people to new opportunities, and ultimately, transform the lives of their citizens. The time for strategic action is now.

TABLE O.1 Prioritize AI investments on the basis of AI readiness

AI capability and 4Cs	Country AI readiness level		
	Low	**Medium**	**High**
AI capability	Adopt	Adopt and adapt	Adopt, adapt, and innovate
Connectivity	• Provide universal access to electricity • Improve broadband coverage, quality, and affordability • Support device ownership and access	• Upgrade broadband infrastructure • Provide internet exchange points • Promote digital goods and services exports	• Upgrade broadband infrastructure • Support and develop the local digital sector and digital ecosystem
Compute	• Rely mostly on cloud computing and foreign data centers	• Invest in domestic data centers • Provide data embassy and regional data centers for small countries • Partner strategically with foreign cloud and AI chip providers	• Develop and purchase cutting-edge AI chips • Build high-performance computing systems • Build AI data centers
Context	• Rely largely on translation and existing AI models • Collaborate and partner with global companies and initiatives to collect local data • Improve government statistical and data collection capacity	• Combine translation of and investments in local data sets in select domains; develop synthetic data • Customize open-source AI models • Develop local AI applications in niche markets	• Invest in local training data across major domains • Customize open-source AI models; create cutting-edge domestic models • Enhance data governance
Competency	• Improve digital literacy, as well as basic and intermediate digital skills	• Focus on intermediate and advanced digital skills • Attract and retain talent	• Develop advanced digital and AI skills • Develop and support top-notch AI researchers • Attract and retain talent

Source: Original table for this publication.

Note: AI = artificial intelligence.

Notes

1. Refer to OECD.AI (https://oecd.ai/en/).
2. The estimates exclude China because of lack of data availability.
3. *Edge devices* are computing devices that process data in real time, at the edge of a network, to improve latency, security, efficiency, and reliability.

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The recent rapid evolution of artificial intelligence (AI) has outpaced society's ability to fully grasp its implications. Unlike technological shifts that have unfolded over decades, AI's integration is accelerating at an unprecedented speed and scale. Along with AI's immense opportunities come new responsibilities—especially for ethical deployment, accountability, and alignment with human values—that have few precedents in previous technology revolutions.

This 2025 edition of the *Digital Progress and Trends Report (DPTR)* explores how low- and middle-income countries can harness AI to drive inclusive and sustainable development—and avoid being left behind. The report explains what makes AI different from earlier general-purpose technologies and why it matters for development. It introduces the 4*C*s, the foundations essential for AI adoption, adaptation, and innovation: connectivity (infrastructure), compute (processing power), context (training data, algorithms, and applications), and competency (digital skills).

Drawing on rich, novel data sets, this *DPTR* benchmarks countries across the 4*C*s, analyzes supply and demand dynamics, and identifies market failures and externalities where policy action is urgently needed. This report emphasizes the need for global coordination and targeted interventions to close the widening AI gaps, where resource constraints threaten to exacerbate inequality. Policy insights will help governments unlock AI's potential while navigating its risks.

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