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AI and the Global Productivity Divide: Fuel for the Fast or a Lift for the Laggards?

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ABSTRACT/RÉSUMÉ

AI and the Global Productivity Divide: Fuel for the Fast or a Lift for the Laggards?

Artificial Intelligence (AI) has the potential to be an important driver of productivity growth over the next decade, even if with significant cross-country heterogeneity. This paper examines the potential of AI to foster productivity growth in Low-Income Countries (LICs) and Lower-Middle-Income Countries (LMICs). LICs and LMICs risk benefiting less from AI due to low incidence of knowledge-intensive services, where gains from AI mostly occur. Additionally, barriers to AI adoption include inadequate digital infrastructure, low levels of education and skills in the workforce, limited access to financing for high AI adoption costs, and underdeveloped regulatory frameworks. At the same time, LICs and LMICs may benefit from factors such as a young workforce and international spillovers through knowledge transfers. Overall, structural weaknesses in LICs and LMICs risk outweighing these potential advantages. This underscores the need for policies that enhance capabilities for AI adoption in LICs and LMICs and help seizing long-run opportunities from the global AI economy.

Keywords: Artificial Intelligence; Productivity Growth; Low-Income Countries; Lower-Middle-Income Countries; Technology Adoption.

JEL Codes: O33, O47, F63

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L'IA et les divergences mondiales de productivité : facteur d'accélération ou levier de rattrapage ?

L'intelligence artificielle (IA) a le potentiel de devenir un moteur important de croissance de la productivité au cours de la prochaine décennie, mais l'ampleur de cet impact peut varier fortement d'un pays à l'autre. Ce document examine le potentiel de l'IA pour stimuler la croissance de la productivité dans les pays à faible revenu et dans les pays à revenu intermédiaire inférieur. Ces pays risquent de tirer moins de bénéfices de l'IA en raison de la faible présence de services à forte intensité de connaissances, secteur où les gains liés à l'IA se concentrent principalement. De plus, plusieurs obstacles freinent l'adoption de l'IA : infrastructures numériques insuffisantes, faibles niveaux d'éducation, un accès limité au financement face à des coûts d'adoption de l'IA élevés et de compétences dans la main-d'œuvre et cadres réglementaires sous-développés. En même temps, les pays à faible revenu et ceux à revenu intermédiaire inférieur pourraient profiter de certains atouts, tels qu'une population active jeune et les retombées internationales liées aux transferts de connaissances. Dans l'ensemble, les faiblesses structurelles de ces pays risquent toutefois de l'emporter sur ces avantages potentiels. Cela souligne la nécessité de politiques visant à renforcer les capacités d'adoption de l'IA dans ces pays et à mieux saisir les opportunités à long terme offertes par l'économie mondiale de l'IA.

Table of contents

Tables

Figures

Boxes

AI and the Global Productivity Divide: Fuel for the Fast or a Lift for the Laggards

1. Introduction

Global cross-country income inequalities remain striking. GDP per capita in lower-middle income countries (LMICs) is still around one-twentieth of high-income countries (HICs). That figure goes down to one over fifty when looking at GDP per capita in low-income countries (LICs) with respect to high-income countries. An additional concern is that labour productivity growth has been slowing down significantly in emerging markets and low-income economies in recent years, similarly to advanced economies (Kose and Ohnsorge, 2024[1]). As the relevance of LICs and LMICs will increase in the coming decades, with their share of the global population projected to increase from 45% today to 55% by 2050, enhancing productivity growth in these countries will be crucial to ensure income growth for an increasing part of the global population.

At the same time, Artificial Intelligence (AI) is emerging as a General Purpose Technology (GPT), comparable to earlier digital technologies, such as the internet and computers, or electricity (Agrawal, Gans and Goldfarb, 2019[2]; Lipsey, Carlaw and Bekar, 2005[3]). According to several studies, AI has the potential to fuel significant global productivity growth (Filippucci, Gal and Schief, 2024[4]; Calvino, Jelmer and Samek, 2025[5]).[1] However, its effects on countries at different stages of economic development may differ considerably (Filippucci et al., 2025[6]). This paper investigates how AI could impact the global productivity divide. Can AI contribute significantly to productivity growth in LICs and LMICs as well? What are the potential advantages with respect to HICs, and what are the barriers? Are there other channels through which AI may particularly benefit less developed nations and favour their convergence? What are the possible policy measures that would help LICs and LMICs reap the benefits of AI?

A rising stream of the literature, focused on the United States, evaluates the possibilities that AI could significantly lift productivity growth. Views differ widely. On the optimistic side, Goldman Sachs foresees 1.5 pp gains in labour productivity per year due to Generative AI (Briggs and Kodnani, 2023[7]). Academic estimates based on a more refined task-based framework, vary from a virtually null contribution of AI to annual labour productivity growth over the next decade (Acemoglu, 2025[8]), to a more optimistic 1 pp contribution (Aghion and Bunel, 2024[9]). To put these numbers into perspective, ex-post analysis suggest that during the ICT boom in the United States in 1995-2005, the contribution of ICT to annual labour productivity growth was about 1-1.5 pp per year (Byrne, Oliner and Sichel, 2013[10]).[2]

However, expected gains can differ significantly across countries. Early estimates predict a contribution of AI to labour productivity growth of about 0.3-0.4 pp in Europe (Misch et al., 2025[11]; Bergeaud, 2024[12]).

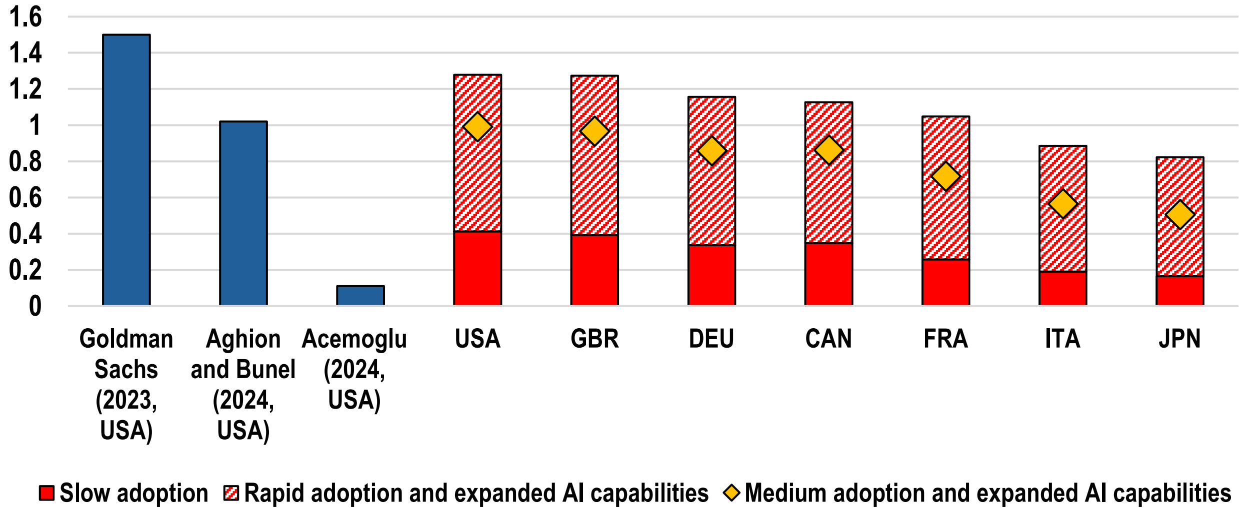
[1] The definition AI used in this paper refers mostly to modern approaches based on statistical AI (including machine learning, deep learning, neural networks) that are the basis for generative AI (using transformer model architecture).

[2] See Filippucci, Gal and Schief (2024[4]) and Calvino, Jelmer and Samek (2025) for further discussion of the productivity effects of generative AI.

Using a consistent methodology across countries, recent OECD work provides a set of comparable estimates of gains from AI across G7 economies (Filippucci et al., 2025[13]). Overall, the authors evaluate the potential AI productivity gains to be lower in other G7 countries than in the US, as a consequence of slower rates of expected adoption and different industrial structures. In a scenario where AI adoption follows the same path of past ICT technologies and covers a broad range of tasks, AI benefits in terms of labour productivity are expected to be around half of those of the US in Italy and Japan (Figure 1).[3] Forthcoming OECD work confirms this trend for OECD and G20 economies (Filippucci et al., 2025[6]), projecting contributions of AI to growth as low as .05-.3 pp annually for countries with a lower incidence of complementary factors to AI adoption, over the next 10 years.[4]

Figure 1: AI will be a key driver of productivity growth in advanced economies, with large cross-country heterogeneity

Predicted labour productivity growth due to AI over the next 10 years, percentage points (annualised)



Notes: In the low adoption scenario AI adoption is assumed to be up by 23% in the US (in line with historical electricity phones adoption path), in the medium adoption up by 40% (in line with historical ICT technologies adoption path), in the high adoption up by 60% (in line with historical mobile phones adoption path). Exposure is taken from Eloundou et al. (2025), with the expanded capabilities assuming full synergies from additional software. Source: Filippucci, Gal, Laengle and Schief (2025).

Focusing on low- and lower middle-income economies, the expected productivity benefits from AI in these countries have been the subject of only a limited number of studies. However, several institutions have proposed global AI preparedness indexes intended to capture the drivers of future AI adoption globally. These indicators are sometimes focusing on specific factors, such as the integration of AI in public services

[3] The study draws three scenarios: a pessimistic one where future adoption is in line with the slow adoption path of earlier GPTs, such as electricity, an intermediate one where adoption is expected to grow similarly to digital technologies and AI capabilities to be larger, and a more optimistic one, where adoption follows the fast spread observed for smartphones.

[4] These very low gains occur primarily because systemic AI adoption in countries with lower complementary factors to AI adoption is projected to remain low over the next 10 years. Systemic adoption is a costly process for firms, and the indicators of firm-level systemic adoption progress slowly today in advanced economies. Therefore, systemic AI adoption is expected to rise significantly within 10 years only in countries at the technological frontier. Growth in non-frontier economies is expected to remain driven by other forms of technologies, and AI is expected to sustain growth significantly in these countries only at a longer horizon (Filippucci et al., 2025[6]).

(Oxford Insights, 2025[14]), or average over different areas such as current digital infrastructure, innovation investment, labour market skills, and regulatory frameworks (Cazzaniga et al., 2024[15]).[5]

LICs and LMICs exhibit significantly lower AI preparedness than HICs (Figure 2, panel A). If future adoption aligns with current AI preparedness, and considering sectoral composition differences, the IMF estimated that AI's contribution to productivity growth in LICs might be roughly half that of more advanced economies (Cerutti et al., 2025[16]). However, early data on the use of popular Generative AI tools such as ChatGPT suggest that adoption of ChatGPT decreases by a factor of ten in LICs compared to HICs, and that while it is rapidly increasing in both high and middle income countries, it remains low in most LMICs and virtually null in LICs (Figure 2, Panel B). This may happen because, while it is plausible that AI preparedness correlates well with future adoption among HICs (Filippucci et al., 2025[13]), specific factors in LMICs and LICs could disproportionately affect AI adoption. For example, complete lack of electricity access or lack of basic literacy may not only reduce but fully prevent AI adoption in large segments of LICs and LMICs. In turn, other aspects, such as the younger workforce of LICs and LMICs or the possibility of knowledge spillovers, might boost the benefits from AI in LICs and LMICs. These unique aspects of LICs and LMICs are only partly captured when assuming future adoption mirrors current AI preparedness. Discussing these factors in detail can complement past analyses based on AI preparedness and reveal key bottlenecks where policy can help ensure LICs and LMICs also reap the productivity benefits of AI.

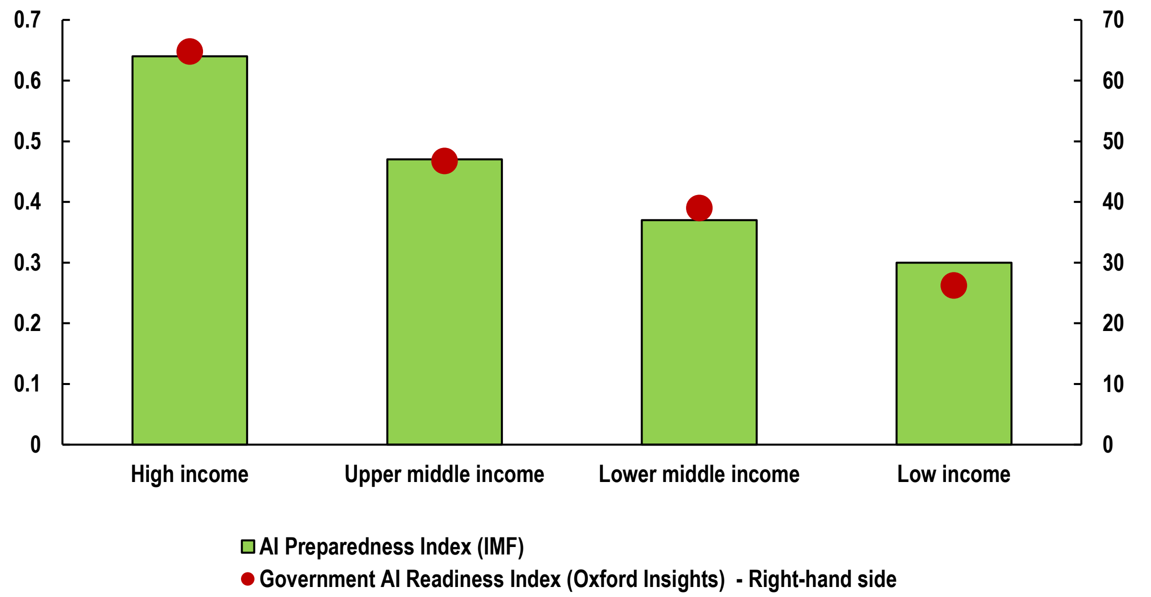
The first part of this analysis provides an examination of the specific strengths and weaknesses of LICs and LMICs that may determine their ability to harness the productivity benefits of AI, reviewing currently available evidence. The exercise is mainly qualitative, but considers the same drivers identified in the micro-to macro framework used in past OECD and academic work (Filippucci, Gal and Schief, 2024[4]; Acemoglu, 2025[8]). This framework suggests that AI-driven productivity gains depend on three main elements: the average productivity improvements from using AI for specific tasks *(AI task-level gains),* the proportion of tasks within the economy that AI can perform *(AI exposure),* which is also related to the industrial structure of the economy, and future *AI adoption* rates.

The analysis suggests that the challenges faced by LICs and LMICs in harnessing AI for productivity gains might disproportionately outweigh any advantages they might possess. Several significant obstacles can impede AI adoption in LICs and LMICs, including: a substantial portion of the population having inadequate skills for AI utilisation, the considerable direct costs of AI relative to prevailing income levels, and limited access to essential infrastructure such as internet and electricity. High prevalence of agriculture, manufacturing and low-skill service could also limit AI exposure in LICs and LMICs. The evidence on task-level gains doesn't clearly suggest that these are significantly different across income levels.

[5] Regarding the AI Preparedness Index developed by Cazzaniga et al. (2024), it is constructed from roughly 30 indicators grouped into four categories: digital infrastructure, innovation investment, labour market skills, and regulatory frameworks. The indicators are normalized and then averaged, with weights assigned to ensure that each broad category carries equal importance, even though some categories include more individual indicators than others. An alternative indicator reporting similar trends across country income groups can be found in (Martey Addo et al., 2025[120]). An OECD AI index is also currently under development.

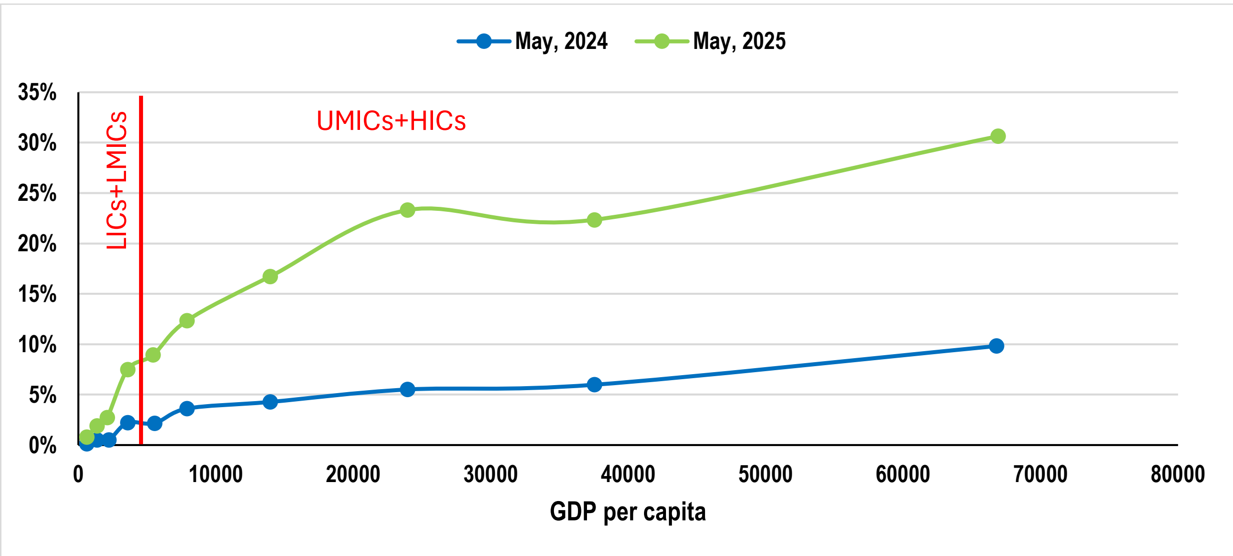
Figure 2: Low- and low-middle income countries have lower AI preparedness and are lagging behind in AI use

Panel A: IMF AI Preparedness Index (2023) and Government AI Readiness Index (2024), income group average



Note: The IMF AI Preparedness Index (AIPI) assesses the level of AI preparedness across 174 countries, based on a rich set of macro-structural indicators that cover the countries' digital infrastructure, human capital and labour market policies, innovation and economic integration, and regulation and ethics. The index ranges on a scale from 0 to 1, with higher values representing more favourable AI preparedness. The oxford insights Government AI Readiness Index examines 40 indicators across three pillars: Government, Technology Sector, and Data & Infrastructure. All scores are normalised to be between 0 and 100, with higher values representing more favourable AI readiness. Source: IMF and Oxford Insights. World Bank income groups are used.

Panel B: ChatGPT adoption per capita by income group, grouped by per-capita GDP decile.



Note: LICs=low-income countries; LMICs= lower middle-income countries; UMICs=upper middle-income countries; HICs= high income countries. Source: OECD calculations based on (Chatterji et al., 2025[17]) and World bank data.

The second part of the analysis discusses the specific policy actions that can help in grasping the benefits of AI in LICs and LMICs and prevent AI from deepening the global productivity divide. Among the dimensions driving productivity gains from AI — exposure, adoption, and task-level gains — the area where policy can make the greatest short-term impact is AI adoption.[6] This includes measures to enhance energy infrastructure and digital infrastructure (the foundation for digital transformation, in particular digital connectivity), workforce skills and education, access to finance, and institutional preparedness.[7] Moreover, a necessary condition for domestic AI adoption in LICs and LMICs is having access to frontier AI models. The OECD AI principles can help promoting international diffusion and trust into AI by ensuring faireness, transparency, robustness and accountability of AI systems

In the long-run, growth in LICs and LMICs will depend on how they are able to increase their productivity, including through human capital (Gethin, 2025[18]). AI can boost the role of some of the key drivers of human capital, such as education and health. International cooperation and aid policies should leverage emerging, scalable AI tools to strengthen human capital and healthcare in low- and lower middle-income countries. However, they shouldn't underestimate reliability concerns and inherent risks, and continuously evaluate program outcomes. AI may also enhance the international flow of knowledge, giving LICs and LMICs an opportunity to climb GVCs into higher VA and AI-powered industries. Therefore, policies should ensure trade openness and support internationalisation, reinforce international accessibility of technology and data inter-operability, and create an environment that is favourable to the growth of firms that benefit from productive transformations.

2. Strengths and Weaknesses of LICs and LMICs in Reaping AI Productivity Benefits

A simple framework for thinking about aggregate productivity gains from AI in different countries

To discuss the strengths and weaknesses of LICs and LMICs in benefiting from AI-related productivity gains, this section relies on a framework widely used in the literature based on three main components (Acemoglu, 2025[8]; Filippucci, Gal and Schief, 2024[4]): 1) the projected AI adoption rate (*AI adoption),* 2) the share of tasks in the economy that can be performed more efficiently with the help of AI (*AI exposure*), and 3) the average task-level productivity gains from AI (*AI task-level gains)*.[8] To better understand the potential productivity impact of AI in LICs and LMICs, we examine how the structural characteristics of their economies are likely to affect each of these three components.

AI adoption: high barriers and a few advantages

LICs and LMICs have historically experienced substantial delays in the adoption of frontier technologies compared to high-income countries (Cirera, Comin and Vargas Da Cruz, 2022[19]). It is therefore plausible to assume a similar lag in the adoption of AI. However, AI is also seen as having very different characteristics with respect to technologies of the past decades (Baily et al., 2025[20]). Some have

[6] In fact, increasing AI exposure requires changing the sectoral composition of the economy, which is difficult to achieve with policy action in the short run.

[7] These drivers were also identified as key ones in past studies, both in LICs (Calvino, Costa and Haerle, 2025[123]) and LMICs (UNCTAD, 2025[42])

[8] Note that this framework estimates a how AI changes productivity at steady state and derives an annualised average contribution of AI to productivity growth over 10 years. It thus abstracts from potential transition dynamics, including potential J-curve dynamics.

hypothesised that AI could even allow leap-frogging past productive technologies and constraints in some of the lower-income economies (Fan and Qiang, 2024[21]). Therefore, whether the adoption gap for AI will widen or narrow relative to past technologies remains uncertain and depends on various factors.

Skills and workforce characteristics

One critical dimension of AI adoption is related to the characteristics of the workforce. For many digital technologies, the presence of a skilled workforce has been a necessary complement to successful adoption (Bartel, Ichniowski and Shaw, 2007[22]; Brynjolfsson and McElheran, 2016[23]; Borgonovi et al., 2023[24]). An emerging body of evidence suggests that this trend may be similar for AI technology, for instance as AI users tend to be highly educated (Bick, Blandin and Deming, 2024[25]; Liu and Wang, 2024[26]; Humlum and Vestergaard, 2025[27]). This presents a challenge for LICs and LMICs, where average educational attainment among workers remains low. Figure 3 illustrates this disparity by comparing the distribution of education levels across countries by income group with the global education profile of generative AI chatbot users.

Notably, virtually no chatbot users fall into the "no schooling" category, indicating that some degree of formal education is in practice required to access even relatively user-friendly AI tools. However, 59% of the population in LICs and 32% in LMICs have no formal schooling, suggesting that large segments of their populations fall well below the education threshold typically associated with AI use. For instance, a significant part of the population would not be able to interact with Large Language Models (LLMs) chatbots through writing, as literacy rates are only 63% in LICs and 78% in LMICs.[9] In turn, over half of chatbot users hold at least a college degree, yet the share of college-educated adults in LMICs is less than one-third of that in high-income countries, and less than one-sixth in LICs.[10] Moreover, while the number of languages supported by LLMs is steadily growing, many are still unsupported by most models, and performance remains significantly lower than in English. For example, Claude's accuracy drops by 21%–54% when responding in Yoruba, as measured in mid-2025.[11] As a result, English proficiency could remain a crucial factor in accessing AI via LLMs, with some studies showing a strong correlation between English skills and higher AI adoption (Liu and Wang, 2024[26]). Additional evidence on the use of ChatGPT in early 2025 also suggests that its use for work is 25% higher for individuals holding a bachelor degree, compared to individuals without such degree (Chatterji et al., 2025[17]).

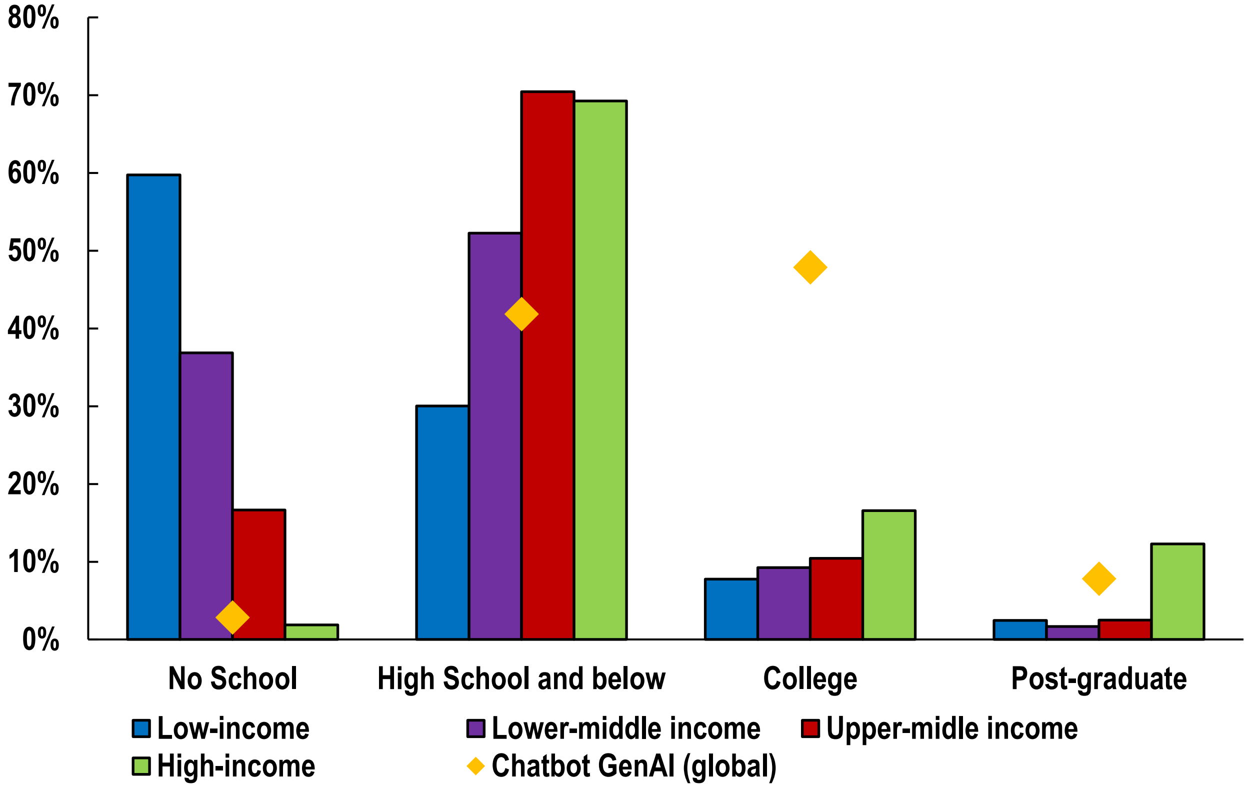
[9] An alternative mean to access AI models in the form of LLMs could be voice-to-voice models, but this requires large computational power and data exchange capacity, and although adoption of voice-to-voice AI models might increase in the future thanks to emerging technologies, it is still very limited (André et al., 2025[118]).

[10] Some technological advancements can attenuate literacy and skills barrier, such as application-based AI tools and visual aids that allow for an intuitive use of AI functions (UNCTAD, 2025[42]). Yet, these modalities may clearly remain confined in non-advanced applications of AI.

[11] According to Claude own data. https://docs.anthropic.com/en/docs/build-with-claude/multilingual-support

Figure 3: Most ChatGPT users have some schooling, but more than half of the population in LICs and LMICs does not

Educational attainment of the population by country income group (2019) and percentage of AI users by qualification across countries (2024)



Note: (Liu and Wang, 2024[26]) sourced the web traffic data for GenAI chatbots from Semrush between January 2022 to March 2024. The education level represents the average across the income group of the percentage of the population that has completed that level of education.
Source: The World Bank and Liu and Wang (2024[26]).

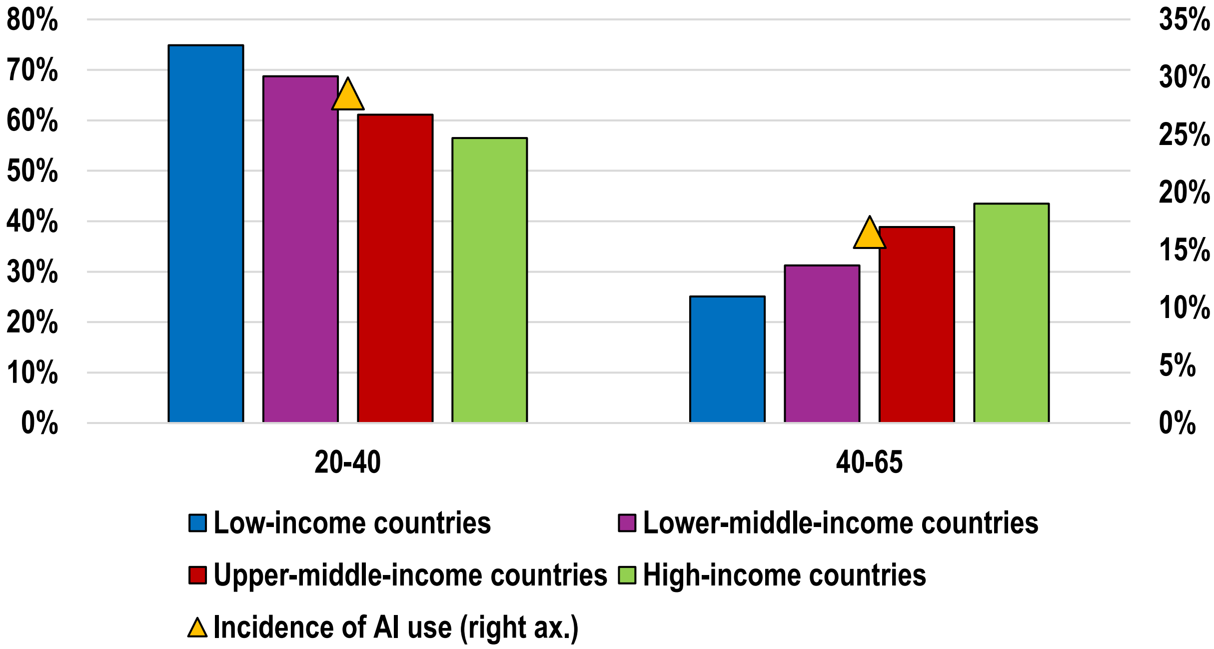
A characteristic of LICs and LMICs' workforce that may constitute a comparative advantage in AI adoption is the young average age. Some recent evidence suggests that young workers are quicker and more effective in the adoption of new technologies (Lipowski, 2024[28]). Younger individuals have longer remaining working lives, which increases the expected return on the investment of time and effort required to learn new technologies (Cavounidis and Lang, 2020[29]; Angelini, 2023[30]). Evidence from psychology also suggests that younger workers are less influenced by preconceived notions tied to the use of the technology (Morris and Venkatesh, 2000[31]) and may be more flexible in adapting their thought process to the new technology. As a result, users of generative AI are younger than the average. In the US, workers under the age of 40 were approximately 1.5 times more likely to use AI than those over 40 (Bick, Blandin and Deming, 2024[25]), as displayed Figure 4.[12] At the same time, the bars in Figure 4 show that the share of workers under 40 is much higher in LICs and LMICs than in other countries, with about 75% of the workforce below 40 in LICs and 69% in LMICs. If the advantage of youth over elders in AI adoption observed in HICs would be extrapolated to LICs, back-of-the-envelope calculations would suggest AI adoption should be 5-10% higher AI adoption in LICs and LMICs than if they had the same age structure

[12] Evidence from Denmark also shows that younger and less experienced workers are more likely to use ChatGPT, with each year of age being associated with 1 percentage point lower likelihood of using ChatGPT (Humlum and Vestergaard, 2025[27]).

of HICs. This suggests that the young age structure of LICs and LMICs can have a significant positive effect on adoption.

Figure 4: A young workforce can be an advantage for AI adoption

Age distribution of workforce and % of workforce using AI by age class across country groups



Notes: AI use refers to Generative AI in the US, and is obtained as weighted average of their estimate, assuming uniform AI adoption within age bracket. Sources: AI adoption from Bick, Blandin, & Deming (2024[25]), population distributions from World Bank, and OECD staff calculations.

In addition to the skill gradient, early evidence shows that users of AI also tend to be more likely male. Although some hypothesised that men could structurally adopt and engage with some technologies more quickly (Otis et al., 2024[32]), the gender gap in AI adoption seems to be quickly closing in advanced economies (Chatterji et al., 2025[17]). Female labour force participation is generally lower in LICs and LMICs, averaging 44% compared to 54% in high-income countries (ILO, 2025[33]). Persistently low female participation is not only detrimental to equity and inclusion, but also a sign of labour misallocation imposing potentially large productivity costs and skills misallocation (Hsieh et al., 2019[34]). Therefore, including talented women into fair and equal education and integrating them into the labour market can enhance the overall skill level of the workforce—a key driver of AI adoption—and amplify the potential benefits of AI.[13]

Digital infrastructure

A significant barrier to AI adoption in LICs and LMICs are digital infrastructure requirements. Productive use of AI relies both on both hardware and software to access and perform specialised AI workloads, known as AI compute, and on access to digital connectivity infrastructure, meaning high-quality and affordable communication services.

First, from the user's perspective, accessing AI tools requires a smartphone or a computer, though the latter is better suited for more advanced use. While access to technology such as mobile cellular phones and personal computers has increased significantly in LICs and LMICs, they continue to lag behind high income countries. For instance, the share of individuals who own a mobile is about 58% of individuals in

[13] Even if AI could also deliver large productivity for home production, productivity gains are generally larger in formal sector work.

LICs in 2023, and 74% in LMICs. Such value is closer to the whole population (95%) for high-income countries (International Telecommunication Union, 2024[35]).[14] In line with this pattern, mobile cellular subscriptions per 100 inhabitants in LICs amount to roughly half the level observed in HICs, and around two-thirds in LMICs. Fixed broadband penetration is even lower, reaching only 4.8 subscriptions per 100 inhabitants in LMICs and a mere 0.5 in LICs as of 2024 (International Telecommunication Union, 2025[36]). Looking at firm-level data, which better captures the potential for AI adoption at work to boost productivity, only 32% of firms in LICs and 41% in LMICs have a website in 2024 compared to nearly double that in high-income countries, exemplifying the divide in terms of production digitalisation (World Bank, 2025[37]).

Second, efficient economy-wide AI use requires digital connectivity infrastructure, which includes broadband access networks, core backbone networks such as submarine cables, and Internet infrastructure (i.e. content delivery networks, data centres, and internet exchange points, and logical layers such as routing and domain names). Building fully in-house LLMs for local firms is extremely expensive and requires extensive local data and computational capacity. It is thus likely that AI systems will rely largely on cloud-based services, which can also be trained on proprietary data, such as the ones provided by Open AI or DeepSeek. These models are generally hosted on distant data centres (e.g., those run by *hyperscalers* like AWS, Microsoft Azure, Google Cloud, etc.) for training and inference. Queries to these services require running through high-speed Internet at least to the level of 4G networks, which in 2023 were available to 83% of the LICs population in urban areas (dropping to 17% in rural areas) and to 98% in LMICs urban population (dropping to 87% in rural areas) (International Telecommunication Union, 2023[38]).[15] Low-earth orbit satellite internet services such as Starlink can be a viable alternative (while older systems have too low performances), but such technologies don't cover all LICs and LMICs (Appendix Figure 12) and the cost is relatively high for the average user in these countries.[16]

Third, developing and using AI systems requires AI compute, defined as one or more stacks of hardware and software used to support specialised AI workloads and applications in an efficient manner. Previous OECD reports highlighted that up until few years ago in most countries, including high income ones, AI compute capacity was insufficient to sustain the projected rise in AI demand (OECD, 2023[39]). Yet, not all elements of AI compute used to perform an AI workload need to locate in the same country of the final users.[17] As computing needs evolve, digital service architectures rely on a edge–cloud continuum, where computation occurs on user devices ("on device"), local nodes ("on premises"), regional data centers ("edge"), and global cloud platforms ("cloud").

In contexts with lower financial capacity to sustain investment in local AI compute and digital connectivity infrastructure, such as LICs and LMICs, it is possible to hypothesize that the AI ecosystem will rely more on global cloud platforms and foreign-located AI compute. In addition, some AI applications may rely more on edge connectivity solutions, or even work on device, with lower efficiency but more resilient to suboptimal connectivity infrastructure. For instance, in Colombia, the Tumaini banana disease detection app includes an offline mode that preserves most of its diagnostic capabilities, making it accessible and practical for farmers in rural regions with limited Internet access. Yet, more complex applications will surely

[14]Older data from 2016 also report the share of individuals with access to a computer in LMICs was approximately 31% on average, while the same value for high-income countries was closer to 75%.

[15] Recent work shows spatial connectivity divides for several broadband performance indicators for over 60 countries (OECD, 2025[79]).

[16] According to a report by the India Times, Starlink's price in Bangladesh will be around 4,200 Taka per month—about USD 35. Besides the monthly cost, users will also have to pay a one-time equipment fee of 47,000 Taka. According to UNDP, for a remote community in the Philippines the cost of Starlink is around 500$ for each satellite dish and a monthly cost of around USD 100 to USD 200 to be shared amongst the community.

[17] This leaves aside considerations in terms of strategic dependencies.

need an edge–cloud continuum for efficient compute, which includes appropriate digital connectivity and the presence of local nodes and regional data centers.

For example, leveraging cloud-based LLMs often necessitate users to connect to distant data centres, also part of global connectivity infrastructure, but LLMs providers such as Open AI and Anthropic do not run data centres in Africa as of today. Figure 13 in the appendix maps the global distribution of data centres, showing significantly lower concentration in LICs and LMICs. Connection to distant data centres can entail slow response time, i.e.a *latency* problem, delaying queries and making productive use of AI less efficient, for instance preventing real-time interaction.[18] Other important dimensions of broadband that influence LLMs experience include download and upload speed and network reliability, which are also lagging behind in countries with lower income, especially in rural areas (Figure 14 in the Annex). Recognizing the importance of service quality for users, regulators and firms are also increasingly focusing on user-centric measures of quality of experience (OECD, 2022[40]). All these dimensions of connectivity are shaped by digital connectivity infrastructure, including the quality of backbone, backhaul, and last-mile access networks.

Finally, reliable access to electricity is not only important to sustain AI compute and digital connectivity infrastructure (IEA, 2025[41]), but also crucial for any AI application. This might not be guaranteed in LICs and LMICs. As of 2023, only 47% of the population in low-income countries have access to electricity. The figure climbs to 91% for lower-middle-income countries. For complex AI applications and for maintaining AI compute and digital connectivity infrastructure in LICs and LMICs, appropriate electricity grids and production infrastructures are severely under-prepared, even if some silver lining exist (for instance, the abundance of potential energy sources, especially renewables). For simple AI applications, technological developments may help coping with lack of access to electricity infrastructure, even if only with second-best solutions. For example, AI-powered X-ray machines in South Sudan and Tajikistan run on battery power, enabling them to serve remote areas (UNCTAD, 2025[42]).

Adoption costs

A third significant obstacle to AI adoption in LICs and LMICs is its potentially high costs. Systemic AI adoption at the firm level entails large fixed costs, as suggested by the fact that firm-level systemic adoption is often low even in HICs, and significantly lower in SMEs than in larger firms. These include the cost of training ad hoc models for firms (which can be extremely expensive, especially if done through *hyperscalers*), or the expenses for reorganizing production, investing in complementary skills and intangibles, factors already shown to significantly hinder AI adoption even in high-income countries (McElheran et al., 2025[43]). Fixed adoption costs can constitute a severe barrier in LMICs and LICs, were firms are generally smaller and more credit-constrained.

Beyond fixed costs that can emerge for using AI in terms of digital infrastructure and skills, Figure 5 illustrates that even the variable operational cost of AI models is extremely high relative to the mean GDP per capita in LICs and LMICs. The price of a year of mid-intensity use through ChatGPT Plus subscription (the intermediate package of OpenAI) costs around 20 USD per month as of mid-2025, corresponding to about 25% of average annual income in LICs and 10% in LMICs.[19] There exist alternative models with

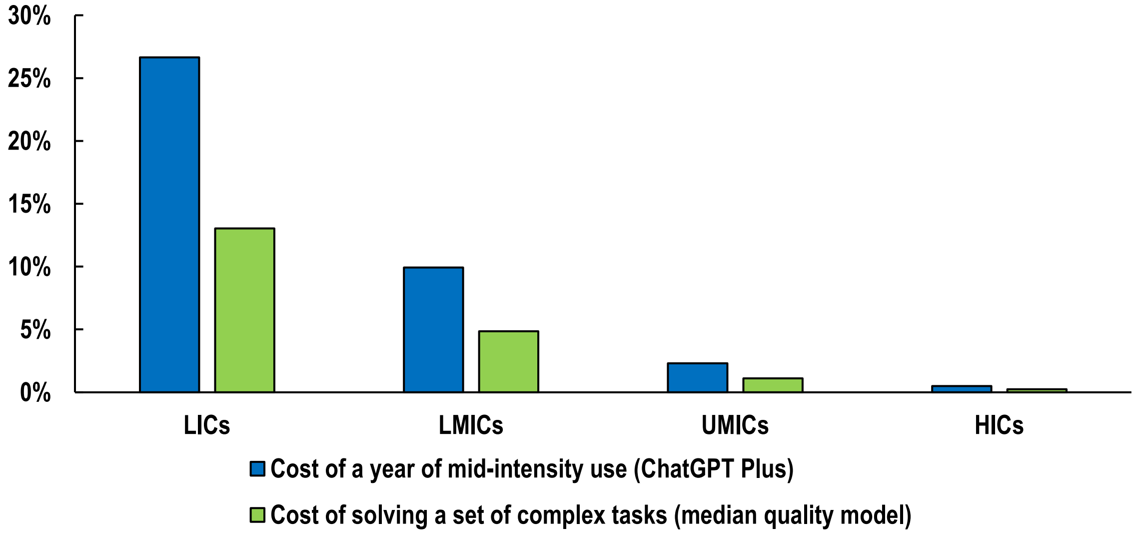
[18] Latency is defined as the round-trip time for information to travel between two devices across the network – in other words, the network response time or delay experienced by users.

[19] The cost is roughly uniform across countries, reflecting the difficulty for providers to apply geographic price discrimination in digital markets, as users can switch access countries via VPNs to take advantage of lower prices. Some small deviations in final use price happen due to local taxes. Rare exceptions have also occurred in time where ChatGPT premium subscription was significantly cheaper in some low-income countries, but these exceptions were short-lived following many attempts of users arbitraging on registration fees via VPNs.

lower costs and slightly reduced performance, some of them developed in emerging economies.[20] For example, the cost of solving the Artificial Analysis Intelligence Index (AAII) -- a set of questions in coding, math and language analysis designed to evaluate LLMs capabilities – can be as low as 20 euros for 52% quality score with cheaper models, relative to more than 900 euros for 69% quality score with OpenAI's GPT-5 (Figure 16 in the Annex). Yet, obtaining an accuracy rate above the median may still entail significant costs relative to financial possibilities of individuals in LICs and LMICs. The second series in Figure 5 shows that using a model of median quality to solve a complex task such as the AAII would still have a significant cost with respect to GDP per capita in LICs and LMICs.

Figure 5: The high costs of AI tools can limit adoption in low- and low-middle income countries

Cost of using AI for different purposes as a percentage of 2023 GDP per capita by country income group



Note: The GDP per capita by income group is taken directly from World Bank aggregates for 2023. The blue bars assume a cost of USD 20 monthly for a premium subscription to ChatGPT. The green bar reports the median cost to complete the Artificial Analysis Intelligence Index (AAII) – a test assessing language model capabilities across reasoning, knowledge, maths and programming – for the 4 best models in terms of quality/cost (MiniMax-M2, Grok 4 Fast, OpenAI gpt-oss-120B, and DeepSeek V3.2 Exp). These models are selected to be at the frontier in terms of cost and performance in solving the AAII. See Annex Figure 16 for more details. . Source: World Bank, https://artificialanalysis.ai/ and OECD staff calculations

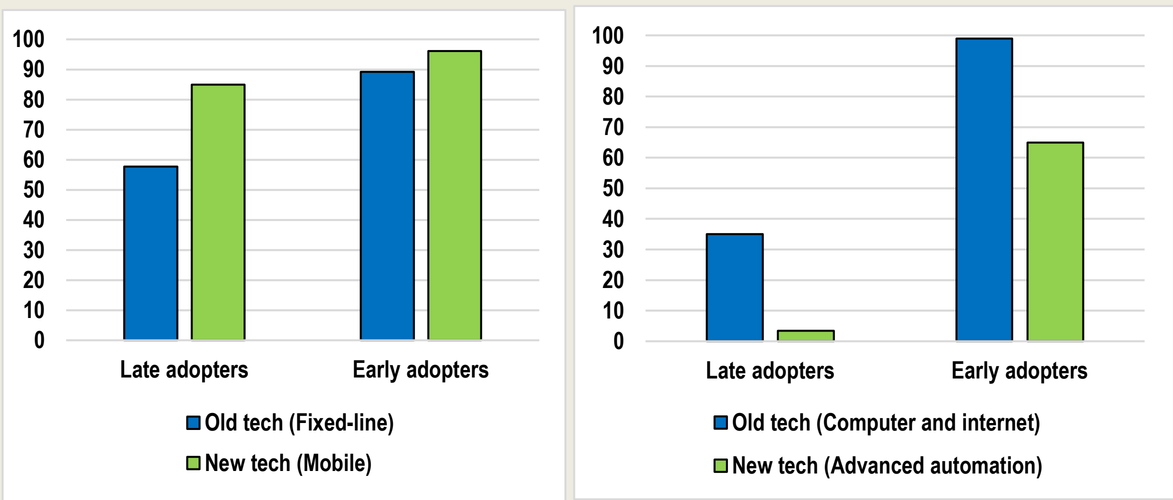
[20] This multi-polar AI landscape can be an important source of competition, maintaining low AI prices (André et al., 2025[118])

Box 1. Can LICs and LMICs leapfrog complementary technologies to AI?

A possible upside risk that may be envisaged in relation to the capability of LICs and LMICs to adopt AI is the potential to “leapfrog” earlier technologies and infrastructures. Technological leapfrogging would favour rapid adoption of AI by avoiding costly investment in possibly surpassed digital technologies and infrastructure. However, leapfrogging cannot be taken as guaranteed, and it didn’t occur for some technologies in the recent past. A World Bank study on a sample of developing economies, summarised in Figure 6, shows that leapfrogging occurred in the case of communication technologies, as laggard firms widely adopted new mobile communication technologies, despite limited use of fixed-line phones (left panel).[21] However, the same leapfrogging did not occur with advanced automation production technologies (Cirera, Comin and Vargas Da Cruz, 2022[19])[22]. In this case, access to internet and to devices to connect (computers, mobile phones)_are necessary prerequisites for adopting advanced automation technologies, together with deeper organisational change to adapt to the new technologies.

Figure 6: Leapfrogging in earlier technologies: happened in communication technologies, but not in advanced production automation

Diffusion of communication technologies -- fixed-line telephones vs. mobile phones across firms (left panel); and diffusion of advanced production technologies -- computers and internet vs. advanced automation (right panel, food industry only)



Note: The right panel refers only to the food industry, one of the specific sectors of focus of the sourced study. Late adopters and early adopters are defined as the smallest (5 workers) and biggest (about more than 1000 workers) firms reported in the study: assuming that larger firms adopt earlier than smaller firms, this is a representation of the diffusion over time of specific technologies. The figure presents estimates of the probability of adoption across all 11 countries in the FAT survey sample, controlling for age group and sector using sampling weights. Digital automation technologies include ERP used for business administration, input testing; robotized cooking, mixing, blending and packaging; and advanced preserving technologies. Source: (Cirera, Comin and Vargas Da Cruz, 2022[19]). This is an adaptation of an original work by The World Bank. Views and opinions expressed in the adaptation are the sole responsibility of the author or authors of the adaptation and are not endorsed by The World Bank.

By now, AI seems to have limited potential for leapfrogging. As discussed in Section 2.1, AI adoption depends on other digital infrastructure, such as broadband access, access to mobile devices and computers, as well as other critical infrastructures, such as electricity.[23] While future innovations might make AI more easily deployable, enabling AI adoption independently of previous technologies, early evidence in advanced economies shows that AI adoption correlates significantly with adoption of other digital technologies (McElheran et al., 2025[43]), suggesting narrow scope for technological or organizational leapfrogging.

Regulatory frameworks to support AI diffusion

Previous studies highlighted the crucial role of effective AI regulation in supporting AI adoption, balancing the goals of ensuring trustworthiness and consumer protection, competition and innovation incentives (Filippucci et al., 2024[44]). Even if some positive exceptions exist, LICs and LMICs tend to report lower preparedness in terms of AI regulation (Mandon, 2025[45]) and lower institutional capacity to enforce it. This increases the risk that adoption stalls as consumers lack trust in AI, fearing fraud, unreliability, bias, unethical behaviour, or falsification. Challenges in insuring against low reliability can particularly hinder technology adoption in LICs and LMICs and generate large aggregate costs (Fried and Lagakos, 2023[46]). In addition, the deployment of energy, AI compute and digital connectivity infrastructure to sustain intensive and stable AI use requires robust regulatory frameworks. Finally, ineffective antitrust action in checking market power can lead to higher direct costs of AI, worsening the affordability problem highlighted by Figure 5.

AI exposure: limited by low specialisation into knowledge-intensive services

Beyond the challenges of AI adoption, a key reason why AI's productivity benefits in LICs and LMICs may significantly differ from those in high-income countries is the proportion of tasks in their economies that can leverage AI – that is, their AI exposure. Past research found that AI exposure estimated for the US is concentrated in knowledge-intensive services, such as Finance, IT services and professions. As reported in Figure 7, services represent a much smaller share of GDP in LICs and LMICs than high-income economies. By contrast LICs and LMICs are characterized by a higher incidence of low-technology sectors, such as agriculture. While use of AI in agriculture has been documented (UNCTAD, 2025[42]; Ayim et al., 2022[47]), for instance for mobile applications that diagnose plant pests, irrigation optimisation, and automated reporting, Figure 7 shows that AI exposure in high-income economies is about three times smaller in this sector than in services. This occurs because most of workers' tasks in agriculture are still rather manual and hard to automate with AI. The exposure estimates in Figure 7 may represent an upper bound on the exposure gap, as it is likely lower in LICs and LMICs compared to HICs. For example, agriculture in LICs and LMICs tends to rely more on manual labour—less exposed to AI—and employs fewer engineers and professionals, who are typically more exposed.[24]

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[21] Similarly, many low- and middle-income countries skipped the long and costly process of building fixed-line copper telephone networks and moved directly to new broadband access technologies, such as fibre and mobile voice and mobile broadband technologies (Figure 15).

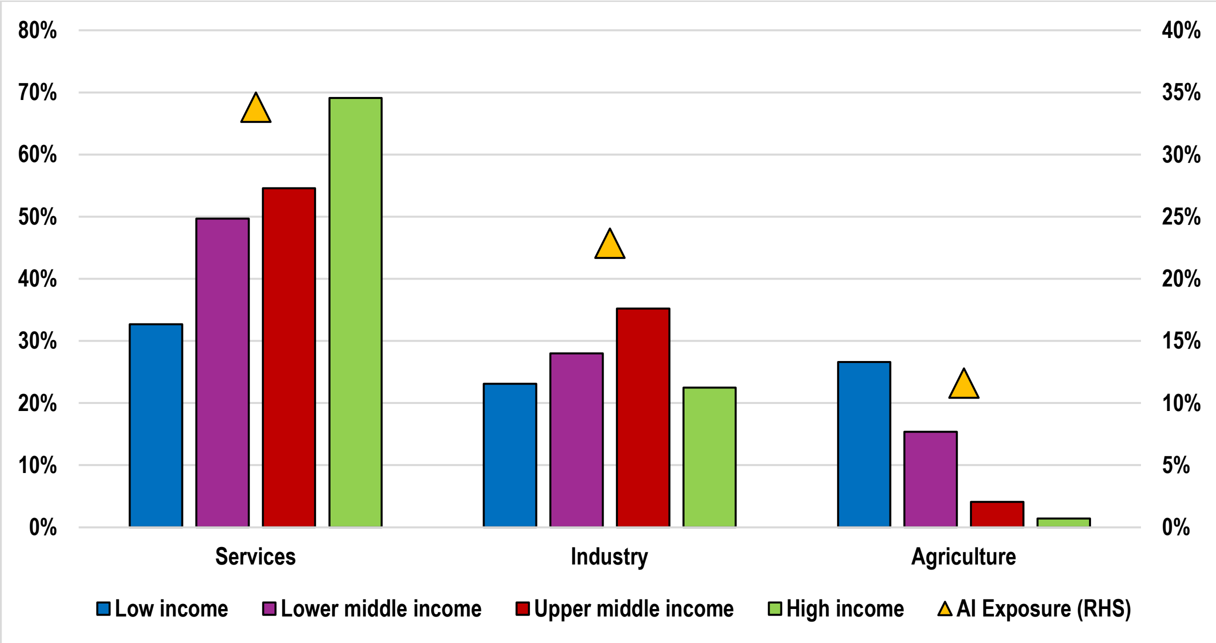
[22] The evidence on automation is presented focusing on the food industry, but other evidence in the same report points reports similar results for Agriculture, Retail and Textile.

[23] For example, deploying broadband access networks—which enable people to effectively access AI tools—requires extensive investment, e.g. digging and trenching for fibre networks; as well as institutional capacity, e.g. for management of spectrum resources for mobile connectivity.

[24] At the same time, a possible alternative hypothesis is that AI adoption will be lower where labour is more abundant, such as in LMICs and LICs, and AI-driven automation will be higher where labour shortages are stronger (Acemoglu and Restrepo, 2021[117]). The relative scarcity of labour, which may generate different elasticities of labour supply across countries, is not captured by our simple long-run equilibrium framework, which also abstracts from frictions. At the same time, AI may lower the expertise requirement to perform certain occupations, and depending on the relative abundance of these cases it may expand the production possibility frontier more in countries relatively less abundant in expertise, such as LMICs and LICs (Autor and Thompson, 2025[119]). The current paper also doesn't investigate this aspect.

Figure 7: More AI-exposed sectors such as services play a much less important role in LICs/LMICs than in HICs

Share of value-added from different industries (LHS) and share of employment exposed to AI across country groups (RHS)

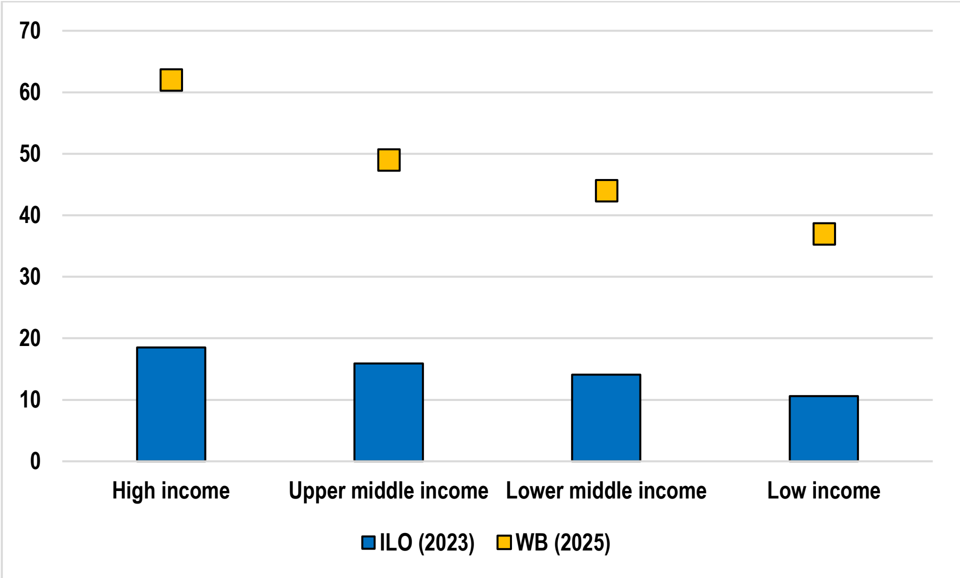


Notes: AI exposure is estimated for the US, and it is from (Filippucci, Gal and Schief, 2024[4]). Value added distribution across sectors is from the World Bank.

Because the economies of LICs and LMICs are more focused on less knowledge-intensive services, a smaller share of their employment can leverage AI to boost productivity. Although the estimated share of jobs exposed to AI varies across studies, a common finding is that exposure sharply increases with a country's income level (Demombynes, Langbein and Weber, 2025[48]; Tavares et al., 2025[49]; Gmyrek, Berg and Bescond, 2023[50]). Figure 8 shows the share of employment exposed to AI according to two different exposure measures, both suggesting that the share of employment exposed to AI in LICs is only about half relatively to HICs.

Figure 8: Exposure in LICs and LMICs is low

Share of employment exposed to AI according to different sources



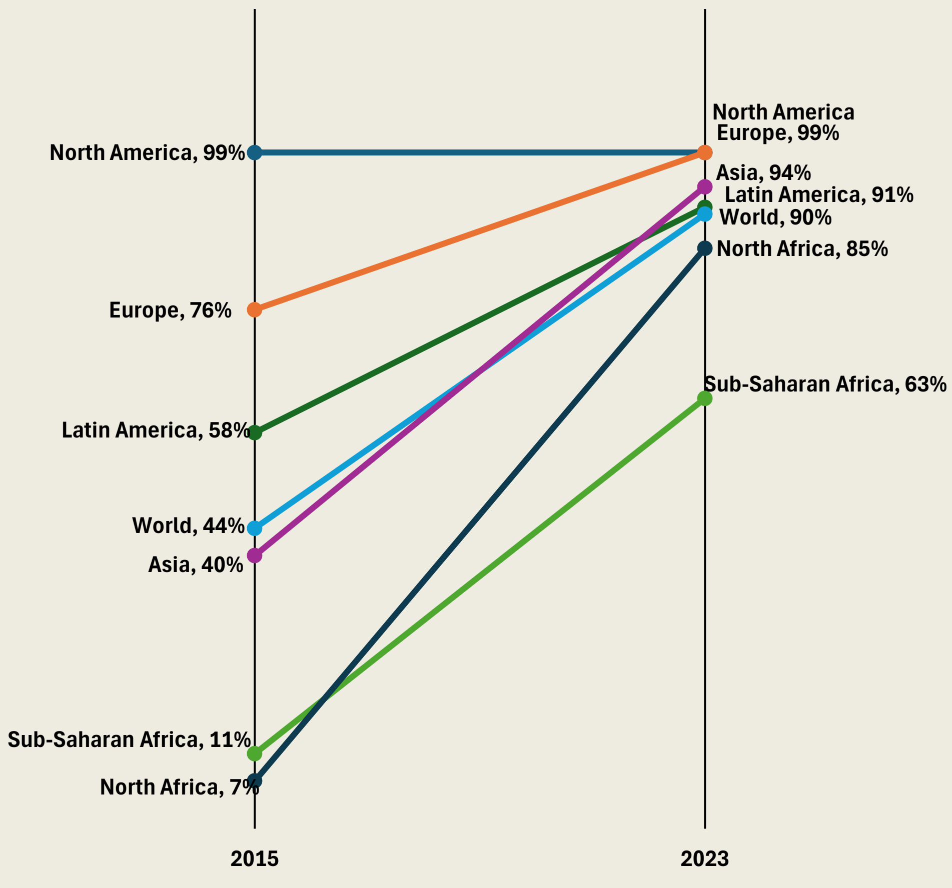
Note: Results are population weighted and include workers aged 15 to 64. Source: Demombynes, Langbein, & Weber, 2025

Box 2. A focus on Africa

Africa is predominantly composed of lower-middle-income countries and low-income countries. Concerns are growing that the emergence of an AI divide will particularly concern African economies. A critical example is digital connectivity infrastructure, which remains underdeveloped in much of the continent. For instance, Africa made significant progress in recent years, with a sixfold increase in coverage in Sub-Saharan Africa and over eightfold in North Africa in 2023 relative to 2015, but this was not enough to close the gap, as the starting levels were too low (Figure 9).[25]The gap is even more pronounced in terms of broadband subscriptions per 100 people, which is virtually non-existent in Sub-Saharan Africa, with convergence stalling (Appendix Figure 17).

Figure 9: Sub-Saharan Africa continues to lag in 4G network access

Percentage of population covered by 4G network by region

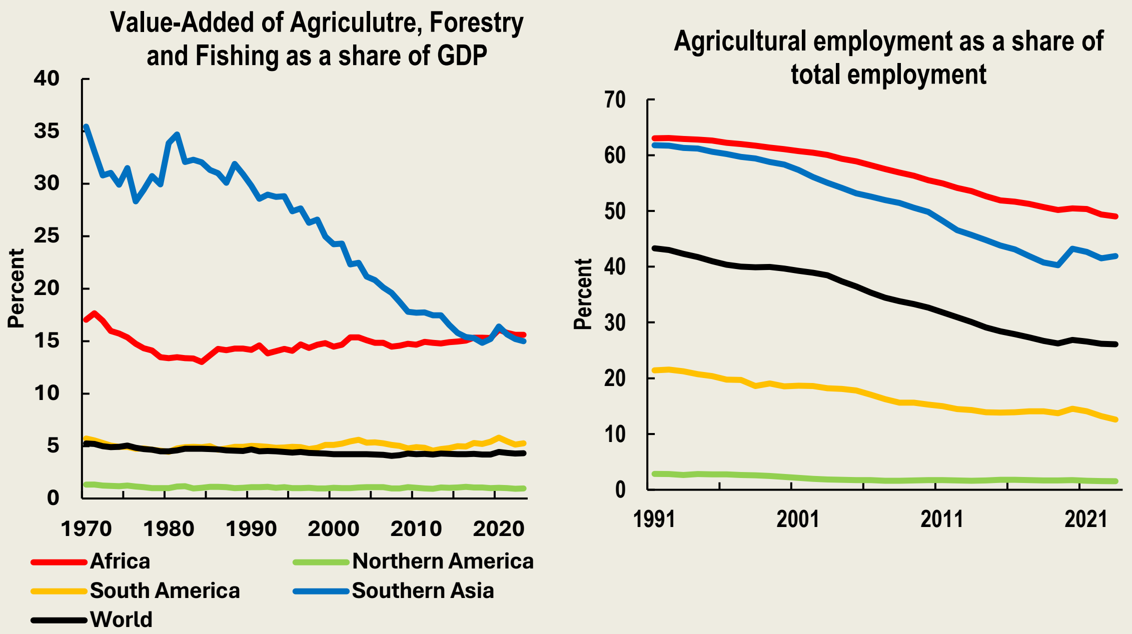


Source: International Telecommunications Union, visualization by Our World in Data (ourworldindata.org)

In addition, Africa’s current sectoral specialisation entails low AI exposure. Agriculture remains a dominant sector, employing 42% of the continent’s workforce. While this share has declined since the 1990s, it has remained the highest globally (Suri and Udry, 2022[51]) (Figure 10). Despite significant heterogeneity across African countries, agricultural production is generally characterised by low levels of mechanisation and a high dependence on rainfed farming. The wholesale and retail sector are the second-largest employer and the primary absorber of labor transitioning out of agriculture (African Development Bank Group, 2024[52]). In contrast, in 2018 sectors with greater potential for AI integration

-- such as financial, business, and public services as well as manufacturing -- accounted for just over 20% of employment in the continent.[26] Overall, nearly two-thirds of Africa's workforce is employed in agriculture and low-skill services, while high-technology services and manufacturing sectors remain small or low-tech, significantly limiting the continent's overall workforce exposure to AI technologies.

Figure 10: Agriculture is an important component of GDP and employment in the region



Note: Regional aggregates may vary depending on the source. Source: FAOSTAT & The World Bank

Looking beyond national averages reveals significant heterogeneity in economic conditions across the continent and even more sharply within countries, but this is only partially reassuring. On the one hand, some countries have invested in improving digital infrastructures (UNCTAD, 2025[42]) and some clusters of highly urbanised, service-oriented cities are emerging as hubs of digital innovation. On the other hand, such uneven development underscores the risk that AI adoption in these areas could exacerbate existing income inequalities within Africa, which are already a pressing issue.

Yet, there are some exceptions of LMICs where sectorial specialisation and high AI exposure can promote productivity gains from AI. The left panel in Figure 11 reports the number of ChatGPT queries normalised by countries' income, for a selection of high-income countries, plus India and the Philippines, selected as the two LMICs with high AI use per capita and outperforming others in terms of technological readiness. Interestingly, India and the Philippines exhibit an AI usage relative to income that is even higher than in high-income countries (Liu and Wang, 2024[26]). Possibly, high AI use in these countries is due to specialisation in sectors that are highly exposed to AI, such as ICT and business services, often reflecting the offshoring of these services by HICs. Indeed, the right panel in Figure 11 shows that ICT goods and services exports account for a strikingly high share of GDP in India and the Philippines.[27]

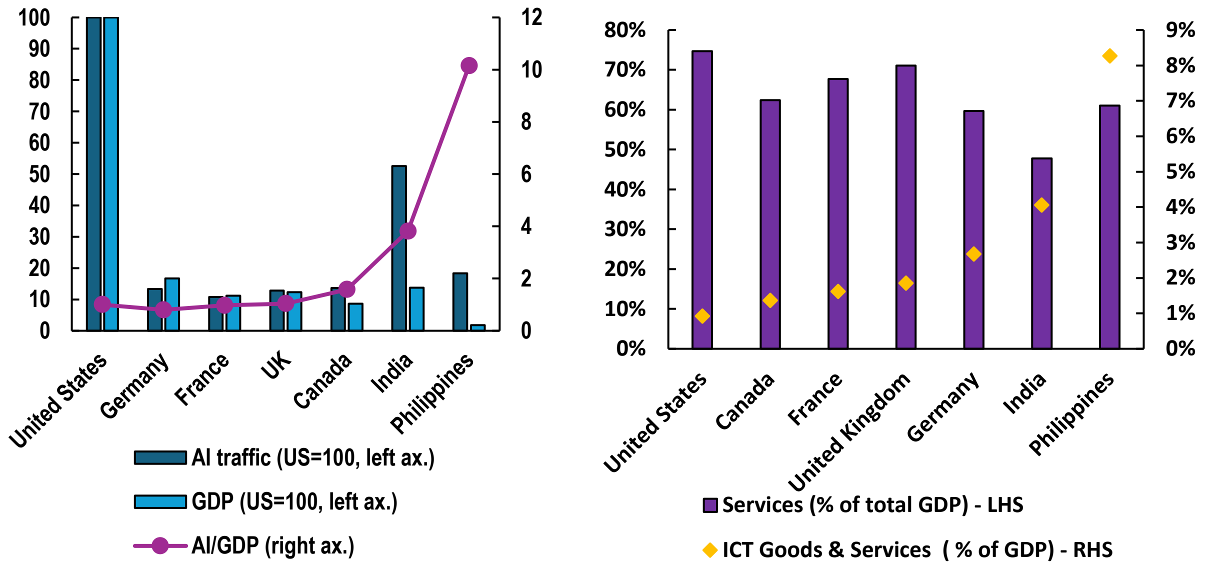
[25] See also https://www.nperf.com/en/map/5g for 5G networks.

[26] Notably, manufacturing, traditionally seen as a key avenue for absorbing low-skilled workers, grew by only 0.6 percentage points between 1990 and 2018 and remains heavily concentrated in low-tech industries like food processing and textiles (African Development Bank Group, 2024[52]).

[27] Alternatively, efforts could focus on exploring AI applications in sectors not traditionally exposed to AI but which account for a large share of output and employment in LICs and LMICs.

Figure 11: Certain low- and low-middle income countries have high AI usage amid strong services export-led sectors

AI traffic with respect to GDP over a sample of countries (2024, left graph) and services value-added and ICT exports as percentage of GDP (2021, right panel)



Note: In the left graph, the dark blue bars report AI traffic in 2024 in terms of the total number of visits to a selection of 40 generative AI tool, normalized to 100 for the US; the light blue bars report GDP normalized to 100 for the US, to proxy for the size of the economy; and the dots report the ratio of the two values. Source: (Liu and Wang, 2024[26]). The right graph reports total services value-added and ICT exports as percentage of GDP in 2021. Source: World Bank and OECD STAN 2025.

AI task-level gains: given adoption, unlikely to differ in low- and high-income countries

Past literature has also investigated potential heterogeneity in workers' task-level efficiency gains from the use of AI. Such heterogeneity was observed for past technologies depending on workers' age and skills (Aubert, Caroli and Roger, 2006[53]; Katz and Murphy, 1992[54]). In the case of AI, productivity gains are often found to be higher for low-skilled workers within specific occupations, across several studies focusing on taxi drivers, call centre workers and coders (Brynjolfsson, Li and Raymond, 2023[55]; Kanazawa et al., 2022[56]; Gambacorta et al., 2024[57]; Calvino, Jelmer and Samek, 2025[5]; Kanazawa et al., 2022[56]; Gambacorta et al., 2024[57]). In LICs and LMICs, where the share of low-skilled workers tends to be relatively high, this could signal a potential for reaping productivity gains from the use of AI in certain tasks. However, there are also opposite results, suggesting that individuals with greater prior knowledge might be better able to leverage AI in the accomplishment of their tasks (Wang, Gao and Agarwal, 2025[58]). Early studies on students even tend to find a positive correlation between initial performance without AI and performance with AI (Nakavachara, Potipiti and Chaiwat, 2024[59]).

However, when focusing on a representative sample of the whole workforce, rather than on individuals engaged in a specific occupation, productivity gains from AI on basic tasks may not be significantly different across education levels, as suggested by evidence from the UK (Haslberger, Gingrich and Bhatia, 2024[60]). In sum, higher task-level gains from AI are observed among individuals in specific occupations but not in a sample representative of the whole population. In the whole population, high and low skill individuals report similar gains, because high-skill individuals tend to work in occupations that gain more from AI. In addition, high-skilled individuals tend to have higher AI adoption. Thus, while AI can boost task-level performance for lower-skilled workers who already meet the basic requirements of a given job, *within* occupation, it is generally less effective at equalising skills *across* occupations. In other words, AI is unlikely to enable workers in low-qualification professions to achieve the same proficiency as counterparts in high-qualification professions. As a result, it is difficult to conclude that AI will disproportionately boost the capacity of low-skilled workers to perform high-skill tasks outside their occupation and allow low-education workers in LICs and LMICs to perform high-skill jobs.

Summary: AI can deepen the productivity divide

Overall, LICs and LMICs face significant disadvantages in AI adoption: workforce limitations (insufficient skills and education), inadequate digital and energy infrastructure and the high cost of the technology relative to their income levels (Table 1).[28] They also lag behind in designing and implementing adequate regulatory frameworks that can stimulate adoption and efficient use of the technology. On the exposure side, they suffer from an unfavourable sectoral composition, with a low share of value added generated by knowledge-intensive services. While skills and age of the workforce may in principle influence task-level gains from AI, their effects are ambiguous according to the available evidence.

Table 1: How LICs and LMICs specific characteristics impact AI adoption, AI exposure, and AI task-level gains

Benefit LICs/LMICs more (+) Benefit LICs/LMICs less (-)	**Drivers of AI productivity gains** (Filippucci et al., 2024 b)		
Low and middle-income countries have…	**1) AI adoption**	**2) AI exposure (share of tasks where AI can be used)**	**3) AI task-level gains**
… Younger workforce	+		**0**
… Lower-skilled and lower educated workforce	-		**+/0**
… Lower digital and energy infrastructure	-		
… Have lower purchasing power/credit constraints/worse capital markets	-		
… lower preparation in terms of regulation	-		
… Lower importance of knowledge-intensive services		-	

The outlook presented in Table 1 is alarming, as it suggests AI may exacerbate the global productivity gap. The analysis predominantly shows negative influences, implying that LICs and LMICs might enjoy

[28] An additional dimension that characterises LICs and LMICs is the high incidence of informality. While the evidence suggests informality can limit human capital accumulation, there is ambiguous evidence on the effect of informality on investment (Ulyssea, 2020[107]) and the few studies on the relationship with technology adoption are not based on credible quasi-experimental settings (Elgin, 2021[108]).

significantly smaller AI-driven productivity gains than HICs. While a younger workforce can be an advantage, the corresponding gains are likely modest (5%-10% higher adoption) and are outweighed by the other adverse features of LICs and LMICs. For example, limited exposure to AI due to a smaller role of knowledge-intensive services results in roughly 40% lower productivity in LICs and 25% in LMICs compared to HICs. Additionally, barriers to AI adoption — including education (with 59% of individuals in LICs and 32% in LMICs at risk of exclusion from most AI tools due to lack of schooling) and energy or digital infrastructure (53% without access to electricity, and around one in four lacking adequate internet coverage in LICs) — could restrict large segments of the population from engaging with AI technologies. Although slower adoption rates were also seen with previous technologies (Cirera, Comin and Vargas Da Cruz, 2022[19]), the specific traits of AI — its reliance on knowledge-intensive sectors, synergy with basic cognitive skills, and dependence on digital infrastructure — make this new technology divide more challenging.

Long-run opportunities and risks from AI

From a long-run perspective, a key question is if AI has the potential to structurally affect convergence of LICs and LMICs towards the productivity frontier. Recently, convergence has lost speed, and its continuation cannot be taken for granted (Kose and Ohnsorge, 2024[1]). In fact, human capital, institutions, and public investment (e.g. in infrastructure) are considered essential prerequisites for growth – consistent with theories of conditional convergence (Shioji, 2001[61]; Acemoglu, Johnson and Robinson, 2005[62]; Barro and Sala-i-Martin, 1992[63]). Such theories also emphasise cross-country technology diffusion as a crucial driver of growth (Howitt, 2000[64]). A country's capacity to absorb frontier innovation depends on trade integration, skills, institutions and investment, elements that are generally lacking in LICs and LMICs (Guillemette et al., 2017[65]; Albrizio, Andrews and Saia, 2015[66]). Moreover, while new technologies have been reaching lagging countries increasingly fast in the last decades, their within-country penetration rates have tended to decline, especially in LICs and LMICs, implying a widening diffusion gap overall (Comin and Mestieri, 2018[67]).

Two channels can be of particular relevance for determining AI's impact on cross-country convergence. First, AI can benefit human capital in the long run through its effects on health and education. In the health sector, there are significant opportunities for AI to improve outcomes, but also critical risks to be addressed (OECD, 2024[68]). In the education area, AI can enhance learning, re-skilling, and problem-solving in both educational and workplace environments (OECD, 2023[69]). AI can facilitate personalising instruction and deliver higher gains for low-proficiency learners (Cheon et al., 2025[70]; Mollick et al., 2024[71]). It can also enable students to complete tasks more efficiently (Zhang et al., 2024[72]; Urban et al., 2024[73]), may function as an on-demand subject-matter expert and search tool for educators and learners (Kestin et al., 2024[74]), and can provide cost-effective tutoring in low-resource settings (Henkel et al., 2024[75]; De Simone et al., 2025[76]). These applications of AI could provide LICs and LMICs with indirect productivity benefits through improving the skills of their workforce. On the other hand, AI tools may have detrimental long-term effects on skill acquisition. This is especially concerning if school systems give incentives to students to rely on AI for short-term gains, e.g. for passing tests, despite these long-run drawbacks. Moreover, it can pose equity problems similarly to other digital technologies if not all students have access to AI platforms and complementary tools.[29]

Second, even if LICs and LMICs experience limited domestic gains from AI, they may still benefit from spillover effects form other countries. On the one hand, countries may reap the welfare benefits of AI adoption in other countries through input-output links, for instance enjoying cheaper imports when their trading partners adopt AI technologies. LICs and LMICs typically import knowledge-intensive goods and services that are highly exposed to AI, such as ICT, finance and health, that can become more cheaply

[29] See also (Si et al., 2024[115]; Henkel et al., 2024[75]; Boateng et al., 2024[116]).

available from foreign partners. However, forthcoming OECD work suggests that, if a country fails to have sufficient domestic AI adoption, the overall benefits from input-output links may be relatively low in magnitude (Filippucci et al., 2025[6]). In fact, if a country keeps producing mainly without AI despite increasing AI adoption abroad, its gains in terms of cheaper imports are balanced out by lower competitiveness of its exports. On the other hand, international trade and investment flows may induce cross-country knowledge and technology spillovers, by facilitating access to best practices and supporting the adoption of frontier technologies. Participation in global value chains (GVCs) has long been a driver of technology diffusion, either through spillovers or better funding access. This is well-documented for developing countries (Delera et al., 2022[77]). Foreign investment is also an important vehicle of technology diffusion. In Latin America and the Caribbean, for example, the main adopters of advanced technologies are often subsidiaries of multinational firms (ECLAC, 2022[78]). Trade, GVCs participation and foreign investment can thus favour higher AI adoption in LICs and LMICs, thanks to learning and capability-building fostered by international production networks.[30]

3. Policies to prevent an AI productivity gap

A growing AI-driven productivity gap might result from weak cross-country diffusion of the technology, due to adoption barriers in LICs and LMICs.[31] However, AI could offer long-term opportunities for LICs, for example through technology spillovers and by moving up GVCs and positioning themselves in higher value-added niches of the AI economy. Therefore, two lines of action emerge: enhancing capabilities for AI adoption in the short run; and seizing long-run opportunities in the global AI economy.

Enhancing capabilities for AI adoption in the short run

Four key areas can be identified, in order of importance, for improving capabilities to adopt AI in the short run: infrastructure (energy and digital), workforce skills, finance, and institutions.[32]

First, investment in both energy and digital connectivity infrastructure is a necessary condition for effective AI adoption. Reliable access to electricity remains a fundamental prerequisite, including strategic siting of AI data-centers in regions where energy grids and production are efficient, expanding and modernising grids, broaden the energy-source mix to ensure reliability as AI loads grow, and use AI to optimise energy production and distribution (IEA, 2025[41]).

Concerning digital connectivity, policies to close broadband connectivity divides include a sound institutional and regulatory framework, setting national broadband targets/strategies, and improve broadband mapping and data (OECD, 2025[79]). OECD recommendations serve as a guide for policymakers and regulators worldwide to harness the full potential of connectivity for digital transformation, emphasising the need for fostering competition, investment, and innovation in broadband development. Particularly in remote and underserved areas, connectivity problems may be of particular importance. It is still early to say if satellite internet technologies may serve as useful alternatives, as they currently face

[30] AI could also deepen integration into GVCs and increase international investment, especially in services, by lowering language barriers (Brynjolfsson, Li and Raymond, 2023[55]) and improving search for suppliers and customers (Guerron-Quintana, Mikami and Nosal, 2024[112]).

[31] While a low share of AI-exposed sectors—such as services—also limits productivity gains in these countries, boosting AI exposure by developing AI-intensive industries is difficult to achieve through short-run policies.

[32] The importance of skills and digital infrastructure was also highlighted in earlier analysis in HICs (OECD, 2024[122]) and LICs/LMICs (UNCTAD, 2025).

limitations in performance, often involve high access costs, and concentration in their production could deepen external dependencies and pose strategic risk, similarly to what is often argued for HICs. [33]

Concerning local AI compute, local data centres can enable more advanced AI applications by reducing latency and improving internet traffic.[34] However, depending on technological and economic trade-offs, only a limited number of such centres may be needed per region, and policies supporting their deployment should be guided by careful assessments of their overall benefits and costs -- particularly considering alternative technologies (such as better internet connection), environmental implications for energy and water consumption (OECD, 2022[80]; IEA, 2025[41]), and the persistent gaps in digital infrastructure.[35] In turn, strategic dependencies and data security considerations may be an advantage of strengthening local computational capacity within each country, but achieving sufficient resilience and security in these domain is often complex and can be particularly costly for LICs and LMICs.

Second, education and workforce skills emerge as essential complementary factors for AI adoption. While there is mixed evidence on the effectiveness of training policies in developing countries (McKenzie, 2017[81]), a recent study indicates that skill development in LICs and LMICs is particularly effective when offered through sector-specific workforce training (Alfonsi et al., 2022[82]).[36] Targeting is crucial and, given the economic structure of these countries, it should include agriculture and focus on SMEs and disadvantaged groups that might be particularly under-skilled (ECLAC, 2022[78]). Due to the nature of AI technologies, particular emphasis could be placed on digital literacy and ICT skills, alongside English proficiency, that are associated to higher gains from AI (Brynjolfsson, Li and Raymond, 2023[55]). Currently, English is not only the language where many AI models perform best, but also English learning may particularly benefit from AI. At the same time, give that large portions of LICs and LMICs population will not catch up in English proficiency soon enough, one way in which international coordination can promote more even global adoption is by ensuring that AI does not train only on specific languages and on data from specific cultures. Governments and organisations could also support multilingual AI development, investing in datasets and research for diverse languages.

Third, this paper highlights that a major barrier to AI adoption is the non-trivial adoption cost. This cost, despite potential productivity gains, can become prohibitive under severe credit constraints, as commonly observed in LICs and LMICs. Therefore, access to finance plays a critical role. In HICs, policies that support efficient capital markets have bolstered more digital and competitive financial sectors, with positive spillovers for downstream firms (Bontadini et al., 2024[83]). Targeted financial support—for instance, for acquiring AI services or complementary hardware such as mobile phones and computers—can help firms in LICs and LMICs manage adoption costs. Some possible instruments include lower taxes on ICT products or providing grants and loans, although these measures should be calibrated keeping in mind

[33] See also (OECD/IDB, 2016[125]) for a review of broadband policies for Latin America and the Caribbean.

[34] An appropriate digital connectivity infrastructure that includes Internet exchange points and data centres that form part of content delivery networks can enhance network efficiency. (ECLAC, 2022)

[35] AI use currently involves high levels of energy and water consumption. Sustaining global AI adoption and investing in global AI-related digital and energy infrastructure may bring significant environmental trade-offs, particularly in terms of increased electricity and water usage by data centres. For water in particular, the trade-off can be particularly binding if LICs and LMICs aim at installing local data centres, as these countries are often concentrated in hot weather areas and where water is scarcer due to natural constraints (Gallup, Sachs and Mellinger, 1999[114]). In turn, negative environmental impacts are likely to be felt most acutely by LICs and LMICs, given their greater vulnerability to natural disasters. A comprehensive policy and a strategic approach are therefore needed to align digitalisation with environmental sustainability goals.

[36] While recent evidence suggests high effectiveness of sectoral vocational training, it doesn't exclude the importance of a systemic approach to learning, and of focusing also on critical thinking, ethical awareness, and civic competencies to promote the responsible and informed use of AI.

countries' fiscal constraints and considering the often-constrained fiscal environment of LICs and LMICs. For instance, credit schemes that target farmers with unmet credit needs were beneficial to the dissemination of agricultural technologies (Ruzzante, Labarta and Bilton, 2021[84]). In this context, International Financial Institutions and regional Development Banks could play an important role by providing concessional finance to support such interventions.

Lastly, AI regulation preparedness and enforcement are relevant. Institutions must strike a balance between minimising unnecessary regulatory burdens (Grazzi and Jung, 2019[85]) and establishing robust frameworks for trustworthy AI. Such frameworks can enforce core principles—beneficence, non-maleficence, and explicability —which align with user expectations for ethical and reliable systems, strengthening both cognitive and emotional trust in AI technologies. The OECD AI principles constitute a key reference in this respect to ensure fairness, transparency, robustness and accountability of AI systems. Also, strengthening mechanisms for worker dialogue and representation is essential to raise awareness of labour rights (ECLAC, 2022[78]). While recent policy studies discussed what is the role of social dialogue for AI adoption in HICs (OECD, 2023[86]), how would this translate in LICs and LMICs remains an open policy question. Some LICs and LMICs, such as India, Ghana, and Rwanda, stand out as relative outperformers in regulatory preparedness for AI (Mandon, 2025[45]). Peer learning and the exchange of best practices among countries can further build institutional capacity and support effective policy design. Given the global nature of AI-related challenges—and the ease of accessing AI tools across borders, including via VPN—international cooperation may also be necessary to advance common principles and frameworks for AI regulation.

Seizing long-run opportunities from the global AI economy

Policies aimed at fostering long-run convergence through the AI economy should prioritise, first, facilitating access to the technology. In particular, countries should sustain AI adoption and experimentation in domains such as health and education that can be key drivers of long-term growth, while maintaining continuous impact evaluations to ensure effectiveness and guide improvements, given that there may be unintended negative effects of AI tools. Here, ensuring effective and sufficient foreign aid remains an important complementary factor in supporting technology adoption and capacity building in LICs and LMICs.

Second, additional opportunities stem from AI's ability to foster trade and knowledge spillovers to LICs and LMICs, so that promoting international access to knowledge can speed up AI diffusion and spread out its productivity benefits. A key condition for this is trade openness and international collaboration. Ensuring interoperability of data systems and access to frontier AI models, e.g. though open-source platforms, is essential to maximise these benefits. Policy should also encourage the internationalisation of firms, including fostering better managerial culture and awareness of AI tools.[37] The rise of the AI economy might open a window of opportunity for LICs and LMICs to climb global value chains (GVCs), which reinforces the need for trade openness. Philippines and India are examples of such opportunities, as both countries supported their focus on ICT and service exports with strong capabilities—including English proficiency and skilled labor. To reap these opportunities, policies should focus on enabling firms to scale up and ensure an efficient reallocation of factors of production toward sectors that see increases in demand.[38]

[37] Evidence from HICs also shows that improving managerial skills and promoting internationalisation can yield benefits (Manaresi et al., 2022[113]), although the cost-effectiveness of these measures should be carefully assessed.

[38] Sluggish factor reallocation within countries can lower the gain from AI, because factors cannot move to support production in sectors that have benefited relatively less from AI (Filippucci, Gal and Schief, 2024[4]).

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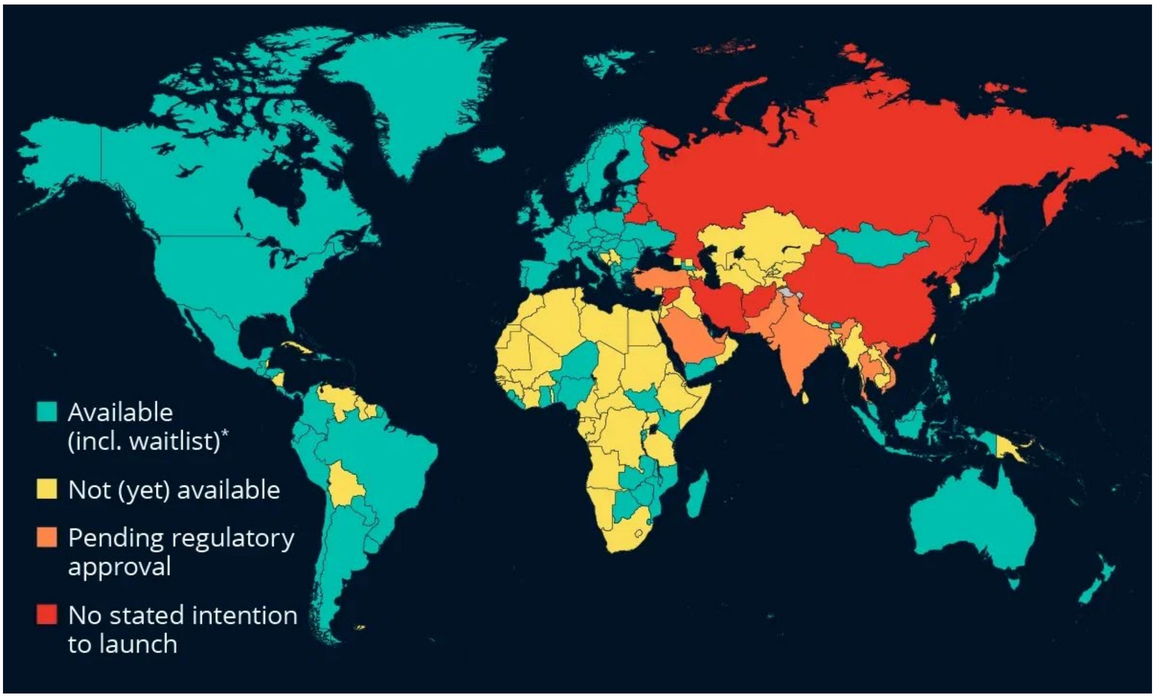
Annex A. Additional Tables and Figures

Table A 1: Not all languages are supported in AI models, and English remains the one with best performances

LLM	Best performances	Number of Languages	Sources and notes
ChatGPT	English	59 officially supported, about 95 according to unofficial sources	ChatGPT support, https://seo.ai/blog/how-many-languages-does-chatgpt-support and https://joingenius.com/statistics/chatgpt-supported-languages/;
Claude	English	11 interface languages, 40+ query	Anthropic support. Performance data by Anthropic show that among 15 among the 20 most popular languages performance declines 21%-54% relative to English for Yoruba.
Gemini	English	140 languages for the latest Gemma 3 version	Google support
Mistral	English and French	8 native languages in medium model, up to 11 supported in large model	Mistral support. Stronger multilingual support with fluency in English, French, Spanish, German, and Italian.
DeepSeek	English and Chinese	2-3 primary languages, 100 + in recent update	Reddit and Trunic.com

Figure 12: Main new satellite connection systems are not available in many LMICs and in most LICs

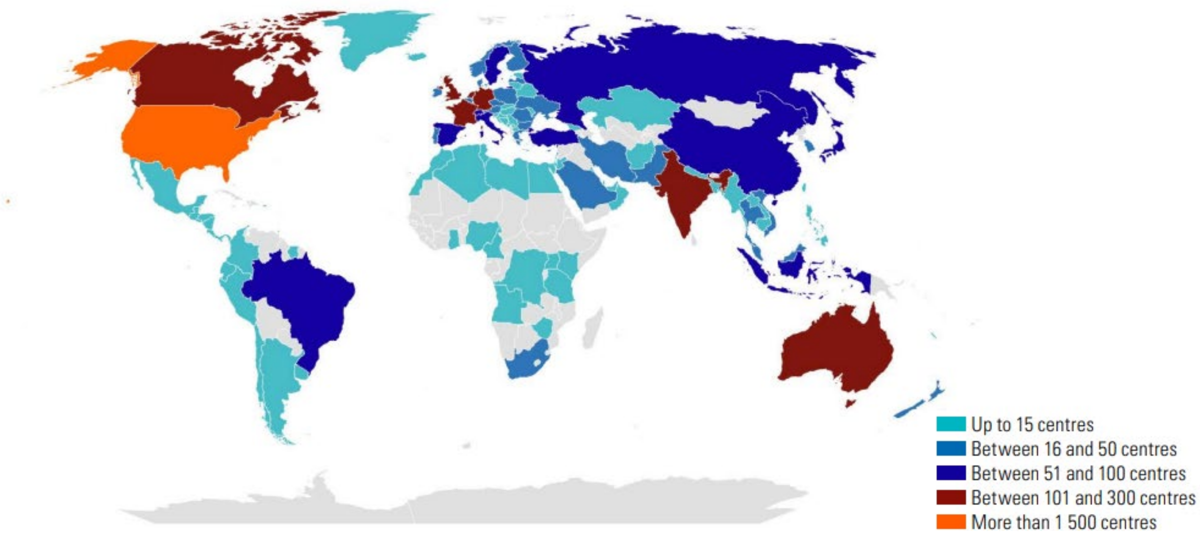
Countries covered by Starlink



Source: Statista and Starlink, as of May 2025

Figure 13: There are few data centres in LICs and LMICs

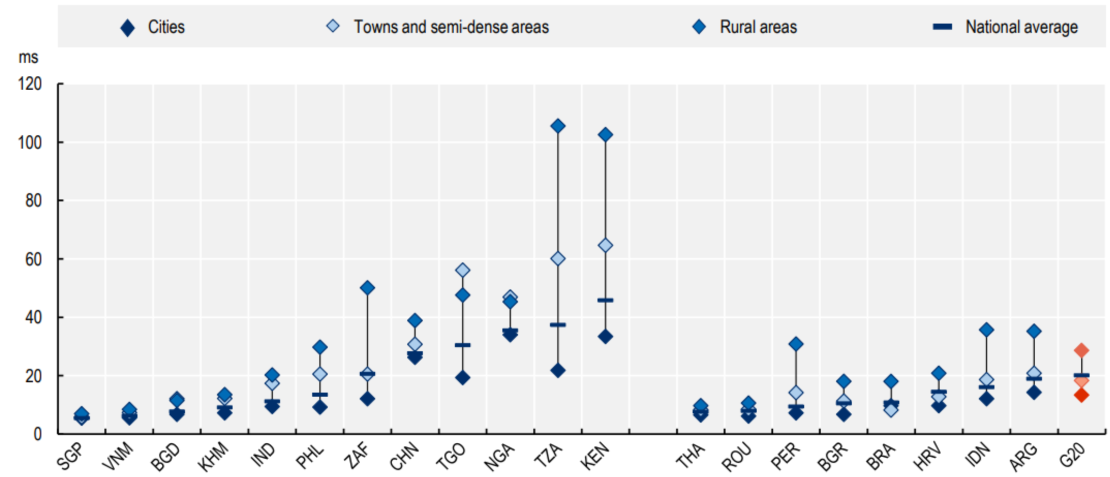
Number of data centres, 2022



Note: for grey shaded countries data are not available. Source: European Commission for Latin American and the Caribbean, based on Data Centre Map

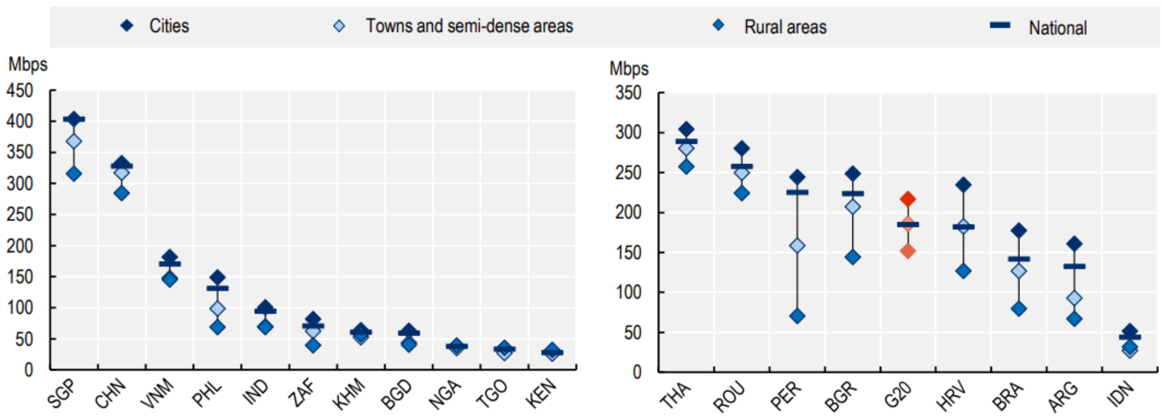
Figure 14: Territorial gap in latency and broadband speed are large between rural areas and cities, and get uniformly low in countries with lower income

Panel A: mean latency over fixed networks in select economies



Notes: Measurements are based on tests performed by users around the globe via the Speedtest platform. Source: (OECD, 2025[79]).

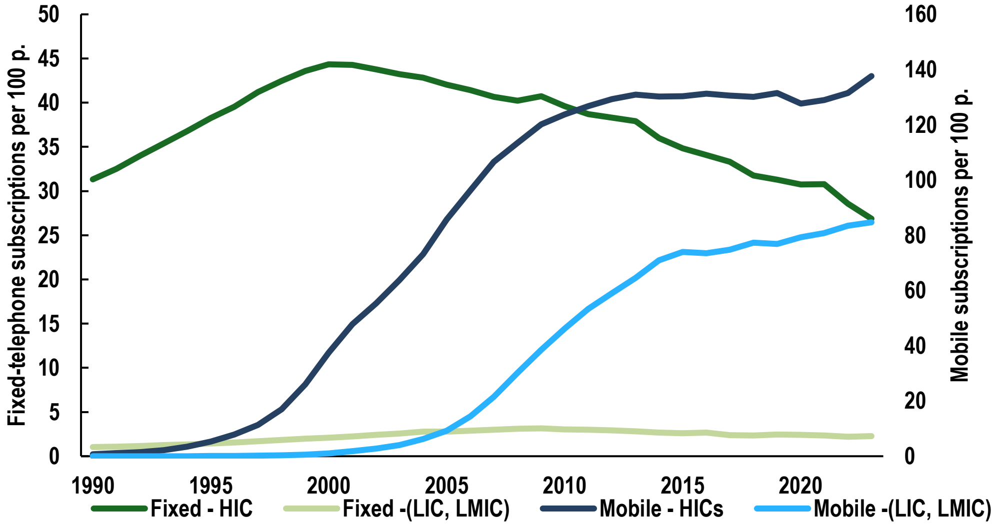
Panel B: mean fixed download speeds in selected economies, Q4 2024, by degree of urbanisation



Notes: Measurements are based on tests performed by users around the globe via the Speedtest platform. This graph shows two groups: selected partner economies on the left and OECD accession countries on the right. Source (OECD, 2025[79])

Figure 15: Mobile phone adoption leapfrogging

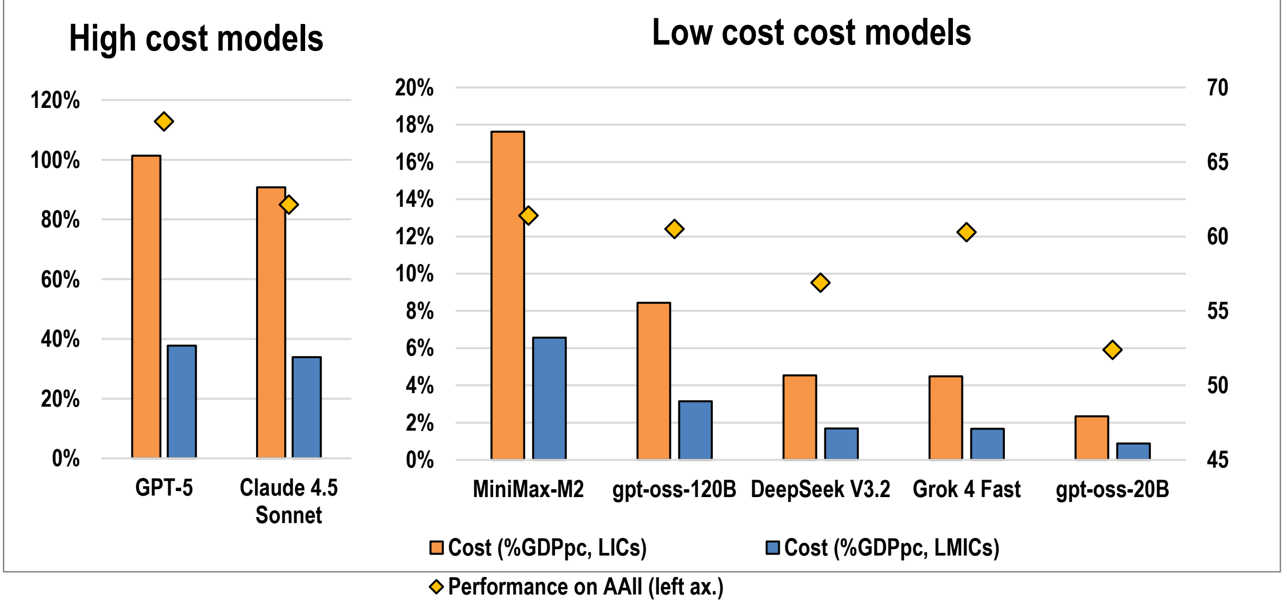
Fixed-telephone subscriptions vs. Mobile-telephone subscription (per 100 people) by country income levels



Note: Country income level taken from World Bank classification. Source: International Telecommunication Union

Figure 16: Highest quality models have prohibitive costs for LICs and LMICs

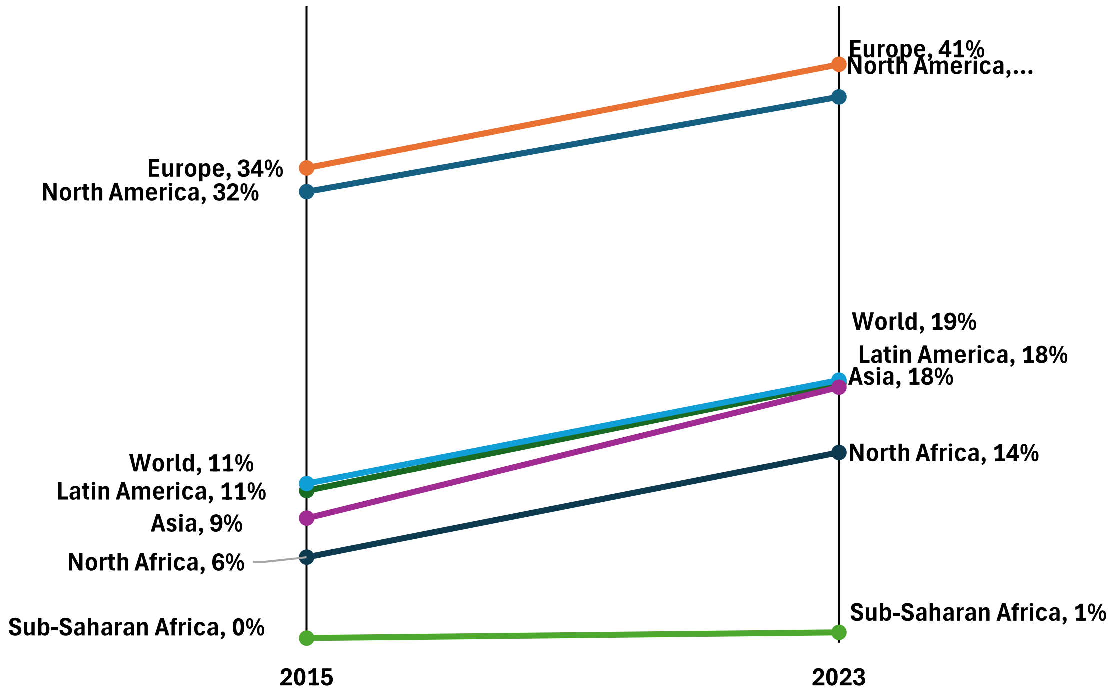
Performance and cost in terms of GDP per-capita (2024) of solving the Artificial Analysis Intelligence Index, by model



Source: OECD staff calculations based on Artificial Analysis (artificialanalysis.ia) and World Bank.

Figure 17: Gaps in broadband connectivity remain significant

Broadband subscriptions per 100 people



Source: (International Telecommunication Union, 2025[36])