

B AI, trade and inclusive growth: opportunities and challenges

This chapter provides a detailed economic analysis of the transformative potential of AI, focusing on its impact on trade and inclusive growth. AI has the potential to strengthen workforce skills, improve public service delivery, boost productivity and reshape trade patterns. WTO simulations suggest that AI-driven trade cost reductions and productivity gains could generate substantial increases in global trade and real income. However, risks associated with AI include job displacement, inaccurate information and negative environmental impacts. Under the right conditions, AI can enable more inclusive growth through trade, but it also presents distributional challenges across and within economies. Currently, access to AI is not diffused uniformly across economies, and the ability to develop AI is concentrated in a few economies and firms. Trade can play a vital role in ensuring broad access to AI-enabling goods and services, and in helping to accelerate the diffusion of AI innovation.

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KEY POINTS

- WTO simulations suggest that AI-driven reductions in trade costs and productivity gains could translate into increases in global trade and real income. The impact of AI on inclusive growth will critically depend on how the digital divide is addressed and how the technology spreads globally.
- AI could enable more inclusive growth through trade, but currently AI adoption is not uniform, as it tends to cluster in large, urban, digitally connected firms in high-income economies. Although AI can enhance many workers' productivity, it displaces others by automating tasks or occupations.
- Key segments of the AI supply chain, such as semiconductor manufacturing and data centre infrastructure, are currently dominated by a small number of firms and economies. This concentration poses risks to equitable access and highlights the importance of trade and policy measures to diversify supply chains and promote broader participation.
- Trade can enable economies without strong domestic AI capabilities to access AI-enabling goods and services, such as raw materials, which are vital for their participation in the AI value chain and to prevent enlarging the global digital divide. Global trade in AI-enabling goods was worth US\$ 2.3 trillion in 2023.
- Trade accelerates knowledge diffusion. WTO analysis shows that economies more open to trade experience stronger innovation spillovers: a 10 per cent increase in digitally deliverable services trade is associated with a 2.6 per cent rise in cross-border AI patent citations, when one patent filed to protect intellectual property rights references another.
- AI can create new opportunities for economies rich in resources, such as critical minerals or energy, needed for AI infrastructure. To capture these opportunities, targeted investments in digital infrastructure and skills, as well as enabling policies, are required.

1. AI and trade can act as catalysts for trade-led growth

(a) AI can reduce trade costs, boost productivity and expand global trade

AI can influence trade through two primary channels: it can reduce trade costs and it can increase productivity. This section builds on the 2024 WTO report on trade and AI, *Trading with Intelligence* (WTO, 2024a), while placing a stronger emphasis on the inclusive growth potential of AI. It draws on new evidence from a growing body of literature on the economic impact of AI, and offers fresh insights through a business survey on firms' use of AI in trade, an analysis of trade in AI-enabling goods, and an examination of the diffusion of AI innovation. The analysis in this chapter recognizes the uncertainty surrounding the pace and diffusion of AI development and adopts a scenario-based approach, using simulations to illustrate potential outcomes under different assumptions about AI adoption and global diffusion.

(i) AI is helping to reduce trade costs

Trade costs represent all the expenses involved in moving goods and services across borders from producers to final consumers. These can include transportation costs, tariffs and non-tariff barriers, costs incurred due to time spent, and information and compliance costs. Global trade costs declined by 15 per cent between 2000 and 2018, although trade costs for services are higher than those for agricultural or manufactured goods (Egger et al., 2021). In recent years, trade costs have been increasing due to factors like tariffs and supply chain disruptions (WTO, 2025).

AI can help to reduce these costs through various channels. AI-enabled improvements are helping to make trade less costly and more efficient overall by optimizing trade logistics, streamlining regulatory compliance and contract enforcement, reducing language barriers, enhancing international communication, and improving search and matching processes between suppliers and buyers.

AI technologies can help to optimize logistics operations, including inventory and warehousing management, real-time tracking, predictive maintenance of fleets and route optimization. This can reduce delays and increase efficiency, or can even transform the supply chains (see Box B.1 for a case

study of Maersk, a major shipping company, using AI to improve trade logistics and compliance). AI can help to detect or predict demand surges and bottlenecks in international supply chains, thereby facilitating trade. It can also be used to assess the resilience of supply networks and reduce trade disruptions caused by unexpected events. For example, by integrating data from suppliers, manufacturers, logistics providers and customers, AI can provide real-time visibility of the entire supply chain, allowing for a quicker response when disruptions occur (WTO, 2024a).

AI can be used to reduce overall trade costs by facilitating regulatory compliance.

It can help to automate and streamline customs clearance processes and border controls, and to navigate complex trade regulations and compliance requirements. This can greatly reduce the costs of complying with trade regulations. For instance, AI-powered solutions have been developed to tackle the complexities of reporting and complying with the EU's Carbon Border Adjustment Mechanism (CBAM), by integrating machine learning into a data management platform to help collect, manage and report emissions data more efficiently (Nexer, 2025). AI can support the real-time validation of electronic certificates. For instance, machine learning models can be trained to identify inconsistencies in sanitary and phytosanitary (SPS) certificates based on origin, type of product or past non-compliance history. This facilitates the automatic verification of documentation and improves the efficiency and integrity of border processes (Turchetto, 2025).

AI could help to overcome trade costs related to regulatory divergence in services trade.

Differences in regulations and unclear processes for recognizing qualifications and standards continue to present significant obstacles to trade in services, particularly for professional and other regulated services. While past waves of digitalization did little to overcome these challenges, AI may have the potential to reduce information asymmetries, strengthen indications of quality and reputation, and help navigate complex regulatory environments, thereby facilitating cross-border services trade (Nordås and Tang, 2022).

AI is also helping to reduce the cost of contract enforcement significantly. By automating tasks like contract drafting, review, negotiation and monitoring, AI-powered legal tools can lower costs, shorten enforcement timelines and minimize errors.

Box B.1: Case study: Global trade 2.0: Navigating a new complicated trade and customs landscape with AI

The global trade environment is undergoing a profound transformation. Rising protectionist measures, escalating tariffs and stricter regulatory enforcement have significantly increased the cost and complexity of cross-border commerce. Businesses are facing challenges such as tariff volatility, changing trade sanctions, compliance with environmental and social regulations, and complex rules of origin and product classifications.

In this context, AI and machine learning are emerging as tools that can help firms to better anticipate, understand and manage trade-related risks. These technologies are being used to improve visibility, enhance compliance and support strategic decision-making in global supply chains.

Data visibility as a foundation for risk management

Currently, supply chains are increasingly reliant on data visibility. Companies are integrating data about sourcing, production, logistics and sales to create unified data systems that provide real time insights into the movements and characteristics of goods. Externally, open platforms and interoperability with partners generate large quantities of data that can be leveraged for more informed trade management.

AI can help to make sense of these complex data flows by offering predictive insights and automated alerts. Some businesses are using AI tools to model tariff exposure, analyse compliance risks and simulate sourcing scenarios under different trade policy conditions. The goal is to shift from reactive compliance to proactive risk management.

AI in action: risk signals and compliance screening

The growing complexity of global trade is driving demand for AI-enabled solutions, particularly as two key trends take hold. First, the use of trade remedies and targeted tariffs is expanding, with duties increasingly applied in layered and often unpredictable ways. Second, customs authorities are stepping up enforcement through more frequent audits and post-clearance reviews, resulting in higher retroactive duty collections and greater compliance risks.

In response, companies are exploring AI-powered compliance tools that analyse trade documentation at early stages, such as during purchase order creation, to flag possible regulatory issues. For example, a pilot Maersk Trade & Tariff Studio¹ has screened thousands of products and identified hundreds of potential compliance concerns, enabling early intervention before goods reach customs. AI-enabled trade analytics are being applied across different sectors. In manufacturing, product-level tariff modelling has revealed potential exposure over short timeframes. In retail, AI-supported scenario planning has helped firms to diversify suppliers and adjust sourcing calendars to align with changing tariff regimes.

Such tools aim to take account of a wide range of regulatory risks, including sanctions, environmental, social and governance (ESG) requirements and rules of origin, in integrated platforms. The objective is to provide end-to-end supply chain oversight and to support timely operational decisions in a rapidly evolving policy landscape.

As global trade becomes more dynamic and fragmented, AI offers firms new ways to improve visibility, reduce compliance costs and better manage uncertainty. While adoption varies across sectors and regions, the integration of AI into trade operations reflects a broader shift toward data-driven, anticipatory approaches to managing regulatory and geopolitical risk.

Source: Lars Karlsson, Global Head of Trade and Customs Consulting, Maersk.

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AI-based contract analysis tools can process large volumes of documents to flag ambiguous or non-compliant clauses, highlight negotiation levers and suggest improvements, thereby cutting review time and costs significantly. For instance, one study found that large language models (LLMs) reviewing legal invoices achieved up to 92 per cent accuracy in mere seconds, reducing costs by 99.97 per cent (Whitehouse et al., 2025).

AI enhances international communication and can eliminate language barriers. Several empirical studies have shown that reducing language barriers has a positive impact on trade (Egger and Lassmann, 2012; Melitz and Toubal, 2014). For example, a study of eBay's Machine Translation (eMT) programme found that eMT increased US exports to Spanish-speaking Latin American countries by 17.5 per cent in terms of quantity and 13.1 per cent in terms of revenue. The trade effect was equivalent to reducing the distance between economies by 37.3 per cent (Brynjolfsson, Hui and Liu, 2019). AI-driven translation technologies can make communication faster and more cost-effective, particularly benefiting small producers and retailers by enabling them to expand into global markets.

AI has the potential to increase participation in global value chains by enhancing their overall efficiency. It can improve coordination among suppliers, reduce lead times and minimize the need for inventories. AI tools used in predictive maintenance and just-in-time delivery systems can substantially lower the costs associated with participation in GVCs and help cut carbon emissions through more efficient vehicle deployment and charge schedules (Falck, 2025). A substantial portion of GVC-related costs also arises from the need to build trust and relationships among cross-border suppliers and buyers. AI can help to mitigate these costs by improving search and matching processes between suppliers and buyers, enhancing communication efficiency, and reducing the reliance on long-term relationship-building to ensure coordination and reliability. AI can also support compliance with due diligence requirements, by automating tracking, data collection and reporting. These efficiencies can be particularly beneficial for developing economies that are trying to move up the value chain.

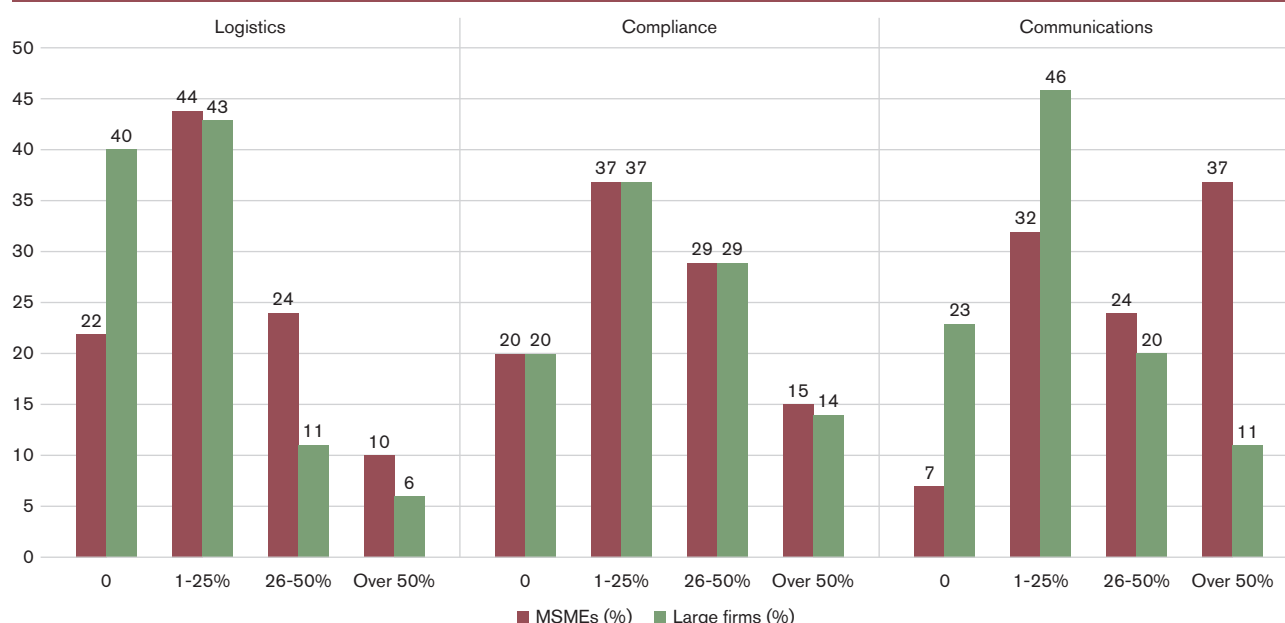
A business survey shows that firms expect AI to reduce trade costs, particularly in logistics, regulatory compliance and communications.

The recent survey,² developed and circulated by the International Chamber of Commerce (ICC) and the WTO in March 2025, gathered responses from 158 businesses across major regions, capturing their perspectives on the current and potential impact of AI on trade. Of the respondents, 35 per cent were based in Europe, 23 per cent in Asia, 15 per cent in the Middle East and North Africa (MENA), 11 per cent in Central and Eastern Europe and Latin America and the Caribbean (CEELAC), 9 per cent in Sub-Saharan Africa and 6 per cent in North America. The sectoral distribution was similarly diverse: 25 per cent of respondents were from finance and insurance, 25 per cent from manufacturing and 49 per cent from other services. Sixty-three per cent of firms were micro, small and medium-sized enterprises (MSMEs, defined as having 249 employees or fewer), while 37 per cent were large firms (more than 250 employees). Nearly half of the respondents (49 per cent) reported that they currently use AI, and 79 per cent indicated that they are engaged in international trade activities. While other surveys track AI adoption more broadly, this is the first to focus specifically on trade. Its aim was to better understand companies' use of AI in trade, the opportunities that AI creates, and the challenges that firms face.

Over 70 per cent of firms anticipate that using AI can lead to trade cost savings, with MSMEs generally more optimistic than larger firms. When asked by how much AI could potentially reduce trade costs for their business, the majority of firms reported the expectation of significant cost savings. As shown in Figure B.1, 10 per cent of MSMEs expect logistics cost reductions of over 50 per cent, while 24 per cent foresee savings of 26 to 50 per cent, compared to just 6 per cent and 11 per cent, respectively, of larger firms. For communication costs, 37 per cent of MSMEs anticipate reductions of over 50 per cent, and 24 per cent expect 26 to 50 per cent savings, versus 11 per cent and 20 per cent among larger firms. This greater optimism may reflect the relatively larger gains that smaller firms expect to achieve from AI, given their limited resources to manage trade-related costs.

Firms surveyed by the WTO and ICC reported a range of positive effects from adopting AI in their trade activities. AI is being used in diverse ways, with workflow automation and language-related tasks the most common applications. Nearly 90 per cent of firms using AI reported benefits in trade-related

Figure B.1: Firms expect AI to reduce trade costs related to logistics, compliance and communications



Source: WTO Secretariat calculations based on WTO-ICC business survey (2025).

activities. The most commonly cited benefit is improved trade efficiency (22 per cent of responses), followed by optimized trade decision-making (14 per cent). Other reported benefits include expanding the foreign customer base (10 per cent), enhanced supply chain management (9 per cent), and broader import and export product ranges (9 per cent and 8 per cent, respectively). Larger firms primarily use AI for compliance with trade regulations, contract analysis and trade finance. Smaller firms, in contrast, tend to focus on market intelligence and improving communication.

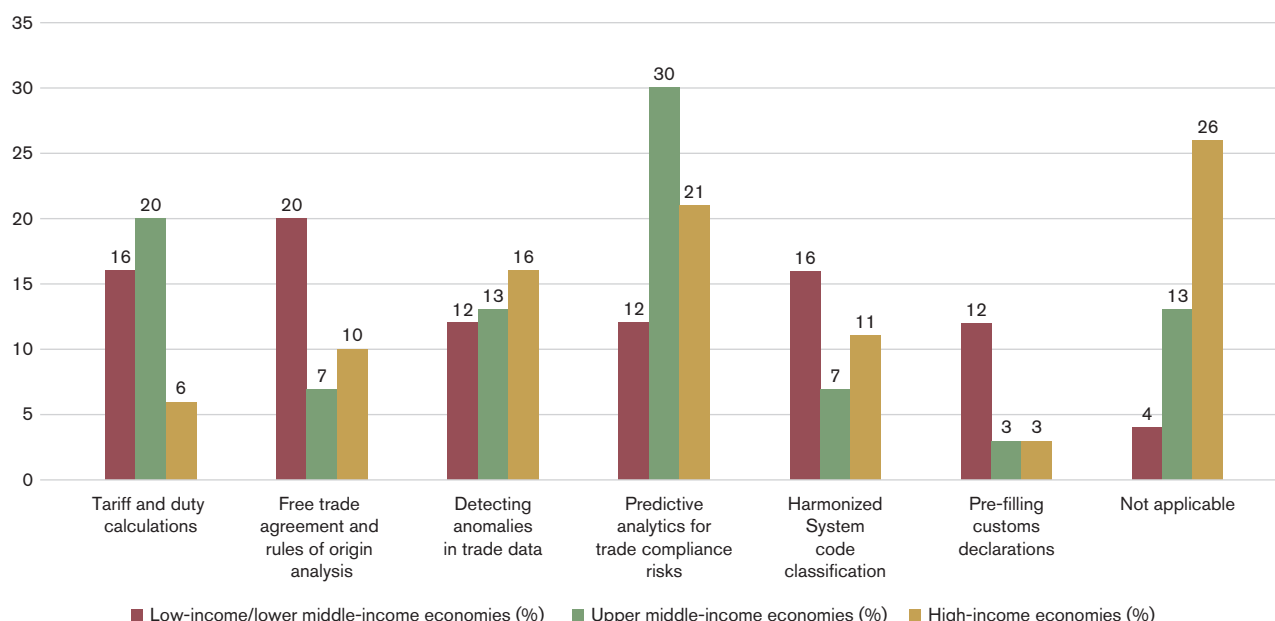
The survey shows how AI may help firms to navigate complex trade rules and benefit from trade agreements. Three-quarters of firms that currently use AI responded that they were using AI for customs-related applications. When the results by income level were examined, as shown in Figure B.2, it was observed that a greater percentage of firms in low-income and lower middle-income economies are using AI to understand how to benefit from preferential trade agreements and how to use the right HS code classification and pre-fill customs forms. The findings suggest that AI could help to increase the participation of firms from low-income and lower middle-income economies in global trade.

(ii) AI is boosting productivity across sectors

Productivity growth is central to long-term improvements in living standards. It determines how efficiently an economy can transform inputs, such as labour and capital, into goods and services. Higher productivity means that more output can be produced with the same resources, supporting higher wages, lower prices and greater competitiveness in global markets. Productivity growth is often driven by innovation and “creative destruction”, whereby new technologies and processes replace outdated ones, fostering dynamic efficiency and long-term growth (Aghion and Howitt, 1992). Productivity can be measured in several ways, including labour productivity, defined as output per worker or per hour worked, and total factor productivity, which captures the efficiency with which all inputs (such as labour, capital and sometimes materials) are used in production.

A growing body of research highlights the potential of AI to improve productivity, though its effects vary across tasks and contexts. For instance, a study of customer-support agents found that access to AI assistance increased productivity, measured by issues resolved per hour, by an average of 15 per cent, with less experienced and lower-skilled workers improving both the speed and quality

Figure B.2: AI use cases in customs-related applications among firms using AI



Source: WTO Secretariat calculations based on WTO-ICC business survey (2025).

Note: The percentages refer to the percentages of respondents among firms that have adopted AI.

of their output (Brynjolfsson, Li and Raymond, 2025). A study of taxi drivers found that access to an AI navigation system that predicted high-demand routes reduced cruising time and increased productivity, particularly for less efficient drivers (Kanazawa et al., 2022). In the consulting sector, an experiment at a major management consulting firm showed that GPT-4 helped consultants to complete a greater number of simple tasks better and more quickly, but that it also reduced their performance on complex tasks outside AI's core capabilities (Dell'Acqua et al., 2023). Meanwhile, evidence from the field of radiology suggests that even when AI outperforms human professionals, combining human and machine judgement does not always improve results, for example if the human professionals do not fully trust the AI results, or if they misinterpret its suggestions (Agarwal et al., 2023).

Projections suggest potentially substantial macroeconomic gains from AI. Industry estimates are notably optimistic, particularly over the medium to long term. Goldman Sachs projects annual total factor productivity growth from AI of 1.5 per cent in the United States and 1.25 per cent globally through 2033, with moderate effects before 2027 and stronger gains thereafter (Briggs and Kodnani, 2023). McKinsey offers global estimates ranging from

3.4 per cent annually under an early adoption scenario to 0.5 per cent under late adoption through 2040, depending on the speed and scope of adoption (Chui et al, 2023). Academic studies present a more nuanced picture. Acemoglu et al. (2024) project modest total factor productivity gains equivalent to about 0.07 percentage points per year. In contrast, Aghion and Bunel (2024) estimate AI-driven total factor productivity growth of between 0.07 and 1.24 percentage points per year, with a median estimate of 0.68 percentage points. They note this may be a lower bound, as the model does not account for AI's potential to accelerate the generation of new ideas. Similarly, Filippucci, Gal and Schief (2024) estimate that AI could contribute between 0.25 and 0.6 percentage points to annual total factor productivity growth, based on micro-level performance gains, sectoral exposure to AI and projected adoption rates.

However, AI adoption varies widely by firm size, income level and sector. According to the 2025 WTO-ICC business survey, over 60 per cent of firms with more than 250 employees report using AI or AI-based systems, compared to just 41 per cent of smaller firms. Firms make use of a variety of AI tools, including proprietary systems developed in-house, subscription-based solutions and freely available

applications. AI adoption is also more common in high-income economies, where two-thirds of firms use AI, versus less than one third in low-income economies. Sectoral differences are pronounced as well: fewer than one-quarter of manufacturing firms use AI, compared to 52 per cent in finance and insurance and 61 per cent in other service sectors. These patterns suggest that firms with greater resources – whether due to size or location – are more likely to adopt AI, highlighting the untapped potential for broader diffusion.

Despite its promise, firms face several challenges to AI adoption. The 2025 WTO-ICC business survey shows that larger firms most frequently cite data privacy and security concerns, high implementation costs and integration difficulties as barriers to adoption. For MSMEs, additional barriers include limited in-house expertise and the high upfront costs of adoption. Even among firms already using AI, data privacy and security remain the most frequently cited concerns across firms of all sizes, income levels and sectors. More broadly, firms identify cybersecurity risks and regulatory uncertainty as key obstacles to AI adoption in trade. These findings underscore the need for clear and predictable regulatory frameworks to support the responsible and inclusive use of AI in international trade.

(iii) AI's potential impact on trade is substantial

Many of the trends described in this section are evaluated quantitatively using scenario analysis with the WTO Global Trade Model.³ Four scenarios are explored to capture different degrees of policy and technological catch-up between economies, based on projections of operational trade cost reductions, shifts in tasks from labour to AI across a variety of sectors, economies and skill types based on task data, productivity increases associated with the shift in tasks, and increased production of AI services.

Scenario 1: Technology divergence within and between economies. In this scenario, high-skilled workers benefit most from productivity increases associated with the deployment of advanced AI.⁴ These benefits stem from completing more tasks with AI instead of labour. Differences in digital infrastructure and related policies determine the extent to which economies can leverage productivity and trade cost improvements from AI.

Scenario 2: Policy catch-up between economies and technology synergies within economies. In this scenario, medium-skilled workers benefit most from productivity increases associated with the application of more basic types of AI currently in use.⁵ Economies with lower scores of AI readiness in terms of digital infrastructure converge with initially better performing regions (closing 50 per cent of the gap in the digital policies score).

Scenario 3: Technological and policy catch-up between economies. In this scenario, medium-skilled workers benefit most, and economies converge in terms of digital infrastructure-related policies (as in Scenario 2). In addition, the productivity in AI-enabled tasks partially converges to the productivity of the best-performing region.

Scenario 4: AI technological catch-up between economies. In this scenario, economies with low productivity in AI services (reflected in low production shares) partially catch up with economies with high productivity in AI services (closing 100 per cent of the inferred relative productivity gap in AI services relative to country-level productivity). This enables them to expand production in AI services. However, this scenario considers only convergence within economies between AI services and other sectors and not between economies.

The WTO Global Trade Model is extended with a new sector: “AI services”. This sector includes activities that develop (“train”) and operate AI models. Training AI typically builds on existing models and relies heavily on ICT services such as data centres. Once developed, AI services can be deployed in various economic sectors to serve as an intermediate input in production. In this framework, productivity gains are linked to greater use of AI services. The share of AI services in total output is projected to rise significantly by 2040, reaching about 2 per cent of total output. The model also accounts for the upstream inputs required by the AI services sector, including labour, capital, electronic equipment (i.e., semiconductors), electricity, and ICT services like data storage and internet transmission.

The simulations capture three key channels: reductions in operational trade costs from the use of AI, shifts from labour to AI services that vary by sector, economy and skill type, and productivity

gains associated with this shift. Trade cost changes are calibrated based on gravity regression and consider reduced trade costs related to regulatory compliance costs, language barriers (in terms of translation and ease of communication), logistics costs (in terms of timeliness of shipments), contract enforcement and distance. The shift in tasks from labour to AI services is estimated using task-level data and projections on AI's impact on the share of tasks that can be offshored, with variations across sectors, economies and skill types. This approach builds on the methodology by Gmyrek, Berg and Bescond (2023) (see Section B.1(b)(ii) for further discussion on the labour market impact of AI). The average size of productivity increases across all sectors associated with the shift in tasks from labour to AI is determined based on Aghion and Bunel (2024) mentioned above. More technical details can be found in Bekkers et al. (2025).

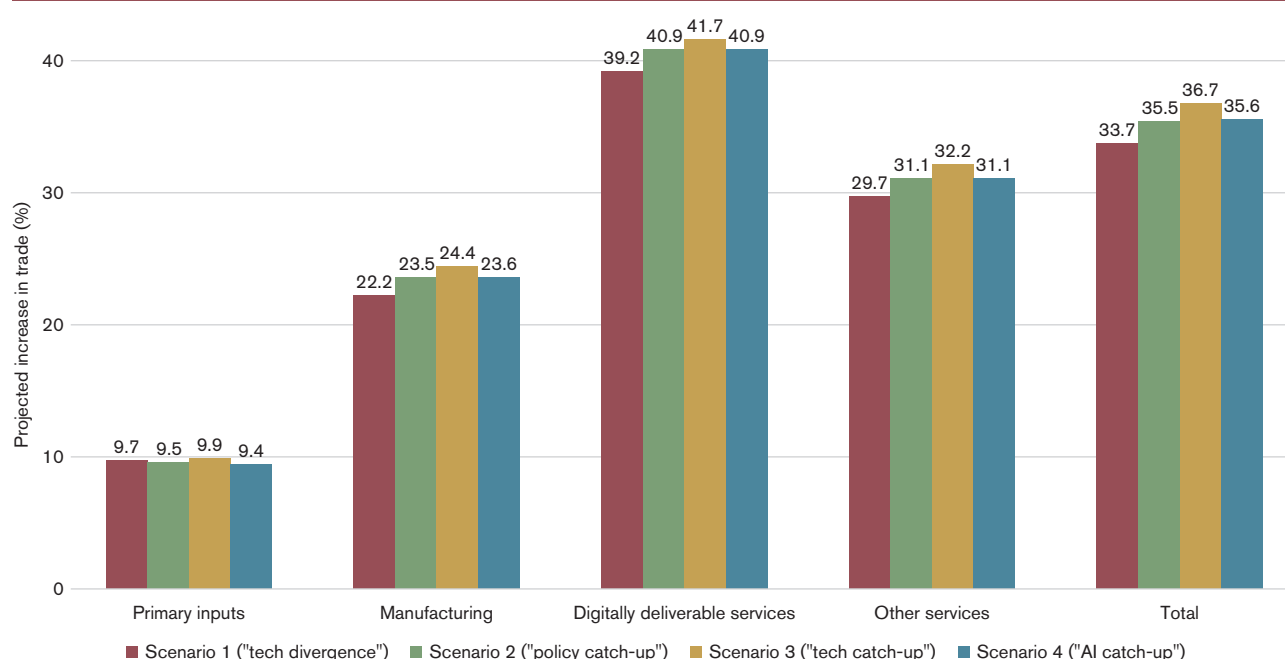
The deployment of AI can substantially change trade patterns. Figure B.3 shows a large projected increase in global aggregate trade, ranging from 34 per cent to 37 per cent across different scenarios. This large increase in trade is driven by three factors: (i) reduced operational trade costs; (ii) the strong projected growth of AI services combined

with the high tradability of AI services, related to its geographic concentration of production in a few regions; and (iii) the above-average productivity growth in more tradable sectors, in particular digitally deliverable services.

Among broad sectors, the largest growth occurs in the digitally deliverable services sector (up to 42 per cent), which includes AI services. The first four sets of bars in Figure B.3 show the projected trade increases across four broad sectors. The particularly high growth in digitally deliverable services reflects the rapid expansion of AI, which makes these sectors particularly responsive to productivity gains and trade cost reductions. Trade growth is also substantial in other services (up to 32 per cent), manufacturing (up to 24 per cent) and primary inputs (up to 10 per cent).

In high-income regions, the projected export growth is relatively stable across scenarios, while low-income regions see much higher trade growth in catch-up scenarios. Figure B.4 demonstrates that trade growth in high-income economies is around 36 per cent across scenarios. For low-income economies, the policy catch-up scenario (Scenario 2) raises export growth by

Figure B.3: AI is projected to expand global trade substantially by 2040, with larger increases in digitally deliverable services (2025-40)



Source: Simulations using the WTO Global Trade Model.

Notes: The figure displays the cumulative increase in trade in per cent for aggregate sectors over 2025-40 for four scenarios in deviation from the baseline. See Section B.1(a)(iii) for the four projected scenarios capturing different degrees of policy and technological catch-up.

6 percentage points compared with the 24 per cent increase under divergence (Scenario 1), while technology catch-up (Scenario 3) adds 2 percentage points. Overall, about half of the trade growth is attributable to the projected reduction in trade costs, with the remaining half from the productivity increases associated with AI (not shown in the figure), which are most pronounced in tradable sectors, and the shift in demand towards the highly tradable AI services.

Rising demand for AI services will also have upstream value chain effects. More specifically, the global demand for electronic equipment (with semiconductors as a key component) is projected to see substantial growth. Figure B.5 shows the projected change in the production of electronic equipment and electricity across aggregate regions. The expansion of AI services further boosts global demand for their intermediate inputs, including electronic equipment (up to 40 per cent) and electricity (up to 21 per cent).

(b) Under the right conditions, AI can enable more inclusive growth through trade

While AI may be poised to reshape trade patterns, its impact on trade-led growth

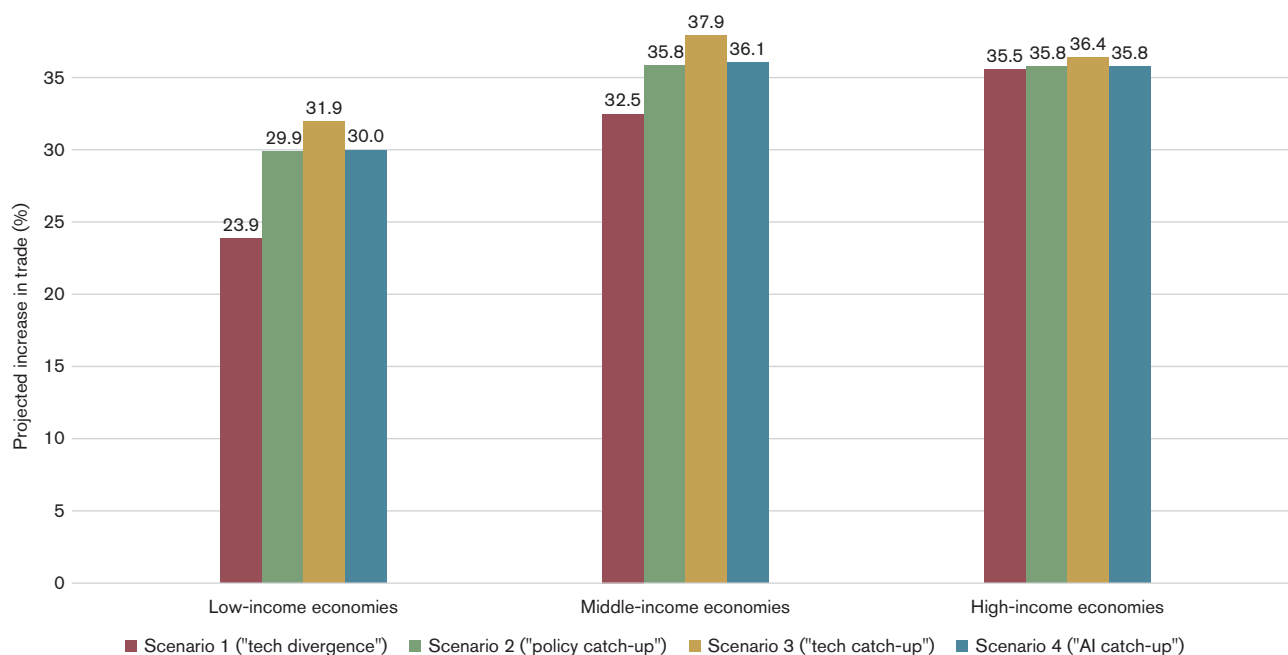
opportunities will depend on a range of factors.

On the one hand, AI can enhance productivity, lower trade costs and enable new forms of trade in goods and services. With the right conditions in place, it has the potential to help developing economies to leapfrog traditional stages of industrial development, and to support the integration of small businesses into global trade. On the other hand, the uneven diffusion of AI technologies, persistent skills gaps and limited digital infrastructure risk reinforcing existing disparities, both between and within countries. The extent to which AI can contribute to more inclusive growth depends on how effectively AI can complement labour in production processes, the level of investment in digital infrastructure and human capital, access to data, and the degree to which “winner-takes-all” dynamics emerge in the digital economy.

(i) AI can support development by improving services and trade opportunities

AI can contribute to development both by improving public services and by opening up new trade opportunities. Directly, AI can enhance the quality and affordability of public services, streamline bureaucratic processes and improve

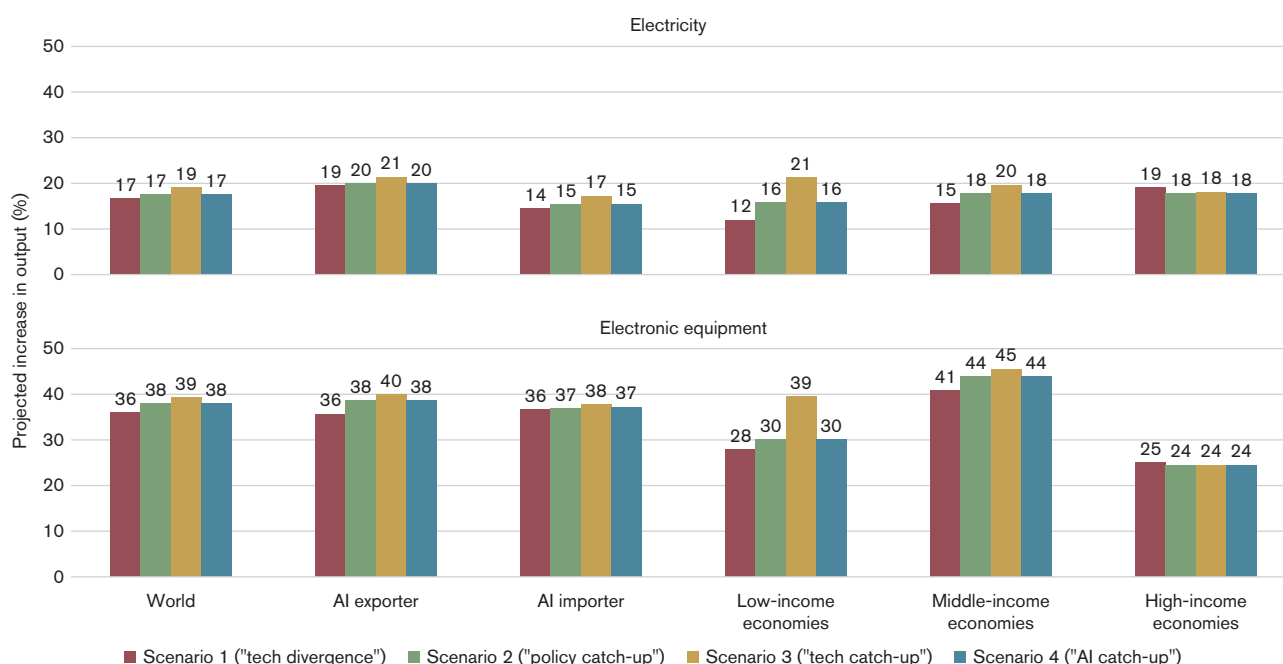
Figure B.4: High-income economies are projected to see the largest increase in exports (2025-40)



Source: Simulations using the WTO Global Trade Model.

Notes: The figure displays the projected increase in per cent in total trade for regional groups split by level of development over 2025-40 for four scenarios in deviation from the baseline. See Section B.1(a)(iii) for the four projected scenarios capturing different degrees of policy and technological catch-up.

Figure B.5: Rising AI services are driving up demand for electricity and computer equipment (2025-40)



Source: Simulations using the WTO Global Trade Model.

Notes: The figure displays the cumulative increase in per cent in output of electricity and of electronic equipment between 2025 and 2040 for four scenarios in deviation from the baseline, globally and for regions split by level of development or by status of AI exporter/importer. See Section B.1(a)(iii) for the four projected scenarios capturing different degrees of policy and technological catch-up.

services delivery, often through imports of AI-enabled services. Indirectly, AI can enable developing economies to expand their exports, particularly in digitally delivered services, thereby fostering more inclusive growth in these economies. It may also reshape patterns of comparative advantage, enabling these economies to engage more effectively in global AI value chains and tap into new sources of growth.

AI can contribute directly to development by improving the quality and affordability of public services. The effective delivery of high-quality public services is often hindered by limited resources, weak institutional capacity and regulatory inefficiencies, especially in developing economies. AI has the potential to reduce the costs and improve the quality of public service delivery, expanding access in much the same way that the industrial revolution broadened access to consumer goods. By improving efficiency and reach, AI can accelerate progress toward development goals in areas such as agriculture, healthcare, education and financial inclusion (see Box B.2).

International trade is essential for developing economies to access AI-enabled goods and services. As discussed in more detail in Section B.2, most AI-enabled services depend on underlying technologies that are often developed in a few advanced or emerging economies. These technologies are delivered through global infrastructures, including cloud computing and telecommunications networks. Likewise, goods embedded with AI technologies, such as self-driving vehicles, are primarily accessed through trade. As a result, international trade plays a critical role in both the diffusion and delivery of AI solutions.

AI could boost services trade, including services exports from low-income and middle-income economies, but realizing its development potential depends on key enabling factors. The development potential of AI-enabled services exports is especially noteworthy given the inherent characteristics of many services sectors – economies of scale, innovation potential and strong linkages with other sectors, similar

From flow to foresight: how AI is redefining trade

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As global trade converges with AI, we may be witnessing the beginning of a profound transformation. This convergence combines the scale and complexity of cross-border exchanges with the analytical power of AI. Trade supplies the diverse data that AI systems learn from; in turn, AI is reshaping the efficiency, structure and reach of global commerce. This signals a shift toward more intelligent, data-driven trade.

Think of it this way: trade has always been about moving goods, services and ideas across borders. Now we are moving intelligence itself. Every shipment, every transaction and every customs declaration becomes a data point that feeds back into systems that are getting better by the day. It is like watching a massive learning organism come to life.

Nowhere is this more exciting than in Africa right now. The African Continental Free Trade Area (AfCFTA) is trying to turn 54 separate economies into one integrated market. It is not just about trying to harmonize policies; these economies are building the digital backbone to make it all work. We are talking about identity systems that span borders, payment networks that let you send money from Lagos to Nairobi as easily as transferring funds within a single city, and customs systems that actually talk to each other.

The Pan-African Payment and Settlement System is a perfect example of this in action. Before this platform existed, sending money across African borders was expensive, slow and frustrating. Now, businesses can make real-time payments in local currencies. That might not sound revolutionary, but imagine trying to run a business when every transaction takes days and costs a fortune in fees. That single change has unlocked trade relationships that simply were not viable before.

And here is where AI enters the picture. All this digital activity is creating an incredible treasure trove of data, including transaction patterns, shipping routes, seasonal trends, and even regulatory bottlenecks. AI does not just collect this information; it turns it into something actionable. Suddenly, a small manufacturer in Ghana can get insights that used to be available only to multinational corporations.

This is a game-changer for policymakers. Instead of making decisions based on reports that are months out of date, they can see what is happening in real time. They can test policies in regulatory sandboxes, using live data to gauge impact before scaling these policies continent-wide. It is evidence-based governance in real time, at scale.

This is already happening across the continent. In East Africa, logistics companies are using AI to predict delivery times by analysing traffic patterns, weather forecasts and road conditions. Digital trade finance platforms are leveraging AI to assess credit risks more accurately, thereby helping small businesses gain access to capital that was previously out of reach. Governments are exploring AI-informed regulatory sandboxes, using live data to test and improve trade policies before they are scaled.

The trajectory is clear. When AI becomes central to trade systems, it delivers more than just operational gains. It expands access to markets, accelerates trade timelines, strengthens governance and creates new pathways for inclusive development. These are converging forces that, together, are shaping a future where digital infrastructure, data and insights move in concert to drive broad-based and sustainable growth.

That is the real promise here. We are not just talking about making existing trade more efficient. We are talking about creating entirely new possibilities for people who were previously locked out of global markets.

When AI becomes the invisible infrastructure supporting trade, it does not just move goods faster, it moves opportunities to where they are needed most.

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Box B.2: How AI can impact development

AI could accelerate progress across key development sectors and is already being applied to address challenges in areas like agriculture, education, and financial inclusion.

In agriculture, AI tools can help farmers to detect crop diseases, manage pests and optimize resource use. For example, Nuru,⁶ an AI-powered app by PlantVillage,⁷ diagnoses crop issues using satellite and ground data, providing real-time advice to farmers. It has been deployed in Kenya and other East African economies for uses such as detecting cassava and potato diseases and infestations of fall armyworm, a pest that feeds on certain crops. The app relies on satellite imagery, often provided by international providers, such as the National Aeronautics and Space Administration (NASA) or the European Space Agency (ESA), and cloud computing services, which are part of digitally delivered cross-border services. Given that 84 per cent of the world's smallholder farmers live in low-income economies, improving their productivity is essential for global food security.

In education, AI can ease teacher workloads and enhance learning, particularly in settings with large class sizes and limited resources. Studies show that AI tools enabled teachers to spend less time on routine grading tasks, which can be dedicated instead to focusing on more complex, non-routine activities, such as individualized student interactions (Ferman, Lima and Riva, 2021). Access to such AI solutions hinges on the affordability and availability of internet access and of devices such as smartphones or tablets, which are typically imported electronics.

In finance, AI can expand access to credit and financial services for underserved populations. MSMEs in developing economies face a financial gap of more than 30 per cent of GDP in their respective economies. Integrating AI in trade finance can effectively reduce the cost of servicing credit while utilizing non-traditional alternative data sources to reach those at the bottom of the socioeconomic pyramid. Financial technology (fintech) companies worldwide are increasingly leveraging AI tools to extend credit to first-time borrowers. When these services are delivered from abroad – whether from a regional hub or global provider – they constitute cross-border trade in financial services (mode 1 of the General Agreement on Trade in Services – GATS).⁸

Source: Dixit and Gill (2023).

to manufacturing (Nayyar, Hallward-Driemeier and Davies, 2021). While convergence in labour productivity in manufacturing is widely documented (Rodrik, 2013), there is also evidence of convergence in aggregate labour productivity between developing and developed economies in the service sectors over 1975 to 2012 (Kinfemichael and Morshed, 2019). However, the ability of developing economies to benefit from AI-driven trade opportunities is not automatic. It depends on factors such as digital infrastructure, access to data and computing power, education systems, effective policy frameworks, and the future trajectory of AI technologies themselves.

AI-enabled services trade, being typically intangible, data-driven and knowledge-intensive, if combined with balanced intellectual property (IP) frameworks, can facilitate the cross-border diffusion of ideas. Knowledge flows through diverse channels, including open-source platforms (e.g.,

GitHub),⁹ research publications and AI patents. These spillovers can translate into tangible productivity gains, as illustrated by Sun and Trefler (2023), who show that when some firms embed cutting-edge AI in their apps, other competing firms also improve their performance. In addition, AI-enabling products such as software, cloud computing and research and development (R&D) services generate forward linkages across sectors and lower entry barriers, enabling “scale without mass” and giving individuals and small firms access to global markets.

Learning-by-doing is a key channel through which AI-enabled services exports can build up the workforce and drive innovation in developing economies. AI systems improve with use as they process more data; firms and workers gain expertise by implementing and interacting with AI; and service providers learn from sophisticated foreign clients. Exporting AI-rich services allows

workers to acquire advanced skills that often spill over into the domestic economy, fostering entrepreneurship and broader innovation. However, these benefits depend on a country's ability to absorb and apply new knowledge.

Overall, AI-enabled services trade has the potential to catalyse structural transformation.

By accelerating knowledge diffusion and enabling integration into evolving global value chains, AI-enabled services trade can allow latecomers to leapfrog technologically (Lee, Malerba and Primi, 2020). Scale economies allow certain standardized digital products to expand at near-zero marginal cost, creating unprecedented market access opportunities, particularly for developing economies that can export services without heavy infrastructure requirements (World Bank, 2016). AI-driven learning-by-doing mechanisms generate dynamic productivity gains, fostering self-reinforcing cycles of innovation and economic growth, particularly in sectors leveraging AI-intensive processes (Damioli, Van Roy and Vertesy, 2021).

Shifting comparative advantages

Over time, AI could significantly reshape economies' comparative advantages by shifting the relative productivity of labour, capital and knowledge across sectors and economies.

Its impact on trade-led development will depend largely on whether AI substitutes for or complements labour. On the one hand, AI can automate routine and cognitive tasks, diminishing the comparative advantage of economies that rely on low-skilled and low-cost labour. On the other hand, AI can help developing economies to overcome limitations in experience and skills in certain services sectors, allowing them to enter new markets – particularly those involving AI-assisted services delivered through the internet.

Since AI-driven productivity gains are likely to vary across sectors, economies may begin to specialize differently depending on how AI transforms key industries. Economies with early AI implementation advantages may experience productivity gains that allow them to capture larger market shares internationally. This could lead to a realignment of trade patterns and a reconfiguration of global value chains. Research by Bonfiglioli et al. (2025) finds that comparative advantage in AI-reliant sectors is associated with factors such as the

presence of a higher number of graduates in science, technology, engineering and mathematics (STEM), widespread internet access, a strong export base and supportive digital trade regulations. Jakubik, Rotunno and Saini (2025) also find that AI has a significant positive correlation with trade.

Investment in digital infrastructure and workforce skills is increasingly recognized as a key driver of comparative advantage in the emerging AI-driven global economy.

Expanding broadband access, cloud computing and data infrastructure enhances an economy's capacity to enter and scale in AI-intensive global markets. At the same time, computer literacy and education in AI-related skills are essential to leverage comparative advantage in the AI-driven economy. While basic digital skills are sufficient to use AI-enabled services, economies seeking to develop or adapt AI models will require a workforce with more advanced competencies in information technology and machine learning. These capabilities not only support domestic innovation but also attract foreign investment and facilitate integration into the rapidly growing digital services trade.

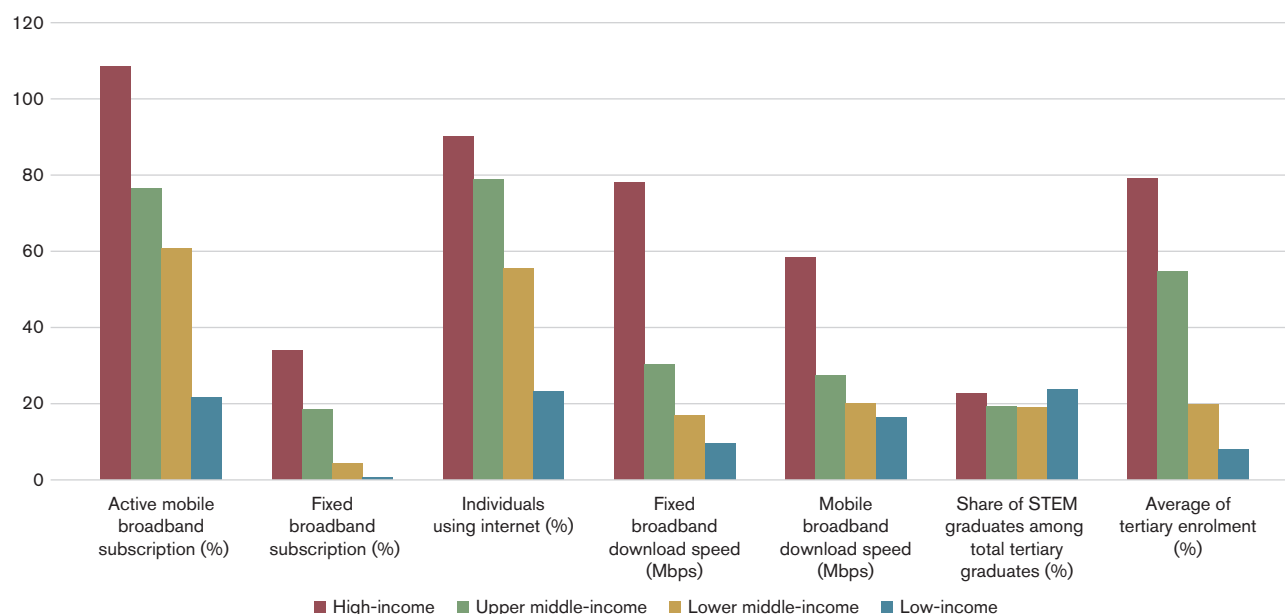
Comparative advantage in AI-intensive sectors also depends on upstream inputs.

Since the training and adoption of AI requires substantial energy and raw materials for hardware production, economies rich in critical minerals and low-cost energy, especially renewable energy, are well-placed to attract AI-enabling activities such as mineral extraction and processing, hardware manufacturing and data centre operations (see Section B.2). This, in turn, could shape comparative advantages in the upstream segments of the AI value chain for some economies.

The digital divide across economies

A key limitation to AI adoption is the digital infrastructure gap, including disparities in broadband access, cloud computing capabilities and reliable hardware.

As shown in Figure B.6, indicators of digital infrastructure, such as the share of the population with active mobile and fixed broadband subscriptions, internet usage and internet speed, are strongly correlated with income levels. While high-income economies tend to have near-universal internet access and relatively high-speed connections, lower middle-income and low-income economies continue to lag behind both in terms of access and performance. This persistent

Figure B.6: Access to digital infrastructure and education is uneven across income groups

Sources: Data on mobile, fixed broadband and internet users from the International Telecommunication Union (ITU); internet speed data from Ookla (2025); share of STEM graduates from the United Nations Educational, Scientific and Cultural Organization (UNESCO) and tertiary enrolment rate from the World Bank.

Note: Broadband, internet user and STEM graduate data are in percentage shares for the latest year available. Internet speed data is represented in Megabits per second (Mbps) for the year 2022.

digital divide poses a significant barrier to inclusive participation in the AI-driven economy.

Variations in the capacity to collect and access data limit the ability of developing economies to develop and adapt AI to local needs. The lack of quality data, which is essential for AI training and optimization, further restricts AI development in many economies. Collecting, cleaning, storing and managing data for AI models requires robust institutional and infrastructural capacity, including scalable data storage solutions, the ability to source data from public and proprietary sources, and the ability to ensure data quality and compliance with data regulations. Without targeted investments in digital infrastructure, these inequalities will persist, limiting the ability of emerging markets to integrate AI into their economies (Oxford Insights, 2023).

The availability of skilled labour and the development of a local AI ecosystem present major challenges. Successful AI research and commercialization often depend on strong academic institutions, well-funded research laboratories, and high levels of venture capital investment – resources that are frequently lacking in lower-income countries. As with comparative advantage in AI-reliant sectors

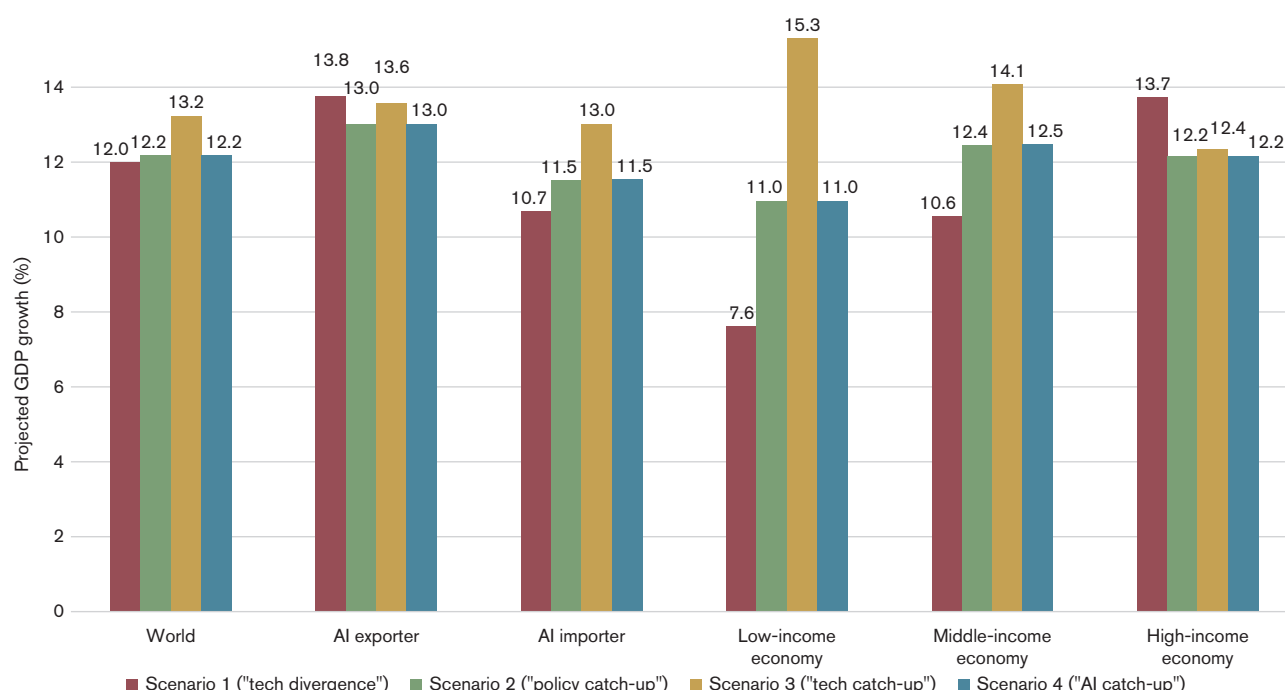
(see above), one useful indicator of an economy's readiness for AI adoption is the number of its STEM graduates. As shown in Figure B.6, while the share of STEM graduates among total tertiary graduates is relatively similar across income groups, lower-income economies tend to have much lower overall enrolment rates in higher education, meaning that there is a comparatively lower absolute number of skilled professionals available to support AI development and adoption in lower-income economies.

AI's impact on inclusive growth

WTO simulations show that the development and deployment of AI raise real GDP substantially by between 12 per cent and 13 per cent across scenarios. Figure B.7 shows the projected change in real GDP globally and by region under different scenarios. While high-income economies are projected to experience substantial GDP gains across all scenarios, the growth impact on low-income and middle-income economies will depend largely on the extent of catch-up in infrastructure and technology.

Without policy catch-up and technology synergies between economies, the divergence scenario projects widening income levels. As

Figure B.7: AI is projected to raise global GDP, with wide variation across scenarios (2025-40)



Source: Simulations using the WTO Global Trade Model.

Notes: The figure displays the impact of AI on real GDP for 2025-40 in per cent for four scenarios in deviation from the baseline, both globally and for aggregate regions, split by level of development, and between AI exporters and importers. See Section B.1(a)(iii) for the four projected scenarios capturing different degrees of policy and technological catch-up.

shown in Figure B.7, in Scenario 1 ("tech divergence between economies"), GDP is projected to grow almost twice as much as a result of AI in high-income economies (13.7 per cent) compared to low-income economies (7.6 per cent). This gap narrows substantially in Scenario 2 ("policy catch-up between economies"), with projected growth rates for low-income economies of 11 per cent, and 12.2 per cent in high-income economies. In this scenario, middle-income economies would see their projected GDP growth rise to the level of high-income economies (12.4 per cent). Hence, improvements in digital infrastructure, essential for the deployment of AI, play an important role in the catch-up of income levels.

With policy and technology catch-up, low-income and middle-income countries are projected to benefit more from AI-driven GDP growth. In Scenario 3 ("tech catch-up between economies"), the projected GDP increase of low-income and middle-income economies rises to 15.3 per cent and 14.4 per cent, respectively. In this scenario, economies catch up to the productivity level of the technological leader for tasks that are

AI-automated. Finally, Scenario 4 ("AI catch-up between economies"), which introduces technological catch-up in AI services, brings very limited additional GDP gains for virtually all economies and therefore does not lead to much income convergence.¹⁰

The results of these simulations suggest that the catch-up between economies in AI infrastructure and deploying AI technology is important for inclusive growth across economies. Income convergence is mostly driven by catch-up between economies in digital infrastructure and related policies, as well as technological catch-up between economies in the deployment of AI, which allows economies to converge in productivity levels with those economies that are leading technologically in terms of tasks that can be automated by AI. This technological catch-up scenario between economies is a stylized representation of views expressed by Autor (2024) and Baldwin (2024), who argue that middle-skill workers, as well as low-income and middle-income economies, stand to benefit more from AI-driven productivity gains precisely because they are further from the technology frontier, i.e., the

most advanced level of technology or productivity currently achievable.

The catch-up between economies in technology for the production of AI, on the other hand, is not critical for income convergence. The reason is twofold. First, AI is relatively tradable, like other digitally deliverable goods. Therefore, an economy's own AI production capacity is not necessary to benefit from AI deployment advancements. Second, the share of the AI sector is relatively small despite its rapid growth, so economy-wide productivity gains coming from AI deployment are more important in the simulations than the productivity advancements within the production of AI.

Although net exporters of AI services are benefitting from the shift towards AI services, this shift does not play a dominant role in the difference in projected income effects. Although there is a positive correlation between the AI production share and the projected income change, it is weak. Moreover, Scenario 4 ("AI catch-up between economies"), which incorporates productivity catch-up in AI services, does not impact the gains for either AI-importing and AI-exporting countries significantly.

(ii) The key factors that shape how AI could affect inequality within and across economies

AI holds both promise and risk for inclusive growth, depending on a range of economic and social factors. While AI can expand access to essential services, it also poses risks by automating tasks, displacing jobs, reshaping labour markets and concentrating economic activity in ways that may exacerbate both within-economy and cross-economy inequalities, whether through sectoral agglomeration or an increase in the market power of firms.

The impact of AI on the workforce

AI can influence labour markets through both direct and indirect channels. Directly, AI is affecting the quality and quantity of employment by automating tasks, reshaping job requirements and altering the demand for certain skills. While some tasks may be eliminated, others may be created or transformed, depending on how AI complements or substitutes for human labour. Indirectly, AI is also impacting labour markets through its effect on trade. These trade-induced shifts can create new

employment opportunities in export-oriented sectors while potentially displacing jobs in others, with implications for wage inequality and labour market polarization.

AI may act as an equalizing force by disproportionately benefiting workers in developing economies. AI can enhance the productivity of medium and low-skilled workers in developing economies. When combined with reduced trade costs associated with cross-border service delivery, this could enable greater participation from professionals in developing economies in global markets. Baldwin and Dingel (2021) describe this as a "telemigration" effect, whereby AI tools, such as translation and process automation tools, enable professionals in developing economies to compete more effectively for contracts in high-income markets. However, this increased competition could also exert downward wage pressure and lead to job losses in affected sectors in advanced economies, potentially prompting protectionist responses such as services trade restrictions or data localization requirements. As a result, such measures risk fragmenting digital trade and limiting the inclusive growth potential of AI in developing economies.

If AI primarily boosts the productivity of high-skilled workers, this could reinforce existing inequalities both within and across economies.

AI adoption may contribute to job polarization by displacing routine tasks while increasing demand for high-skilled labour. At the global level, it could widen existing productivity gaps between economies. If effective AI deployment depends on investments and infrastructure that favour incumbent firms and developed economies, then without policies to bridge the digital divide, the technology could reinforce existing patterns of comparative advantage or even favour the reshoring of previously offshored activities, further slowing down trade-led growth.

In practice, both dynamics are likely to unfold simultaneously, with AI generating diverse effects across sectors and worker groups.

The emerging literature on the impact of generative AI suggests that its effects on productivity and inequality depend on the nature of the task and the skill level of the worker. For instance, regional data from the United States show that areas with higher rates of AI adoption have experienced a steeper decline in the employment-to-population ratio over

the past decade. This negative employment effect has been most pronounced in manufacturing and low-skill services sectors, and among middle-skill workers, non-STEM occupations and individuals at the two age distribution extremes (Huang, 2024). Meanwhile, other studies point to the potential of AI to reduce skill gaps in routine and structured tasks. Brynjolfsson et al. (2025) and Noy and Zhang (2023), for example, find that low-skilled workers in fields such as customer support and professional writing experience significant productivity gains when using generative AI tools. Similarly, Peng et al. (2023) show that AI assistance via platforms like GitHub Copilot¹¹ substantially improves the efficiency of less experienced software developers.

The effects of AI are also visible in more complex domains, such as business and innovation. Choi et al. (2023) demonstrate that AI-assisted law students complete tasks faster, but at the cost of reduced quality. Meanwhile, Otis et al. (2024) show that AI business assistance benefits high-performing entrepreneurs using tailored AI solutions more than lower-performing entrepreneurs implementing generic solutions. Roldán-Monés (2024) finds that while AI has an overall insignificant effect on debating skills, it enhances performance among students at the top of the skill distribution. Together, these studies suggest that while AI can help level the playing field for routine tasks, it also has the potential to widen disparities in higher-skilled occupations. In areas requiring complex judgment or creativity, skill-biased productivity effects may prevail, as those with greater expertise are better positioned to extract value from AI-generated outputs.

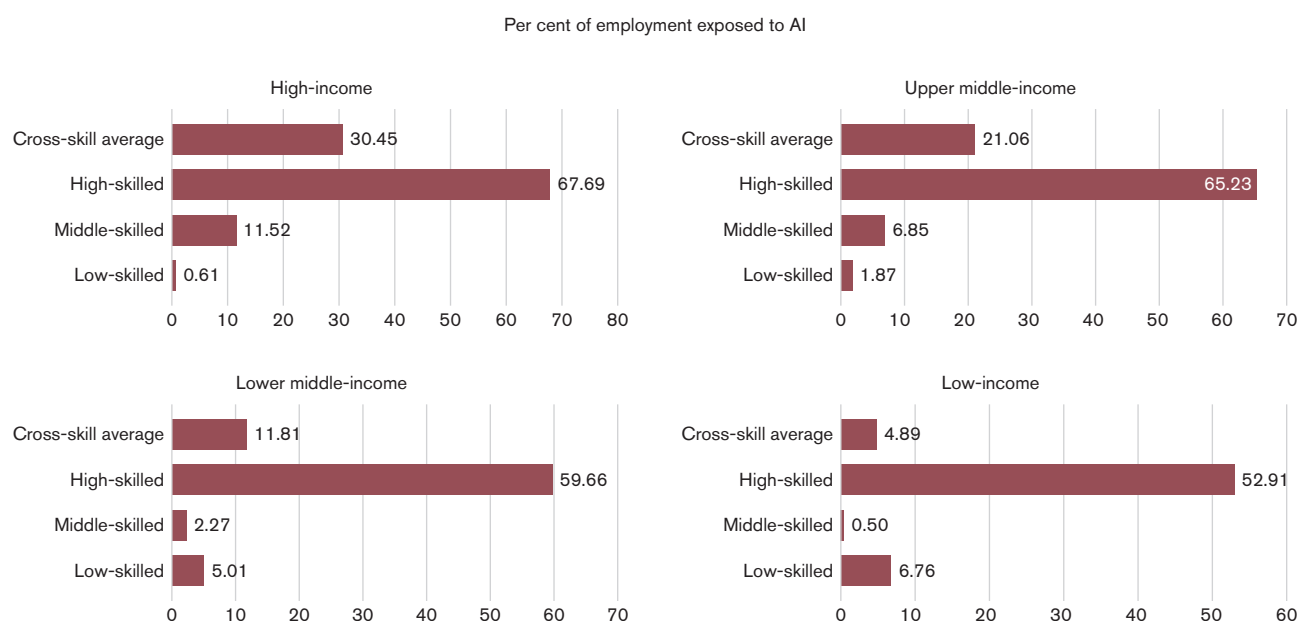
A task-based approach, rather than economy-wide assessment, may thus provide a more accurate understanding of how AI reshapes the nature of work across different industries. According to the AI Occupational Exposure Index developed by Felten et al. (2021), broadly defined managerial and professional roles are most closely aligned with AI capabilities, while occupations performing manual work face the lowest exposure. This approach evaluates the potential impact of AI on jobs by measuring the overlap between AI applications and the skills required in specific occupations. Autor and Thompson (2025) argue that automation may replace experts in some occupations while augmenting expertise in others. Automation that decreases expertise requirements reduces wages but permits the entry of less expert workers;

automation that raises requirements raises wages but reduces the set of qualified workers.

Globally, the potential for labour market disruption due to the onset of AI technologies tends to be mitigated by the fact that relatively more workers are employed in the less exposed occupations. To measure this, “highly exposed occupations” have been defined as those in the top 30 per cent of the AI exposure index. Using this definition, only 17.1 per cent of global employment falls into the high-exposure category. However, exposure varies across income levels. High-income economies, which tend to specialize in more skilled jobs, have a greater share of workers in highly exposed occupations, with around 30 per cent of jobs falling into this category. In contrast, in low-income economies, where employment tends to be concentrated in medium-skilled and low-skilled work, only 5 per cent of jobs are classified as highly exposed (see Figure B.8). Income levels also influence exposure within similar skill groups. Among high-skilled and middle-skilled workers, employment is more concentrated in high-exposure jobs in higher-income economies: 68 per cent of high-skilled workers in high-income economies are in occupations highly exposed to AI, compared to 53 per cent in low-income economies. For example, financial and insurance services occupations, which are both highly AI-exposed and highly skilled, make up a larger share of employment in high-income economies.

To assess the balance of the likelihood that AI will complement workers and the risk that it will replace them, AI exposure was decomposed into two components: exposure through an occupation’s core tasks and through its supplementary tasks.¹² Following the intuition proposed in Auer et al. (2025) and Autor and Thompson (2025), this approach assumes that automation of core tasks poses a greater risk to occupations, whereas automation of supplementary tasks is more likely to complement workers by allowing them to specialize further in their primary functions. Figure B.9 indicates that the introduction of AI technologies may be particularly disruptive for high-skilled workers, whose exposure largely stems from the automation of core tasks.

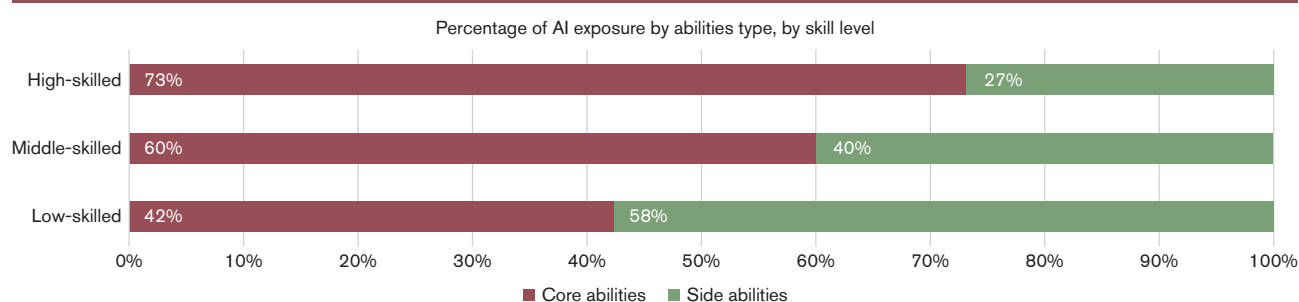
WTO simulations show that the skill premium – i.e., the ratio of wages of high-skilled workers relative to low-skilled workers – is expected to fall moderately as a result of the shift in tasks due to AI. Figure B.10 presents the projected

Figure B.8: A greater share of employment (%) is exposed to advanced AI in high-income economies

Source: WTO Secretariat calculations based on AI exposure measure based on Felten et al. (2021) and global employment data for 118 countries using ILO Harmonized Microdata.

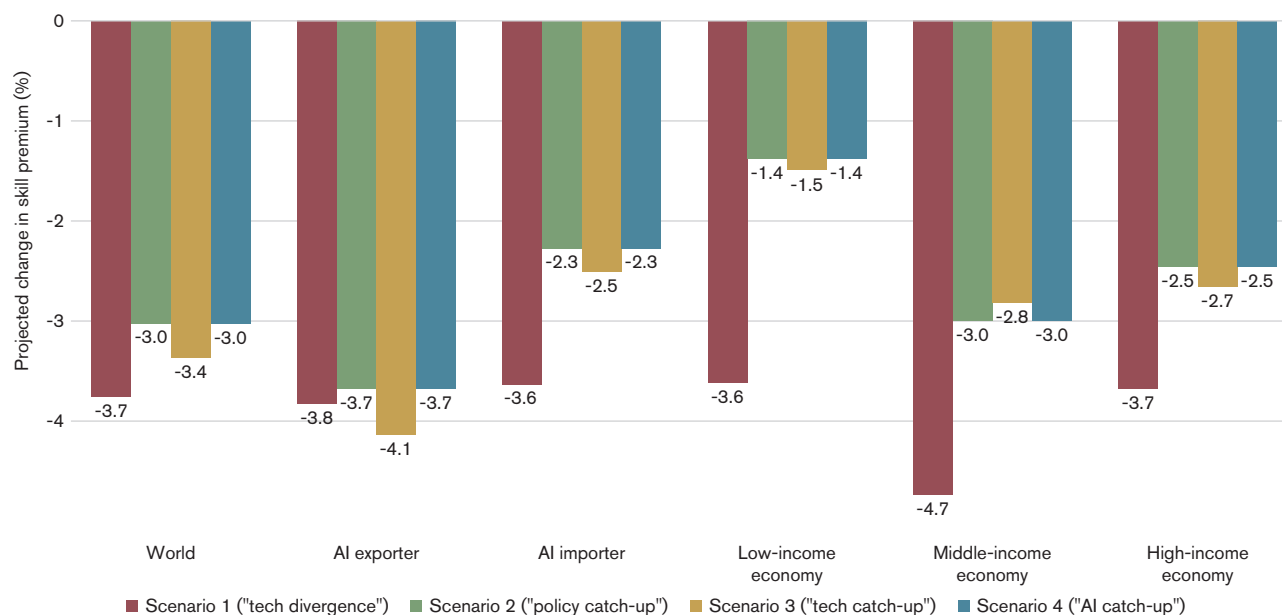
percentage change in the difference between wages of high-skilled and low-skilled workers. Globally, while the real wages of all labour groups are expected to rise, the skill premium is projected to fall by between 3 per cent and 3.7 per cent. The reason for this projection is that the shift in tasks from labour towards AI is much stronger for high-skilled and medium-skilled workers than for low-skilled workers. As a result, the demand for high-skilled and medium-skilled workers falls relative to low-skilled workers. Nevertheless, the real incomes of all workers (the nominal wage relative to the price level) is projected to increase moderately (not displayed in the figure).

Two main forces shape the impact of AI on employment across skill groups. On the one hand, higher productivity raises output and, in turn, increases demand for human labour. On the other hand, some tasks previously performed by human labour are expected to be automated, which reduces the demand for human labour. This effect of AI substituting for labour is expected to place downward pressure on the employment and wages of medium-skilled and high-skilled workers. Nonetheless, the share of tasks replaced remains relatively modest – about 3 per cent for low-skilled workers, and 7 to 9 per cent for medium-skilled and high-skilled workers.

Figure B.9: High-skilled workers face greater disruption from AI due to automation of core tasks

Source: WTO Secretariat calculations based on Felten et al. (2021) and O*NET (<https://www.onetonline.org/>) data.

Figure B.10: AI is projected to reduce the skill premium moderately (2025-40)



Source: Simulations using the WTO Global Trade Model.

Notes: The figure displays the change in the skill premium, i.e., the ratio of wages of high-skilled workers relative to low-skilled workers, for four scenarios in deviation from the baseline, both globally and for aggregate regions, split by level of development and between AI exporters and importers. See Section B.1(a)(iii) for the four projected scenarios capturing different degrees of policy and technological catch-up.

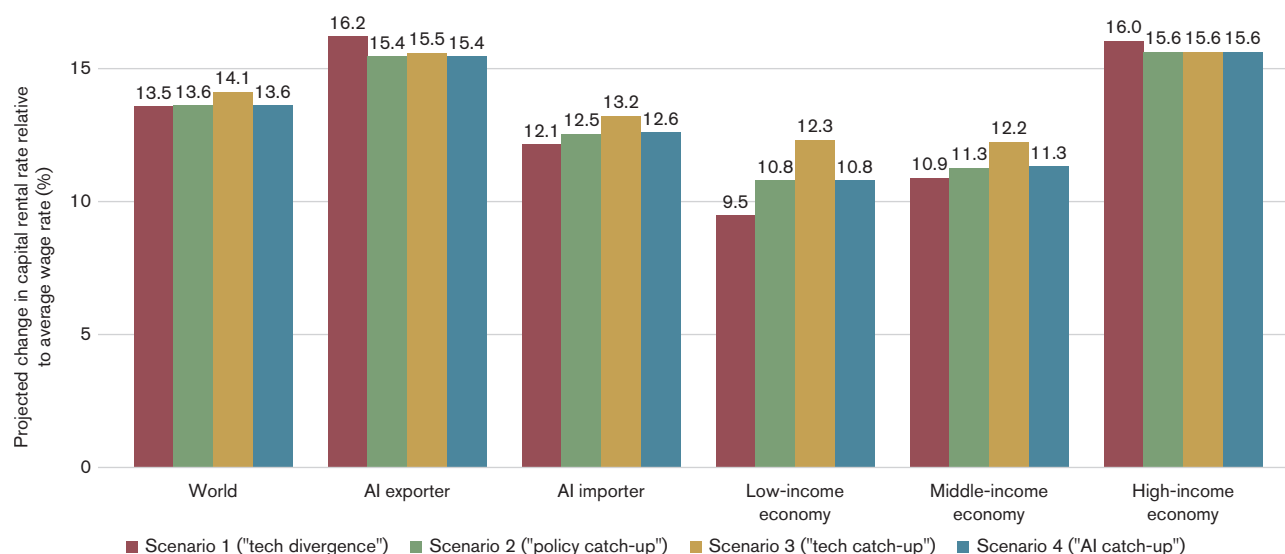
Overall, employment is projected to increase, although the gains are lowest for high-skilled workers, who are most affected by AI automation. Specifically, low-skilled employment is projected to rise by 3 to 4 per cent, compared with a 1 to 2 per cent increase for medium-skilled and high-skilled employment. The variation in employment gains reflects the reallocation of tasks across skill groups. However, the result is sensitive to the assumptions used in the model. If the AI services sector were to expand beyond the assumptions underlying the four scenarios presented, the effects of AI substituting for labour would dominate for medium-skilled and high-skilled workers, leading to a decline in both their employment and their real wages.¹³

At the same time, the rental rate – the cost for a firm of using capital inputs – is projected to rise more than the average wage rate. Figure B.11 displays the projected change in the difference between the rental rate on capital and the average wage rate. The rental rate is projected to rise globally by about 14 per cent relative to the average wage rate. This reflects several factors. AI services, produced with both capital and labour, increasingly substitute for labour. This raises the demand for capital and, as a result, the rental rate on capital will inevitably increase. Put differently, value-added previously generated by

labour is being replaced with value-added generated with a combination of capital and labour. Furthermore, the production of AI services is relatively capital-intensive. Hence, the large expansion of AI services increases the demand for capital relative to labour, driving up the rental rate. It is important to note that the model used is a recursive dynamic model, meaning it is solved sequentially for each period, with a fixed savings rate. Alternative modelling approaches could yield different capital rental rates.¹⁴

The effects of AI on the skill premium and the difference in the rental and wage rates also vary by scenarios and by region. Figure B.11 shows that, across all scenarios, the increase in the difference between the rental rate and wage rates is largest in high-income countries and smallest in low-income economies. The increased difference is also larger for AI exporters than for AI importers, which reflects that the increased demand for capital-intensive AI services plays a quantitatively meaningful role in the projected rise in the relative remuneration of high-skilled workers. Middle-income economies are projected to see the largest fall in the skill premium. The fall in the skill premium is also projected to be more pronounced in the tech divergence between economies scenario (Scenario 1).

Figure B.11: AI is projected to raise the rental rate relative to the average wage rate (2025-40)



Source: Simulations with the WTO Global Trade Model.

Notes: The figure displays the projected percentage change in the rental rate minus the projected percentage change in the wage rate for four scenarios in deviation from the baseline, both globally and for aggregate regions, split by level of development and between AI exporters and importers. See Section B.1(a)(iii) for the four projected scenarios capturing different degrees of policy and technological catch-up.

Incentives for agglomeration and/or offshoring

Economic activity tends to cluster in specific locations due to agglomeration effects, where firms and workers benefit from proximity.

By locating in dense industry and population centres, firms benefit from a larger pool of workers, specialized skills and intermediate inputs that can raise their output, reinforcing economies of scale (Krugman, 1991). Moreover, due to the exchange of ideas between firms or workers, knowledge spillovers contribute to productivity gains. Trade further reinforces these effects by reallocating market share toward more productive firms, which are often concentrated in urban hubs (Bakker et al., 2024).

Digitalization has amplified agglomeration dynamics. Advances in information technologies (IT) have disproportionately benefited large firms, which are typically more IT-intensive. As IT prices decline, scale economies increase, reinforcing the advantage of firms located in large cities (Lashkari, Bauer and Boussard, 2024). This is partly because large firms adopt IT to manage complex production processes more efficiently, improve organizational coordination and invest in digital innovation. These effects are most visible in IT-intensive business services, where growth has been concentrated in major urban centres, further attracting skilled workers and generating productivity-enhancing knowledge

spillovers (Eckert, Ganapati and Walsh, 2022; Davis and Dingel, 2019).

Early evidence suggests that AI exhibits similar spatial patterns of agglomeration dynamics.

AI adoption has so far been led by large firms – particularly those with more than 5,000 employees – and is concentrated in highly productive metropolitan areas and innovation hubs, including start-up clusters (Copestake et al., 2023; McElheran et al., 2024). Because AI delivers significant productivity gains to early adopters and relies on specialized skills and data infrastructure, its deployment is likely to deepen the attractiveness of already productive regions and firms, reinforcing agglomeration patterns similar to those observed with earlier waves of IT and automation (Lashkari, Bauer and Boussard, 2024; Stapleton and Webb, 2020).

These trends may contribute to widening inequalities within economies. Large, technology-intensive firms active in tradable services tend to pay higher wages, attracting skilled workers to cities and generating knowledge spillovers that further enhance urban productivity (Davis and Dingel, 2019; Eckert, Ganapati and Walsh, 2022). The result is a concentration of high-wage, AI-enabled jobs in urban hubs, increasing wage premiums and widening gaps between dynamic cities and less urbanized regions.

Agglomeration effects are also likely to play out globally. Without widespread investment in digital infrastructure and AI capabilities, technologically advanced economies are likely to consolidate their lead, as seen in the software industry, where productivity gaps between developed and developing economies exceed those in manufacturing (Birkholz and Gomtsyan, 2024). Skilled labour mobility, particularly the migration of software engineers to AI-intensive hubs, could further reinforce global concentration.

However, AI does not necessarily substitute for international production links. On the contrary, firms that adopt AI are more likely to engage in offshoring, as AI enables remote monitoring and coordination of geographically dispersed operations, reducing the complexity and cost of managing foreign subsidiaries and suppliers (Kinkel et al., 2023), suggesting that, like earlier information and communication technologies (ICT), AI may facilitate geographic expansion and trade, rather than purely domestic reshoring.

Market power of large digital firms

The impact of AI on income distribution also depends on how much economic income is captured by large digital firms. Economies of scale and winner-takes-all dynamics in the digital economy allow these firms to capture significant global market shares. This raises concerns about their excessive profits, decreased wage rates for workers and reduced innovation, potentially hindering broader societal progress.

The roots of this market power lie in the nature of the digital economy itself. Large firms earn disproportionate benefits from intangible investments because their (high) fixed costs can be spread over more customers. They can also leverage more data and bigger brands, and integrate these more effectively across vast operations, all of which can lead to more sales growth per US dollar invested than a small firm could achieve (Bajgar, Criscuolo and Timmis, 2021). As a result, firms in digital-intensive sectors are, on average, larger and charge markups 2 to 3 percentage points higher than firms in other sectors (Calligaris, Criscuolo and Marcolin, 2018). AI could reinforce this trend because its adoption often requires access to vast data resources and costly model development, potentially creating barriers for smaller firms.

If these dynamics persist, AI could accelerate existing trends toward greater market concentration and declining business dynamism. Large firms already enjoy advantages in terms of digital infrastructure, proprietary data and intangible capital, which strengthen their ability to adopt AI and maintain their market dominance. “Winner-takes-most” incentives encourage firms to invest heavily in intangible assets, rewarding early leaders. There are concerns that these firms may use their scale not only to innovate, but also to limit technology diffusion and protect their dominant positions (Autor et al., 2020).

The ultimate effect of AI on competition in digital markets remains uncertain. Historically, market profits in many economies have been driven upward by a handful of large digital-intensive firms, reinforced by high upfront investment costs, proprietary knowledge and the near-zero marginal cost of replicating digital products (Calligaris, Criscuolo and Marcolin, 2018). However, this dominance is not guaranteed to persist. Smaller firms and start-ups may be able to experiment, scale and compete in areas once reserved for established technology giants. For example, the recent breakthrough by DeepSeek,¹⁵ a relatively new entrant in AI model development, illustrates how innovation can shift competitive dynamics. By leveraging open-source technologies and focusing on cost-efficient model training, DeepSeek was able to deliver performance levels comparable to leading proprietary models at a fraction of the cost.

Risks associated with AI

Beyond distributional challenges, the rapid evolution of AI introduces additional, potentially severe risks. These include malicious uses, such as scams, deepfakes, disinformation campaigns, and cyber or biosecurity threats; risks arising from malfunction, such as unsafe products, biased decision-making, or opacity to human supervision; and broader systemic risks linked to labour markets, data privacy and environmental impacts (see Box B.3). A growing segment of the AI research community also warns of more extreme scenarios, including existential risks to humanity, either from the deliberate misuse of AI by malicious actors or from the possible emergence of superintelligent AI systems that operate beyond human control (United Nations, 2025). Some scholars have argued that, if they are trained in the same way as the current most capable models, artificial

Box B.3: AI and environmental sustainability: opportunities and challenges

AI holds significant promise for advancing global sustainability goals, including climate change mitigation (Stern et al., 2025). At the same time, the potential adverse environmental impacts of AI are raising concerns.

AI applications are already reshaping key environmental sectors. In agriculture, AI tools support precision farming by optimizing water and fertilizer use, forecasting crop yields and reducing food loss during transport and storage. Energy systems are benefitting from AI-enhanced forecasting and grid management, and this is improving the integration of intermittent renewable energy sources (i.e., sources of renewable energy that do not produce a consistent, continuous output because their generation depends on natural conditions that fluctuate over time) and limiting reliance on fossil fuels. Meanwhile, heavy industries, such as steel and cement, are using AI to monitor processes, cut energy use and anticipate maintenance needs, helping to decarbonize traditionally high-carbon-emitting, hard-to-abate sectors. AI is also supporting emissions measurement and disclosure, improving the accuracy and timeliness of carbon accounting, a critical element of climate policy and corporate net-zero commitments.

However, these benefits are complex, as AI development and deployment rely on energy-intensive data centres, large datasets and high-performance computing infrastructure, all of which also have significant carbon footprints. Training generative AI models demands vast computational power, resulting in high electricity consumption and pressure on power grids. These energy requirements persist after the initial training of AI models, as models are continually fine-tuned and updated. The rapid growth of generative AI applications has also increased demand for advanced computing hardware, adding further environmental costs from production and transportation. In 2022, data centres, cryptocurrencies and AI altogether consumed almost 2 per cent of global electricity production – a figure projected to double by 2026 (IEA, 2025).

Governments and international organizations are beginning to address these spillovers. However, ensuring that AI contributes positively to sustainability goals without exacerbating environmental pressures or inequality will require complementary policies, including transparent reporting, resource-efficient AI design, and investments in skills and infrastructure (see Chapter D for a discussion on international initiatives).

general intelligence models (AGIs) could learn to act deceptively in order to receive higher rewards (see Annex B on reinforcement learning), or could learn to pursue goals that are in conflict with human interests (Ngo, Chan and Mindermann, 2025). Risks stemming from this learned behaviour, which include threats to human life from nuclear weapons, biohazards or other frontier scientific developments, echo debates surrounding other high-risk scientific developments, such as nuclear technology and biotechnology (Jones, 2024).

AI-enabled products also raise both material and immaterial risks. However, material risks caused by AI-enabled products, such as physical injury or damage, are often easier to quantify, whereas immaterial risks – such as infringements of privacy or of other fundamental rights – are more difficult to measure (WTO, 2024a). These risks highlight the regulatory challenges of applying one-size-fits-all product specifications to AI-enabled goods that are often highly customized (Lund et al.,

2023). Addressing these challenges may require more adaptive regulatory approaches that can evolve alongside AI technologies, ensuring that both material and immaterial safety and fundamental rights are protected, while supporting the deployment of and trade in trustworthy AI-enabled products.

These concerns underscore the difficult trade-offs between the economic benefits of frontier technologies – i.e., advanced technologies with potentially global applications – and their potential societal costs. To address these concerns, the UN High-level Advisory Body on Artificial Intelligence¹⁶ has proposed a comprehensive plan that integrates technical research and development with proactive, adaptive governance mechanisms. Drawing lessons from other critical technologies, this approach integrates progress in AI safety research with robust oversight mechanisms to ensure that AI development remains aligned with societal values and safety standards (Bengio et al., 2024).

2. Trade can play a crucial role in making AI more inclusive

Trade is a vital mechanism enabling economies both to provide and to access the inputs needed to develop and adopt AI systems across various stages of the AI value chain. The AI value chain comprises interconnected segments that shape how AI technologies are developed, produced and deployed. Trade facilitates the exchange of intermediate goods and services essential for AI systems and supports cross-border technology transfer. However, the concentration of various stages of AI supply chains raises concerns about equity and access, and about the risk of an AI divide in economies' levels of technological development. At the same time, this highlights the need for international trade to facilitate the access and dissemination of AI technologies. Different segments of the AI value chain offer significant opportunities for specialization and supply chain diversification, particularly for developing and emerging economies seeking deeper integration into the global digital economy.

The key components of the AI supply chain include raw materials, computing hardware, cloud infrastructure, training data, foundation models and user-facing AI applications. As illustrated in Figure B.12, each of these segments is enabled and amplified by the cross-border movement of physical components, data flows or digital services

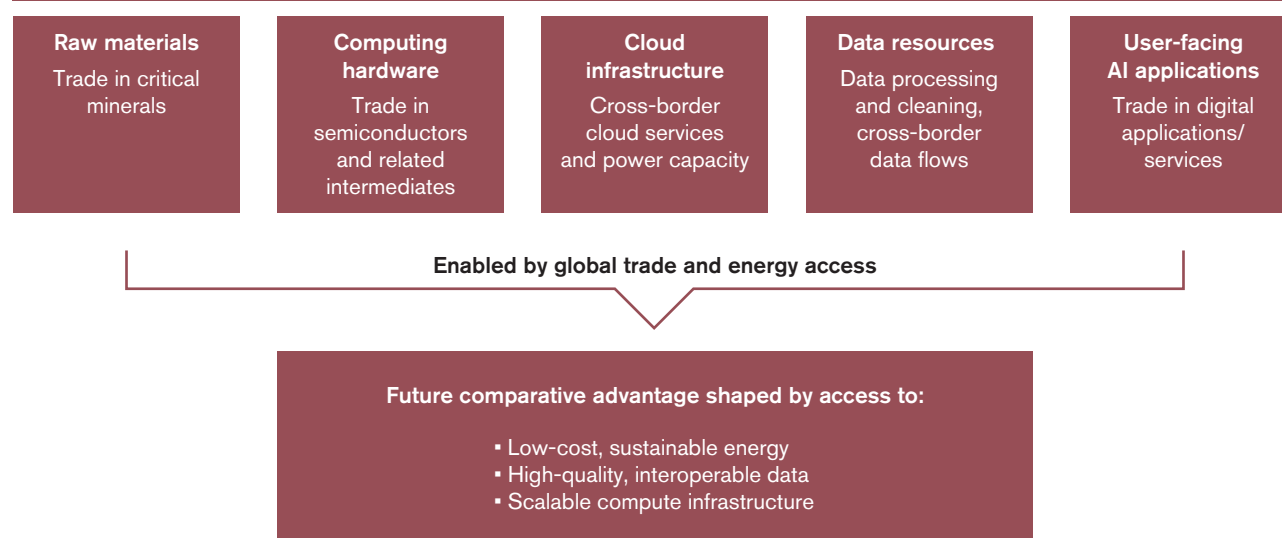
and underpinned by intellectual property (IP) and other trade-related policies. As the development and adoption of AI is energy-intensive, comparative advantages in energy could also contribute to shaping economies' positions in the AI economy and determine which economies draw benefits from the transformation of global digital value chains.

At the same time, trade can influence within-economy inequality through several channels. Greater openness often induces agglomeration (see above), as industries cluster in regions with comparative advantages or strong infrastructure, concentrating high-productivity jobs and income in specific locations. By expanding markets, trade tends to benefit more productive firms that can scale up and compete internationally, while less productive firms may contract or exit, potentially leading to job losses in certain sectors or regions.

(a) Trade facilitates AI development by enabling access to key inputs

International trade plays a critical role in enabling AI development by allowing economies to access essential technologies and services wherever they are produced. Much of the AI research, foundation model development and capital-intensive enabling services, such as cloud computing and data storage, are primarily located in China, a few EU economies and the United States. The production of key AI-enabling goods, including advanced hardware

Figure B.12: Trade plays an important role in different segments of the AI value chain



Source: WTO Secretariat elaboration.

components, is concentrated in a small number of firms. For most economies, trade in both goods and services is therefore indispensable to access these technologies and adapt them to regional needs.

(i) *AI-enabling raw materials and equipment*

AI-enabling goods can be grouped into three broad categories: raw materials and processed chemicals; intermediate inputs; and equipment.

Raw materials and processed chemicals include critical substances such as silicon dioxide, germanium oxides, zirconium dioxide, and silicon carbides, which are fundamental for semiconductor fabrication. Intermediate inputs refer to processed or partially manufactured goods used in producing semiconductors. Equipment covers the specialized tools and machines essential for AI development and deployment, including computers, semiconductors and related machinery. The list of products and their Harmonized System (HS) codes is provided in Annex A.1.

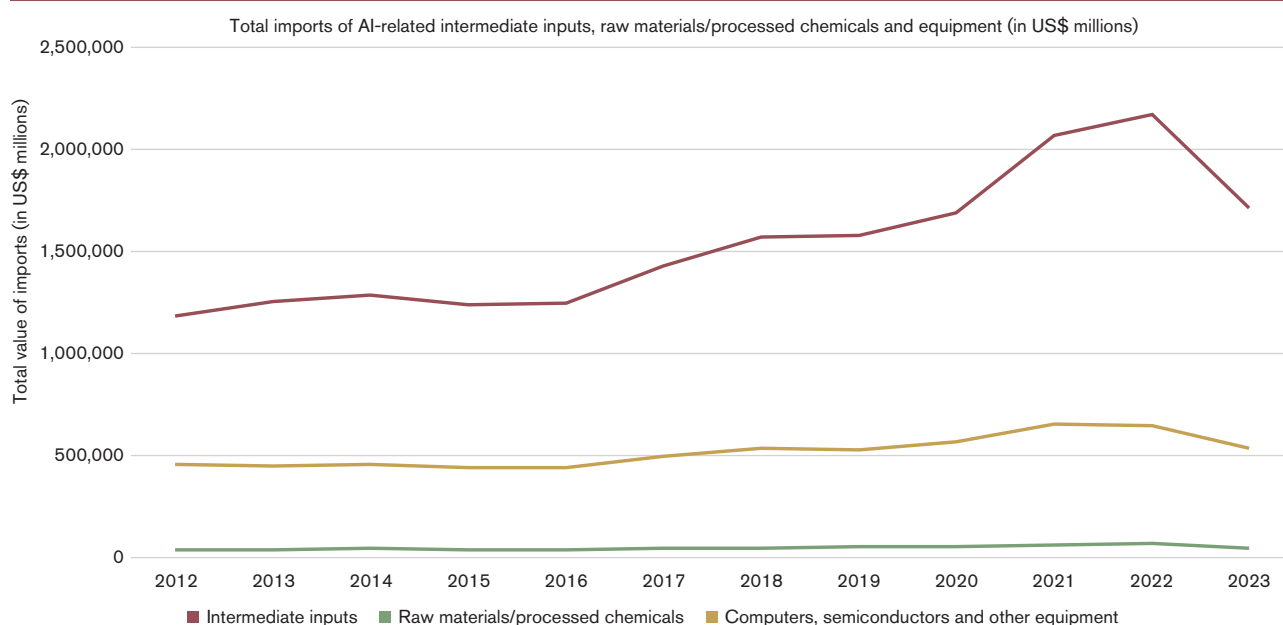
Currently, key AI hardware production and raw mineral inputs are concentrated in just a few firms and economies. For example, the small number of firms producing key AI hardware collectively control over 80 per cent of the global

AI chip market (Sastry et al., 2024). The extraction and processing of critical raw materials such as gallium, germanium and rare earths elements, which are essential for high-performance semiconductors and AI accelerators, are also heavily concentrated in a handful of economies. Such geographic imbalances raise concerns about equitable access to, and diffusion of, AI technologies (Gambacorta and Shreeti, 2025; Sastry et al., 2024), as economies that do not produce essential raw materials, intermediate inputs or specialized equipment must rely on cross-border trade to access these products.

Trade data reveal distinct patterns in the global trade of AI-enabling raw materials, intermediate inputs and equipment. As illustrated in

Figure B.13, global trade in AI-enabling goods totalled US\$ 2.9 trillion in 2022 and US\$ 2.3 trillion in 2023. Imports of AI-related goods have grown sharply since 2012, driven mainly by intermediate inputs, which accounted for the largest share and grew most rapidly between 2017 and 2022 before falling in 2023. This decline may reflect trade restrictions, regulatory changes, shifts in export capacity or earlier strategic stockpiling. Imports of computers, semiconductors and other AI-enabling equipment also increased steadily, though their share remained smaller, while

Figure B.13: Import value of AI-enabling goods has grown sharply in recent decades



Source: WTO Analytical Database.

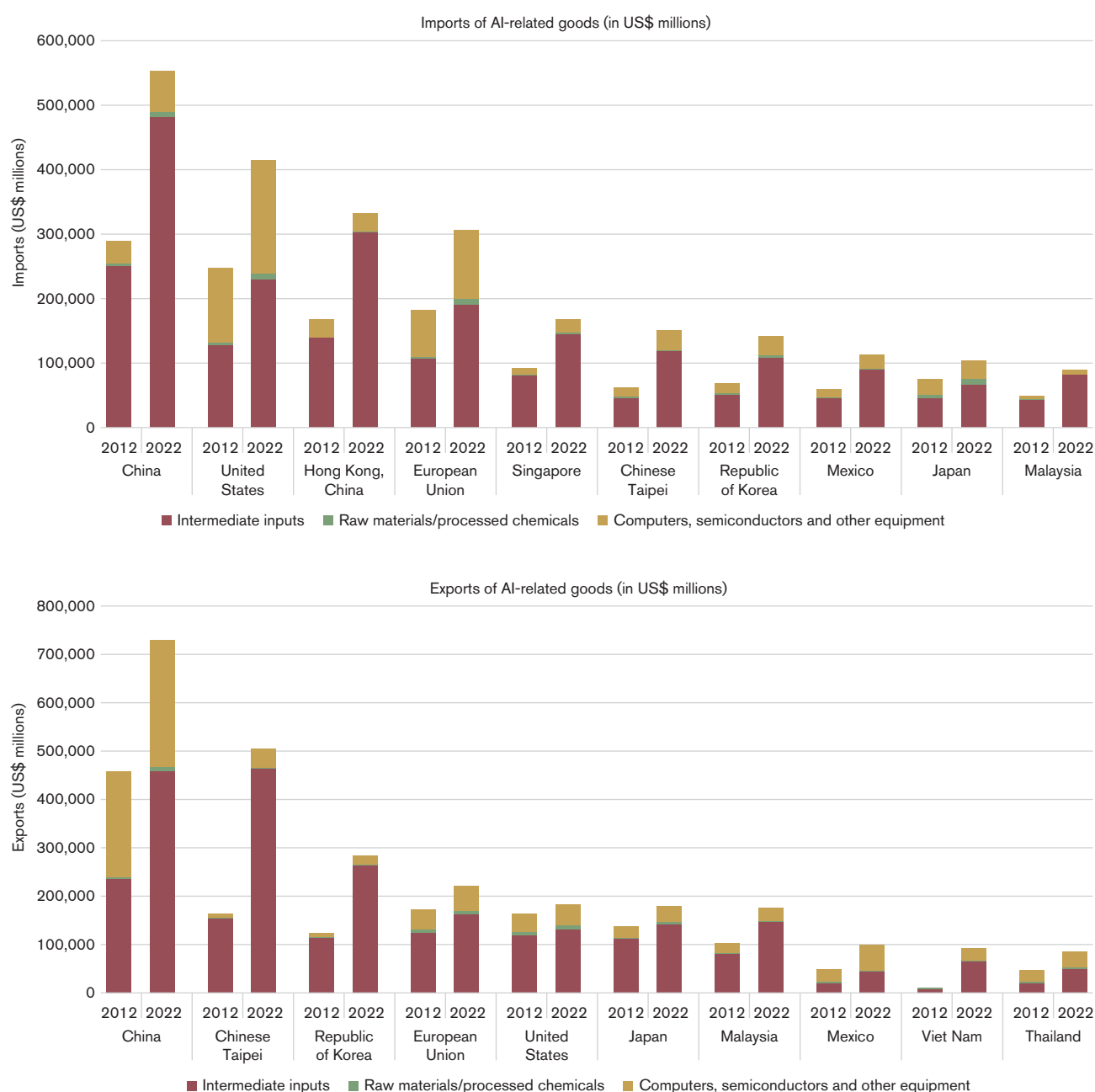
Note: The product categories shown are based on a non-exhaustive list of HS codes, and may include items not exclusively used in the AI value chain. The classification reflects indicative groupings of goods that enable AI development and deployment. The list of AI-enabling goods is compiled by the WTO Secretariat and provided in Annex A.1.

imports of raw materials and processed chemicals were relatively stable, underscoring their limited but strategic role in the AI value chain.

Rising imports of intermediate inputs highlight growing demand for high-performance AI infrastructure. China and the United States are the largest importers of AI-enabling goods. Several East

Asian and Southeast Asian economies, including Singapore, Chinese Taipei, the Republic of Korea, Japan and Malaysia, also recorded rising imports of AI-related goods, reflecting deeper integration into global AI production networks (see Figure B.14). Export activity is also concentrated in East Asia, led by China, Chinese Taipei and the Republic of Korea, particularly in intermediate inputs and equipment.

Figure B.14: Top importers and exporters of AI-enabling goods



Source: WTO Secretariat calculation based on the WTO Analytical Database.

Note: The list of AI-enabling goods is compiled by the WTO Secretariat and provided in Annex A.1.

While the European Union, the United States and Japan remain major exporters of AI-enabling intermediate inputs and equipment, growth of these exports has been more modest. Emerging manufacturing hubs such as Malaysia, Mexico, Viet Nam and Thailand have also increased exports of AI-related intermediate inputs and equipment.

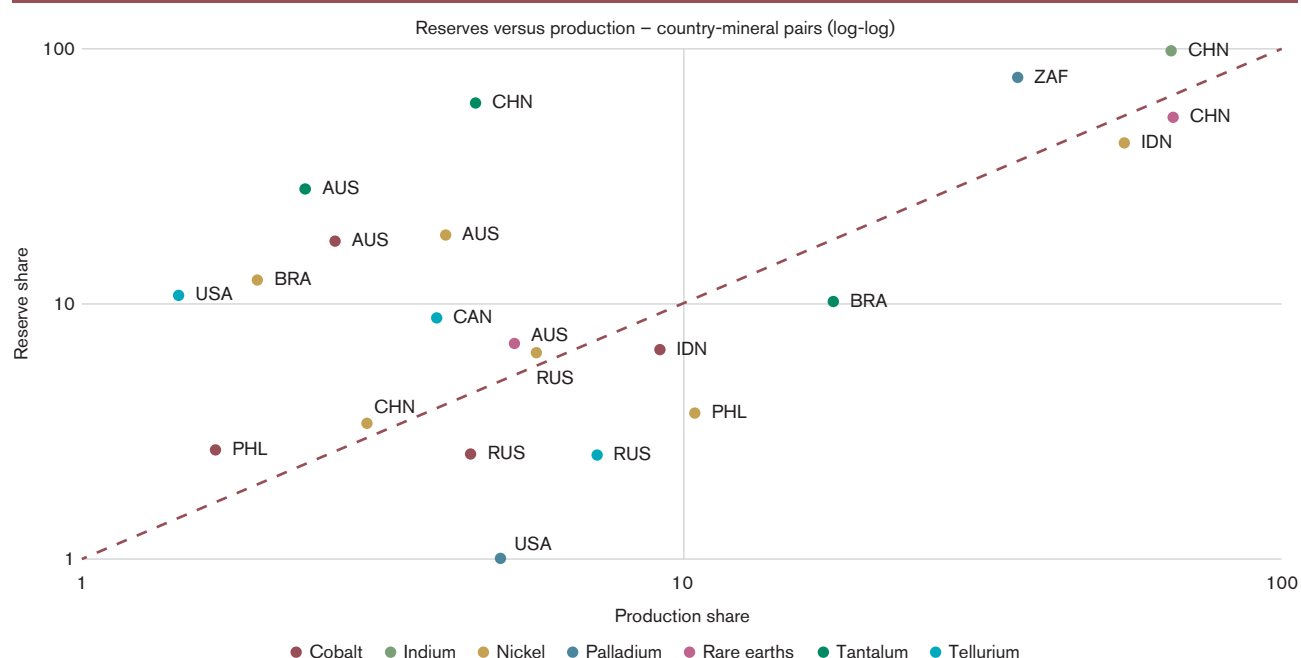
Many mineral-rich economies have yet to fully capitalize on their resource endowments, as production levels often fall short of known reserves (see Figure B.15). This under-utilization limits the value captured domestically and risks creating supply bottlenecks for critical minerals. It also underscores the challenge of resource-rich developing economies in moving up the AI value chain. Resource-abundant economies could improve their position in AI value chains by engaging in related higher-value activities. Such upgrading requires significant investment, coordinated industrial policies and long-term capability development. Research shows that investment in processing and refining, regional trade facilitation and stronger linkages to upstream and downstream activities in the AI value chain can help

retain more value domestically (UNCTAD, 2019; Morris, Kaplinsky and Kaplan, 2011; WTO, 2010).

The manufacturing and trade of ICT hardware is a critical component of inclusive AI development. ICT hardware, including semiconductors, computing equipment and related intermediate inputs, forms the backbone of AI infrastructure. As AI adoption expands, demand for these components is expected to grow significantly, driving investment and reshaping global supply chains. Yet semiconductor manufacturing remains highly concentrated due to high capital requirements, skill intensity and complex supply chain interdependencies.

Historically, ICT manufacturing has followed a pattern of supply chain diversification, allowing different economies to participate at different production stages and gradually upgrade technologically (Coveri and Zanfei, 2023). While a few economies dominate cutting-edge AI hardware, broader production of AI-enabling goods has the potential to become more geographically diverse. This creates opportunities for new entrants, including

Figure B.15: Share of global production and reserves of AI-related minerals



Source: Production data are from World Mining Data 2025;¹⁷ mineral reserve data are from the US Geological Survey (USGS) Mineral Commodity Summaries 2024.¹⁸

Notes: The figure shows the relative share of production by economy and mineral in 2023. Dots above the 45-degree line represent economy-mineral pairs, where the current production share exceeds the share of known reserves, while dots below the line indicate production shares lower than the corresponding reserve shares. Reserves refer to confirmed discoveries. Percentages are presented on a logarithmic scale to improve readability.

low-income and middle-income economies, to participate in mid-stream chip production and benefit from AI-driven demand. Supply chain diversification and specialization, supported by international trade, can help disseminate AI knowledge and innovations across borders (Kowalski et al., 2015). However, the literature has also shown that this can be either constrained or encouraged by several factors, including the importer-exporter status of firms and the income level of export partners (Rigo, 2021).

Competition to attract semiconductor investment is intensifying. While the United States and the European Union have announced substantial funding to boost domestic manufacturing and expand their share of global chip production (Burkacky et al., 2024), emerging economies are also entering the semiconductor race. Viet Nam, for example, has announced fiscal incentives and is pursuing strategic partnerships with major global firms to expand its AI and semiconductor manufacturing capacity (Lam, 2024; Hanoi Times, 2025). Several African economies, including Ghana, Kenya, Nigeria and Rwanda, are positioning themselves as future hubs, leveraging reserves of critical minerals and a growing digital workforce (Clynch, 2024). Although investment remains concentrated in high-income economies, low-income and middle-income economies may increasingly begin to participate in assembly and testing, drawing on cost advantages, infrastructure and proximity to key markets (Torsekari and VerWey, 2019). These shifts underscore broader trends in the global semiconductor value chain, including growing trade dependencies and the geographical concentration of critical segments (OECD, 2025b).

(ii) AI data centres and energy demand

The rapid expansion of AI applications is driving a sharp increase in global energy demand. AI data centres consume significantly more electricity than conventional cloud computing due to their intensive computational requirements, particularly for model training and inference. Currently, server computing accounts for about 40 per cent of data centre electricity use, cooling systems for another 40 per cent, and storage and other IT equipment for the remaining 20 per cent. The International Energy Agency (IEA) projects that data centre energy demand will rise by 25–55 per cent by 2026 (IEA, 2025), while Goldman Sachs forecasts a 160 per cent increase in global data centre power demand by 2030 (Goldman Sachs, 2024).

The location of data centres is determined primarily by three factors: cost, proximity to users and reliable energy access (Greenstein and Fang, 2022). Building a new data centre typically takes over a year and costs more than US\$ 100 million for a 5 MW facility, with hyperscale sites (i.e., sites designed to support massive computing and data storage needs) reaching a cost of several billion US dollars (Hidalgo, 2025). Labour, land and advanced equipment raise costs, while operations are dominated by electricity use for servers and cooling. Proximity to users reduces latency and ensures faster response times, motivating suppliers to build near major customer bases and high-speed data lines to avoid network congestion. Equally critical is uninterrupted and affordable energy access, given the exceptionally high-power requirements of AI infrastructure. There are important trade-offs between geographic dispersion, which boosts resilience and market access, and concentration in large facilities, which increases efficiency and scale.

Many large-scale data centres are currently concentrated in major economic hubs, serving as key nodes in the global trade of digital services. The capacity of these data centres to host AI model training and deployment makes them critical for exporting and importing cloud-based AI services, software and platforms. Consequently, their location, capacity and connectivity largely determine which economies can participate in, and benefit from, the global AI economy (see Figure B.16). Regional disparities are pronounced. China, the European Union and the United States host most data centres capable of training and deploying AI models, while Africa, parts of Central Asia, and Latin America have little or no comparable infrastructure.

Investment in renewable power infrastructure to meet AI's growing energy needs remains important. Economies with abundant renewable energy and digital connectivity can gain a trade advantage in the AI value chain by hosting data centres that serve regional or global markets. Developing economies in sun-rich regions are well positioned to host data centres powered by solar energy. However, natural resource endowments alone are not enough to attract AI-related investment if the infrastructure is lacking. Africa, for example, holds 60 per cent of global solar potential but produces only 1 per cent of global solar power. Without substantial investment in grid expansion, energy storage and high-speed broadband, resource-rich economies may struggle to turn their

renewable energy potential into a comparative advantage for AI and digitally deliverable services (see Section C.2 on supportive infrastructure and energy policies). Supportive policies on investment, data regulation and cross-border data flows are also essential. For example, Box B.4 offers a case study examining the economic and growth opportunities created by data centres in Kenya.

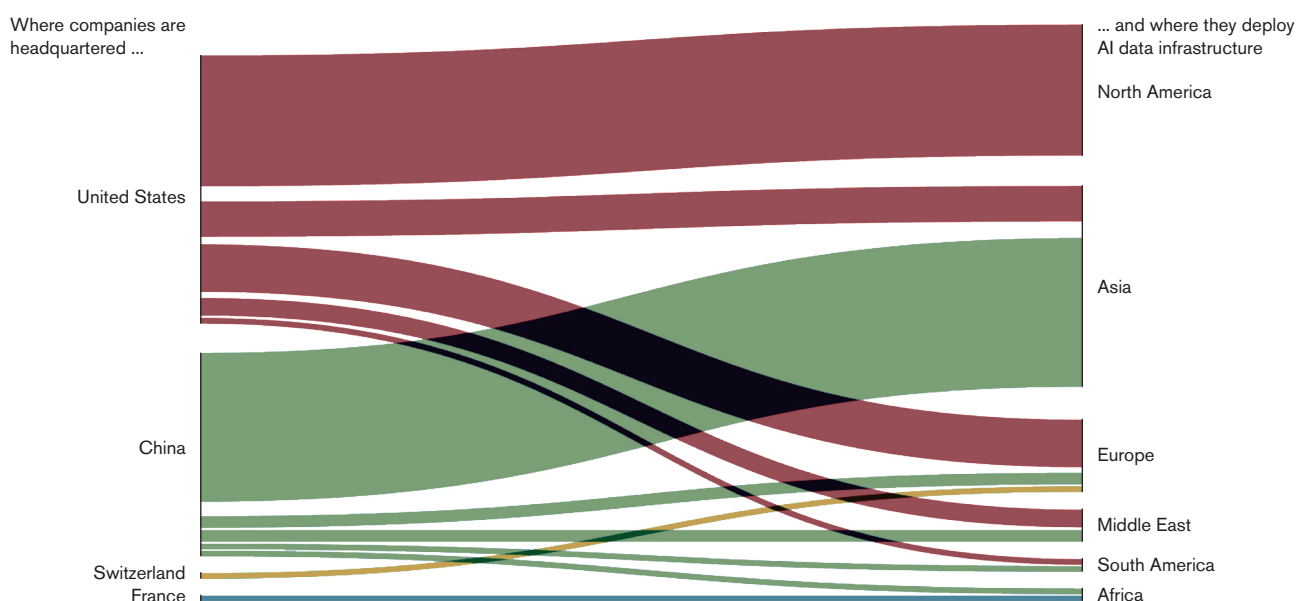
Globally, cloud infrastructure and AI-focused data centres are seeing unprecedented investment. Global spending on AI data centres was projected to reach US\$ 400 billion in 2024 (Fung, 2024), with US hyperscalers Microsoft, Meta, Alphabet and Amazon accounting for half of that spending (Flaherty, 2024). There are currently around 11,000 data centres worldwide (Minnix, 2023), and AI workloads already consume 20–25 per cent of total capacity (Loten, 2023). Rising AI computing demand is prompting governments and firms to invest in semiconductor fabrication plants, energy-efficient data centres and advanced networking, laying the groundwork for a more diversified AI infrastructure landscape.

(iii) Training data in the AI supply chain

AI training data can be considered to be an intangible asset because these data

enhance model performance and enable the development of new AI-driven products and services. These datasets, including text, audio, images and videos, shape how AI models learn and perform across tasks. Much of this content includes copyright-protected materials, and economic benefits earned from their use for rights-holders are dependent partly on copyright frameworks, which vary from one jurisdiction to another. What is clear is that data and data licensing are gaining economic importance with the rise of AI. According to the *World Intangible Investment Highlights 2025* (WIPO and LBS, 2025), software and databases were the fastest-growing category of intangible assets between 2013 and 2022, expanding by over 7 per cent annually, and with growth accelerating further to over 9 per cent in 2021–22, a spurt that coincided with, and was likely driven by, the AI boom. Within this category, the AI training dataset market alone is expected to grow rapidly, from US\$ 2.92 billion in 2024 to US\$ 3.59 billion in 2025 and to US\$ 17.04 billion by 2032 (Fortune Business Insights, 2025). While North America dominated this market in 2024, the Asia-Pacific Region is projected to have the highest growth rate over the forecast period.

Figure B.16: Global distribution of AI data centres



Source: WTO Secretariat adaption from Lehdonvirta, Wu and Hawkins (2024).

Box B.4: Case study: The potential for data centres to fuel economic, employment and technological growth in Africa

In Africa, the last decade saw the transition of IT infrastructure from on-premises server rooms cooled by office air conditioners to outsourced data centres. The COVID-19 pandemic accelerated the digital migration to the Cloud, based outside of any economy or region. As developed economies are investing billions of US dollars in cloud technologies and in the high-density graphics processing unit (GPU) chips required for the AI infrastructure, there is an opportunity for Africa to leapfrog. The continent has harnessed submarine cables, abundant renewable energy and digitally savvy youth to build cutting-edge data centres. Just as Africa skipped landlines in favour of mobile telephony, or grid electricity in favour of decentralized solar power, it can now move to efficient, scalable data centre infrastructure.

A leading example is iXAfrica,¹⁹ the fifth entrant into Kenya's data centre market, which is building a 22.5MW facility suitable for AI and hyperscalers (i.e., massive networks of data centres) close to Nairobi's airport, connected to major fibre-optic routes. It is designed to power highly dense AI GPUs that handle up to 50 kW per server rack – far more than the standard 3-5 kW racks. This kind of investment is poised to unlock a number of socio-economic benefits.

While Kenya's economy has long relied on agriculture, tourism and minerals, it is increasingly recognized as the "Silicon Savannah". The success of innovations like M-PESA – a mobile money service and fintech platform – combined with billions of US dollars' worth of venture capital investment over the past few years, growing fibre bandwidth (e.g., 2Africa and Google's Umoja fibre-optic cable) and smart young talent, makes Kenya a ripe ecosystem for the digital economy and exports.

Kenya is also positioned to export its abundant renewable energy indirectly, via data centres. Already generating up to 93 per cent of its electricity from renewable sources, Kenya, the world's sixth largest producer of geothermal energy, has untapped potential to export energy, talent and innovation via large-scale data centre investments.

Oracle has already announced the deployment of a public cloud region in Kenya, and Microsoft, in partnership with G42, a United Arab Emirates technology group, is planning a US\$ 1 billion investment in a data centre in Kenya that will run Microsoft Azure. Investors such as Helios Investment Partners – which invested US\$ 50 million in iXAfrica in 2022 – Equinix, a digital infrastructure company, Digital Realty, a data centre platform, and the International Finance Corporation (IFC) are also investing in data centres in the region.

Job opportunities are being created in the tech sector. Africa's salary advantage compared to some other economies has attracted the business process outsourcing sector: CCI Global, an outsourcing firm, recently opened a call centre in Tatu City in Nairobi, creating over 5,000 new job opportunities, and major big technology firms, such as Microsoft, Amazon and Google, have opened global product development centres in Nairobi. This is in addition to edtechs (i.e., education technology) such as Moringa School, ALX, Andela and Gebeya, which are training and placing students into remote technology work.

Government policy has been key. Mobile money adoption in East Africa succeeded due to pragmatic and flexible Central Bank regulations. Kenya's Data Protection Act (2019), which is aligned with the European Data Protection Regulation (GDPR) (2018), is providing inspiration for similar laws across the East African Community. Kenya released its National AI Strategy (2025-2030) in April 2025, and has appointed a Special Envoy on Technology, who reports directly to the President of Kenya, to the United Nations High-level Advisory Body on AI.

Still, there is significant potential to do much more to accelerate the deployment of data centres. Kenya is offering a number of incentives to attract hyperscalers to deploy infrastructure at scale, along the lines of similar incentives, for example in the United Arab Emirates. In addition, the Africa Data Centres Association (ADCA), which currently has a membership of 45 data centre operators across the continent, has been instrumental in bridging the gap between the private sector and the government, promoting best practices across the continent.

Source: Snehar Shah, Chief Executive Officer, iXAfrica Data Centre Limited (iXAfrica).

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AI training data are sourced from a diverse mix of real-world and synthetic datasets. Sources of AI training data can include publicly available web content, licensed books and news archives, user-generated platforms, open-source code repositories, and domain-specific collections of images, audio and video for multimodal models. Increasingly, synthetic data generated by AI itself are also being used to expand coverage and reduce copyright risks. A substantial portion of these data, particularly specialized datasets for image recognition, speech processing and domain-specific natural language tasks, require manual tagging or human verification to ensure quality.

The collection, labelling, annotation and verification of training data are labour-intensive yet foundational to AI development. Tasks such as labelling images, moderating harmful content and filtering datasets transform raw data into usable formats that support downstream functions like model development, fine-tuning and deployment (Okolo and Tano, 2024). Much of this work is outsourced to low-income and middle-income countries, where workers often face precarious conditions. Many report delayed payments of remuneration, lack of social protection and frequent exposure to violent or explicit material, which has been linked to emotional strain and desensitization, with potential mental health impacts (Rowe, 2023; Tan and Cabato, 2023).

The availability of training datasets depends both on the capacity to collect high-quality local data and on the ability to exchange data across borders. These factors influence not only where AI models are trained but also who can participate in that training. Many developing economies face difficulties in collecting and accessing high-quality,

representative datasets in regional languages or that reflect regional conditions, without which AI models tend to embed dominant linguistic and cultural paradigms, reinforcing exclusion and bias. In response to these challenges, a consortium of Latin American economies is launching Latam-GPT, the region's first large language model trained on regional linguistic and cultural data, to democratize AI and counter the dominance of English-centric systems (Cambero, 2025). Open data initiatives, collaborative annotation platforms and interoperable data-sharing frameworks are critical to lowering these barriers and enabling more equitable participation. Cross-border access to training datasets is shaped by digital trade policies, data localization rules and licensing arrangements (see Chapter C).

(iv) AI models

Foundation models and AI applications represent different layers of the AI development stack. Foundation models, such as large language models or multimodal systems, are general-purpose models trained on vast datasets and significant computational resources. Companies profit from these models by offering access through subscription-based application programming interfaces (APIs) (i.e., tools that allow software applications to communicate with each other), enterprise licensing, integration into cloud and productivity platforms, and by leveraging usage data to improve future iterations. Adaptation involves fine-tuning or customizing these models for specific use cases.

The combination of economies of scale and scope, high fixed costs of training and low marginal deployment costs can create strong tendencies toward market concentration in the

AI sector. These dynamics often lead to oligopolistic competition among a few dominant firms, raising concerns about long-term concentration, especially in economies with limited domestic AI capacity or reliance on foreign models (Vipra and Korinek, 2023). With concentration, dominant firms may extend market power downstream, restrict competition, raise prices and contribute to systemic risks such as regulatory capture, where a regulatory agency becomes influenced or controlled by the very firms it is supposed to regulate.

The growing availability of open-source and open-weight models provides a partial counterbalance to these concentration dynamics. Open-source models make their architecture and training code, and often their training data, publicly available under open licences, allowing anyone to inspect, modify and redistribute them. Meanwhile, it also introduces new challenges, including quality control and the risk of misuse by malicious actors. Closed-weight models, in contrast, are proprietary: neither their weights (i.e., parameters that determine how much influence one piece of information has on the next step in the AI model) nor training details are disclosed, and they can only be accessed through APIs or limited interfaces. Open-weight models occupy a middle ground: while the trained model weights are freely released for use and fine-tuning, restrictions may be imposed on the underlying training code, data or licensing terms. Meanwhile, more cost-efficient training architectures are quickly developing, significantly lowering the cost and complexity of developing large AI models. If this trend continues, it could enable a more diverse ecosystem of players to build or fine-tune competitive foundation models.

AI models remain concentrated in a few economies, but trade facilitates the diffusion of AI technologies. While the United States remains the clear leader in AI development, China's foundation models are progressing quickly and attracting significant market valuations. Up until April 2024, the United States had developed 439 generative AI models, followed by China with 117 and the United Kingdom with 88, while Germany, France and Canada also made significant contributions (Maslej et al., 2025; OECD.AI, 2025). Trade in ICT services enables economies that do not develop foundation AI models themselves to engage in the downstream development of AI applications and services.

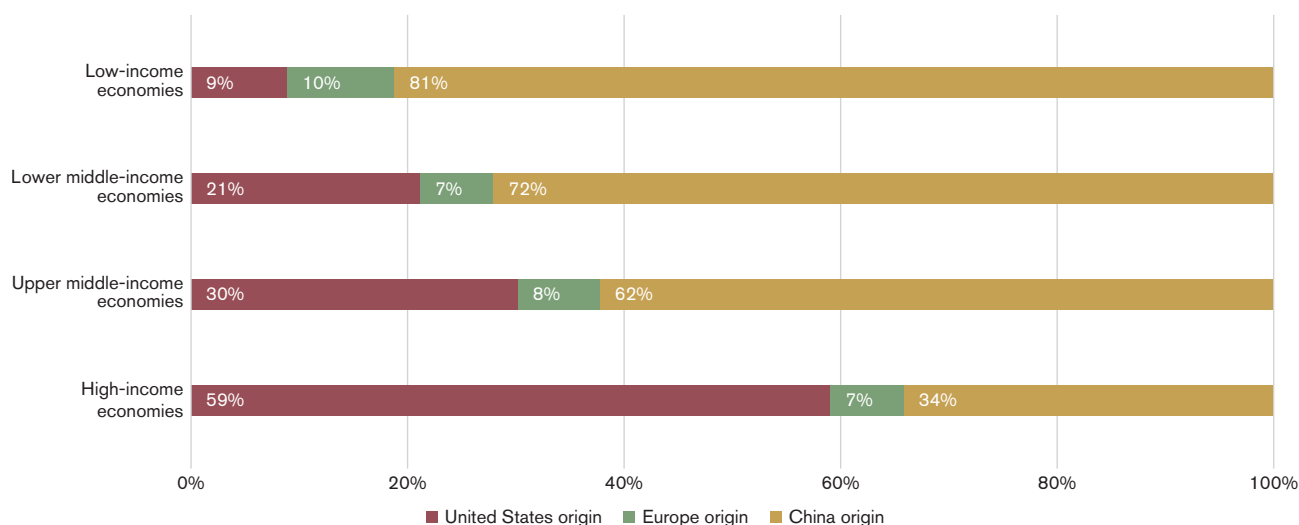
One way for resource-constrained economies to leverage AI is by adapting open-weight models. A notable example is Singapore's Infocomm Media Development Authority (IMDA)'s GPT-Legal, an AI-powered legal research tool launched by Singapore's legal resource database and built on Meta's Llama model. Fine-tuned to the Singapore legal context, including historical case law, GPT-Legal was developed using significantly fewer resources and in a shorter time frame than many large proprietary models. This demonstrates the potential for developing economies to adapt existing models for local needs, offering a resource-efficient way to build context-specific AI applications. Such adaptation would not have been possible without the underlying trade in services that enables access to technical expertise, cloud infrastructure and cross-border collaboration.

While open-source and open-weight models can be fine-tuned, their geographical uptake reflects broader patterns of digital engagement and technological alignment. Figure B.17 shows the adoption and diffusion of several AI models developed in different regions, illustrated by the distribution of “forks”, copies of a model's repository that allow users to experiment without affecting the original project, across economies of different income levels via GitHub,²⁰ the largest platform for hosting and sharing open-source code.²¹ The data reveal systematic variation in AI model adoption patterns across economies. Users from lower-income economies show disproportionately high engagement with models originating in China, relative to the global average. In contrast, users from high-income economies exhibit a stronger preference for tools originating in the United States, while European models maintain a steady but secondary presence across most regions. This geographical clustering suggests that adoption is shaped by underlying economic, institutional and geopolitical factors. Economies with similar development profiles tend to display comparable engagement patterns, possibly due to shared technical requirements or network effects.

(c) Trade in AI-enabled services facilitates AI adoption and diffusion

Trade plays a pivotal role in the global adoption of AI, shaping both the accessibility and diffusion of the technologies. Access to AI depends heavily on the availability of hardware (i.e., computers and mobile devices) and of the broader

Figure B.17: Differential use of open-source and open-weight AI models across income levels



Source: WTO Secretariat calculations based on GitHub data.

Note: This figure shows the distribution on GitHub of “forks” of major open-source and open-weight AI models across economies. To reveal geographical patterns in AI model diffusion, models from different regions were focused on, and relative shares were used to adjust for differences in total fork volumes across economies.

digital infrastructure necessary to support data processing and AI applications. Many products are also increasingly integrating AI to enhance their functionalities, with autonomous vehicles being a prominent example. Equally important is the role of services trade, particularly in digitally delivered services. Annex A.2 outlines the economic sectors that make the most intensive use of AI, the majority of which are services sectors.

AI-enabled goods and services encompass a broad array of sectors that are either incorporating AI in their production processes or are being fundamentally transformed by AI. These sectors include high-tech manufacturing industries of products such as computers and electronics, electrical equipment, transport equipment, pharmaceuticals and chemicals, where AI is used to optimize production lines and to design processes and supply chains. In the services sector, AI is enabling rapid advancements in telecommunications, IT services, finance and insurance, legal and accounting services, scientific R&D and other business services by automating complex tasks, enhancing decision-making and improving efficiency and personalization. The media industry is also undergoing significant transformation through AI-driven content creation and distribution. Together, these AI-enabled sectors represent the

technological frontier of modern economies and are central to the evolving global trade landscape.

There is substantial potential for economies to integrate into the downstream segments of the AI supply chain. For example, there are opportunities for companies to profit from the development and delivery of software-based tools and platforms powered by AI models. These localized models and businesses play a crucial role in AI adoption within economies and in addressing regional challenges. An AI startup from Tunisia, InstaDeep, trained a large language model (LLM) to accurately predict new dangerous variants of COVID-19 before they spread. The company, which was acquired by BioNTech in 2023, gives an indication of Africa’s growing AI potential (Kene-Okafor, 2023). Kenya recently launched its AI Strategy 2025–2030, affirming Nairobi’s role as a regional centre for AI development (see also Box B.4). These developments suggest the diverse pathways possible for AI-driven economic growth beyond hardware manufacturing, and the new opportunities for economies to participate in the AI value chain.

Many AI applications are delivered as services rather than standalone products, often crossing borders via digital networks and bypassing traditional trade barriers. This

enables regions with limited domestic capacity to access advanced AI technologies. Trade in digitally deliverable services has thus become a key channel for the international diffusion of AI capabilities. For example, in Kenya and Egypt, medical images such as X-rays and MRIs are securely uploaded to cloud platforms where AI algorithms analyse them to identify medical conditions (Wight, 2024). Another example is financial services, where AI can support credit scoring, fraud detection and compliance, with financial technology (fintech) platforms leveraging global datasets to serve populations with little access to banks. These applications depend on seamless digital services trade and international data flows.

One major challenge to harnessing the potential of AI for developing economies is the high cost of accessing AI models. Subscriptions to commercial AI platforms or the use of API-based services often require significant financial outlays, which can be prohibitive for individuals, small firms and even public institutions in lower-income countries. In addition to subscription fees, the cost of the necessary computing infrastructure – such as cloud services, GPUs and data storage – can further exacerbate digital inequality. Without targeted efforts to reduce these barriers, there is a risk that the transformative benefits of AI will remain concentrated in advanced economies. While open-source AI can reduce costs, it often requires technical expertise, and may pose greater risks of errors or security issues, limiting its accessibility for users in developing economies.

International trade can support the diffusion of AI technologies by enabling knowledge spillovers. By lowering market entry barriers and promoting regional cooperation, trade can become a powerful lever for inclusive AI-driven development (see sections C and D). Exposure to global markets encourages domestic firms to innovate and improve productivity while exerting competitive pressures on less productive firms. Trade enhances resource allocation and productivity by enabling cross-border technology diffusion and access to a wider set of intermediate goods and technologies, accelerating technical change (Grossman and Helpman, 1991; Buera and Oberfield, 2020; Perla, Tonetti and Waugh, 2021; Cai, Li and Santacreu, 2022). Integration into global markets also expands the market for innovations, incentivizing R&D and boosting technological progress (Rivera-Batiz and Romer, 1991).

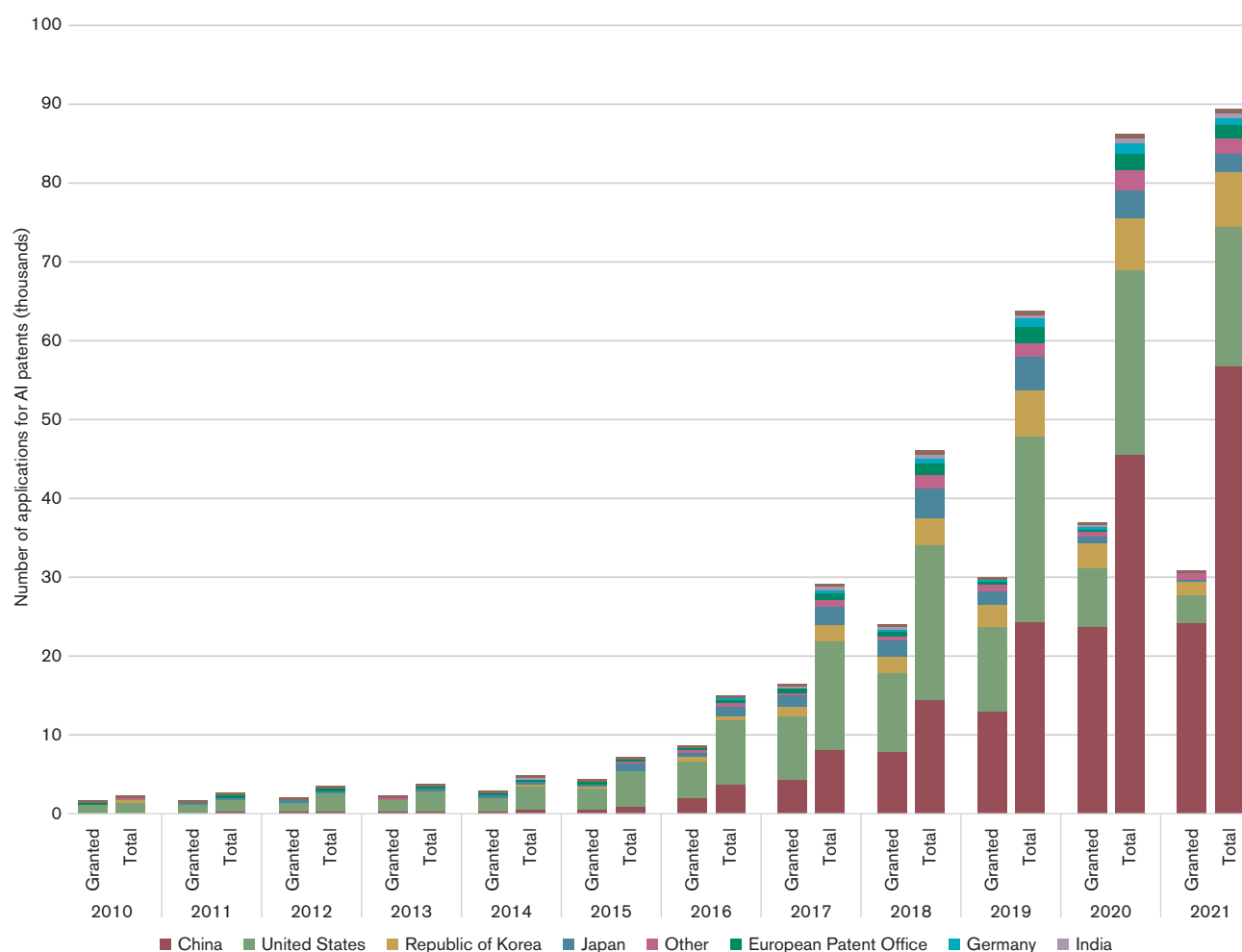
One widely used measure of knowledge and innovation is the number of patents. In this context, a patent is a legal right granted by a government to an inventor, giving them exclusive rights to use, produce or sell their invention for a certain period of time, typically in exchange for publicly disclosing how the invention works. The flow of knowledge in the AI field can be tracked through patent citations, which occur when one patent references another. Recent research has focused on developing methodological approaches to identify core AI technologies through patent data analysis, enabling more precise mapping of AI innovation trends and interdependencies (Calvino et al., 2023).

For this report, AI-related patents were identified and mapped across economies and over time using global patent databases. As illustrated in Figure B.18, AI patent applications have risen sharply in recent years. While the total number of AI patent applications reflects the pace of innovation and provides more timely information, the number of granted patents is a more reliable indicator of innovative activity, albeit with a time lag due to the lengthy examination process. Notably, both applications and granted patents have surged in China, which now leads in the number of AI-related patents, followed by the United States, the Republic of Korea and Japan. The methodology underlying this mapping is detailed in Annex C.

The flow of knowledge in the AI field can be tracked through patent citations. These citations suggest that the newer invention builds upon or is influenced by the earlier one, allowing researchers to trace how ideas evolve and spread across economies, institutions and companies. As shown in Figure B.19, cross-border patent citations are highly correlated with trade flows. Pairs of economies that have larger volumes of bilateral trade in goods and services also tend to have more AI-related inventions that build on AI innovation from other economies.

Economies more open to trade tend to experience stronger innovation spillovers, with bilateral trade flows closely correlated with cross-border AI patent citations. A Poisson Pseudo-Maximum Likelihood (PPML) regression analysis further reveals a significant correlation between AI patent citation flows and trade in digitally deliverable services.²² The results indicate that a 10 per cent increase in digitally deliverable services trade is associated with a 2.6 per cent increase in AI patent citations. This suggests that economies that

Figure B.18: Number of AI patent applications and granted patents (thousands)



Source: WTO Secretariat based on PATSTAT data.

Note: The chart shows the number of applications and the number of granted patent families by economies and by year. AI patent families are defined by a list of AI-related Cooperative Patent Classification (CPC) codes.²³ Patent families are allocated to economies based on the priority economy (i.e., where the first patent application in the family was filed). "EP" refers to the European Patent Office. The year corresponds to the year a patent is filed.

are more actively engaged in AI-related knowledge creation and diffusion also tend to trade more intensively in services that can be delivered digitally.

The global diffusion of AI models depends heavily on international data flows and services trade. Trade, particularly in digitally deliverable services, underpins the cross-border dissemination of AI technologies and capabilities. Adoption patterns suggest that the development of digital infrastructure, trade policies, and ecosystem alignment will strongly influence how economies participate in downstream AI value chains. Early engagement with specific model ecosystems can

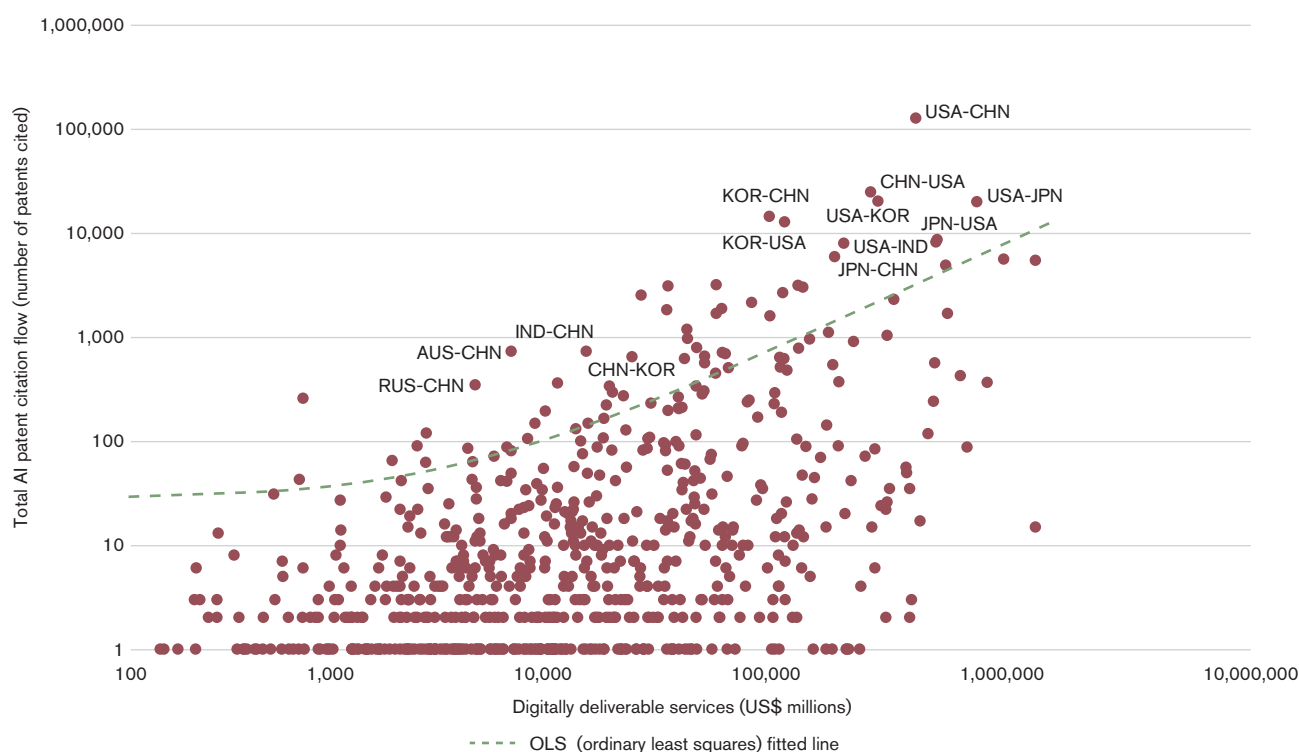
shape comparative advantages in activities such as application development, model fine-tuning, and contributions to open-source repositories.

3. Conclusions

AI has the potential to transform economies and societies. Its widespread adoption could serve as a powerful engine for growth, by strengthening human capital, improving public service delivery and boosting productivity.

By reducing trade costs and enhancing efficiency, AI could reshape comparative

Figure B.19: Cross-border AI patent citations versus digitally deliverable services trade (aggregated 2010-21)



Source: WTO Secretariat based on PATSTAT and the Balanced Trade in Services (BATIS) dataset.

Note: The figure illustrates the correlation between cross-border AI patent citations and trade in digitally deliverable services, after controlling for economy-year and bilateral fixed effects. The line represents the fitted trendline. Both the patent citation and the services trade data are averaged between 2010 and 2021. Digitally deliverable services include insurance and pension services, financial services, charges for the use of intellectual property not included elsewhere, telecommunications, computer and information services, other business services, and personal, cultural and recreational services.

advantages and alter trade patterns. WTO simulations suggest that, under optimistic scenarios, AI-driven reductions in trade costs and productivity gains could translate into significant increases in global trade and real income. However, the impact of AI on inclusive growth will depend on how the digital divide is addressed and how the technology spreads globally. In a scenario in which there are improvements in digital infrastructure and broad AI adoption, the largest relative gains would accrue to low-income and middle-income economies.

Trade is crucial for ensuring that the gains from AI are broadly shared. Trade in AI-enabling goods and services allows economies with limited domestic AI capabilities to participate in the AI value chain, while trade in AI-enabled services broadens access to its benefits, enhances productivity, and facilitates the cross-border diffusion of AI technologies.

Nevertheless, the impact on inclusive growth both across and within economies will depend on targeted policies and international cooperation.

Beyond productivity gains, AI creates new opportunities for resource-rich economies.

In particular, economies that can supply critical minerals and generate clean energy could benefit, as these resources are essential in AI value chains. Capturing these opportunities requires targeted investments in digital infrastructure and skills, as well as enabling policies, including open and trustworthy data frameworks, to attract investment in data centres and promote trade in AI-enabled sectors.

As with any major technological shift, AI has distributional effects that may not be beneficial for all. While AI can enhance the productivity of many workers, it is also displacing others by

automating specific tasks or entire occupations. AI could increase returns on capital and the skill premium in wages. However, its impact on the wage growth of certain income groups across economies will largely depend on the extent to which certain economies can catch up with others in terms of levels of development of infrastructure and technology. AI adoption tends to cluster in large, urban, digitally

connected firms, especially in advanced economies, while smaller and less-connected firms face steeper hurdles. Without appropriate policy frameworks, there is a risk that AI will deepen inequalities both within and between economies and will concentrate benefits among those already best equipped to harness the technology.

Endnotes

- 1 See <https://www.maersk.com/news/articles/2025/06/25/maersk-launches-maersk-trade-and-tariff-studio>.
- 2 The survey will be published shortly after this report in the latter half of 2025. It will be made available on the websites of the WTO and ICC.
- 3 The WTO Global Trade Model is a recursive dynamic computable general equilibrium (CGE) model, which is employed to analyse long run technology and trade policy scenarios. A WTO staff working paper describes the details of the simulations presented in this report.
- 4 AI is considered advanced if it can automate abilities that are highly difficult and complex, such as 'mathematical reasoning' for physicists or 'diagnostic analysis' for neurologists.
- 5 AI is considered basic if it can automate abilities that are relatively less complex, such as 'oral expression' for commercial drivers or 'deductive reasoning' for paralegals and legal assistants.
- 6 See <https://www.fao.org/in-action/remote-sensing-for-water-productivity/applications-and-uses/applications-catalogue/product-detail/PlantVillage-Nuru/en>.
- 7 See <https://plantvillage.psu.edu/>.
- 8 See https://www.wto.org/english/tratop_e/serv_e/gatsqa_e.htm for the four GATS modes of delivering services.
- 9 See <https://github.com/>.
- 10 Scenario 4 is cumulative to Scenario 2 and so should be evaluated in comparison to it.
- 11 See <https://github.com/features/copilot>.
- 12 An ability is classified as core if its occupation-specific importance score indicated in O*NET is equal or greater than 3 (on a 1 to 5 scale).
- 13 The baseline scenarios assume an annual growth rate of 26 per cent in AI services (Statista, 2025). In alternative scenarios where AI services grow more rapidly – at 38 per cent annually (UNCTAD, 2025b) – the substitution of labour by AI becomes stronger and outweighs the productivity gains, leading to declines in both wages and employment for medium-skilled and high-skilled workers.
- 14 If intertemporal optimization were included with the representative agent optimally choosing the path of consumption (and thus savings) over time, the savings rate could rise in response to the rising rental rate as it becomes more attractive to save and postpone consumption. This would temper the rise in the rental rate, while expanding the capital stock.
- 15 See <https://www.deepseek.com/>.
- 16 See <https://www.un.org/en/ai-advisory-body>.
- 17 See <https://www.world-mining-data.info/>.
- 18 See <https://pubs.usgs.gov/publication/mcs2024>.
- 19 See <https://ixafrika.co.ke/>.
- 20 See <https://github.com/>.
- 21 The selection of open-source and open-weight AI models is based on commonly recognized examples and does not aim to be exhaustive. From the United States, models included in the selection are Llama (Large Language Model Meta AI), developed by Meta, and llama.cpp, an independent user-led project enabling Llama models to run efficiently on personal devices. From China, the selection covers DeepSeek, an open-source large language model developed by DeepSeekVision, and PaddlePaddle, Baidu's open-source deep learning platform supporting various AI applications, including image recognition. From Europe, it includes Stable Diffusion, an image generation model developed by Stability AI in partnership with Ludwig-Maximilians-Universität München (LMU Munich) and EleutherAI, as well as Hugging Face, a Franco-American company that supports a wide range of open-source natural language processing and multimodal models.
- 22 Digitally deliverable services, according to the sixth edition of the International Monetary Fund Balance of Payments and International Investment Position Manual (BPM6), available at <https://www.imf.org/external/pubs/ft/bop/2007/bopman6.htm>, include insurance and pension services; financial services; charges for the use of intellectual property not included elsewhere; telecommunications, computer and information services; other business services; and personal, cultural and recreational services (WTO et al., 2023).
- 23 See <https://www.epo.org/en/searching-for-patents/helpful-resources/first-time-here/classification/cpc>.