World Trade Organization

WORLD TRADE REPORT 2025

Making trade and AI work together to the benefit of all

What is the World Trade Report?

The World Trade Report is an annual publication that aims to deepen understanding about trends in trade, trade policy issues and the multilateral trading system.

What is the 2025 Report about?

The 2025 World Trade Report explores the complex and fast-evolving relationship between artificial intelligence (AI) and international trade and how this relationship may shape inclusive growth. It also looks at the central role the WTO can play in ensuring that AI supports broad-based growth.

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CONTENTS

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ABBREVIATIONS

AI	artificial intelligence
AIoT	Artificial Intelligence of Things
AGI	artificial general intelligence
AI-TPOI	AI Trade Policy Openness Index
CPC	Cooperative Patent Classification
DSU	Dispute Settlement Understanding
DTI	Digital Trade Integration database
GATS	General Agreement on Trade in Services
GATT	General Agreement on Tariffs and Trade
GDP	gross domestic product
GPA	Agreement on Government Procurement
GPU	graphics processing unit
GSP	Generalized System of Preferences
HS	Harmonized System
ICC	International Chamber of Commerce
ICT	information and communication technology
IEA	International Energy Agency
IEC	International Electrotechnical Commission
IEEE	Institute of Electrical and Electronics Engineers
IFD	Investment Facilitation for Development
ILO	International Labour Organization
IoT	Internet of Things
IP	intellectual property
ISO	International Organization for Standardization
IT	information technology
ITA	WTO Information Technology Agreement
ITU	International Telecommunication Union
LDC	least-developed country
LLM	large language model
MFN	most-favoured nation
MNE	multinational enterprise
MSME	micro, small and medium-sized enterprise
MW	Megawatt
NLP	natural language processing
OECD	Organisation for Economic Co-operation and Development
QR	quantitative restriction
R&D	research and development
RTA	regional trade agreement
S&DT	special and differential treatment
SCM	subsidies and countervailing measures

SPS	sanitary and phytosanitary
STEM	science, technology, engineering and mathematics
STRI	World Bank–WTO Services Trade Restrictiveness Index
TBT	technical barriers to trade
TFA	WTO Trade Facilitation Agreement
TRIPS	trade-related aspects of intellectual property rights
UN	United Nations
UNCTAD	UN Trade and Development
UNESCO	United Nations Educational, Scientific and Cultural Organization
WIPO	World Intellectual Property Organization
WTO	World Trade Organization

FOREWORD BY THE WTO DIRECTOR-GENERAL

Rapid advances in artificial intelligence (AI) are transforming the world economy, reshaping how work is defined, how value is created, and how opportunities are distributed across societies. Given these far-reaching effects, AI is also transforming world trade. At the same time, rising uncertainty with regard to trade policies threatens to alter the patterns of globalized trade and investment that have underpinned global growth and development for the past several decades. Technological change has always been closely tied to the ways in which people produce and trade goods and services, and this edition of the World Trade Report explores the interaction between trade and the ongoing AI revolution, and what this means for the future of growth and socioeconomic inclusion.

This report builds on earlier WTO research: the *World Trade Report 2024*, which examined how trade can support inclusive growth, and *Trading with Intelligence*, our first dedicated study on AI and trade, which was also published in 2024. The *World Trade Report 2025* also draws on a joint business survey of the WTO with the International Chamber of Commerce that provides insights into how firms worldwide are leveraging AI in their trade activities. In addition, a new AI Trade Policy Openness Index (AI-TPOI), compiled by WTO economists, offers valuable evidence on trade policies shaping the development and diffusion of AI.

AI has vast potential to lower trade costs and boost productivity, as well as to create new avenues for services production and exports. WTO simulations suggest that the use of AI could boost goods and services trade by nearly 40 per cent by 2040.

However, the effects of the development and deployment of AI are raising concerns that many workers, and even entire economies, could be left behind. Recent decades of globalization delivered major gains for both rich and poor countries, but many people and regions did not share adequately in the benefits. This exclusion has much to do with today's tensions around trade – and it is an experience we cannot afford to repeat with the AI revolution. The central question addressed in the 2025 *World Trade Report* is whether, and how, AI can serve as a catalyst for inclusive trade-led growth, or whether it could end up widening divides between and within economies.

The message in this report is clear: trade can be a powerful enabler for an inclusive AI transformation. It can help economies to access AI, as well as AI-enabling inputs, to foster the diffusion of innovation, and to unlock new development pathways. But this potential can only be realized if we act deliberately, by closing digital divides, investing in workers, and promoting regulatory coherence.

Today, however, access to AI technologies and the capacity to participate in digital trade remains highly uneven, especially for many low-income economies. Without proactive policy responses and greater international cooperation, AI could deepen inequalities rather than reducing them. But this report also shows that, with the right mix of trade, investment and complementary policies, AI can create new growth opportunities in all economies.

To explore the potential of AI, WTO economists ran simulations of different scenarios based on whether lower-income economies are able to narrow the gap with the infrastructure and technology levels of higher-income economies. In a scenario in which lower-income economies are unable to catch up, they would see their incomes rise by 8 per cent by 2040, well below the 14 per cent gains of high-income economies. However, in a scenario of partial convergence, in which these economies close their digital infrastructure gap with high-income economies by 50 per cent and adopt AI more widely, their income growth could reach 15 per cent.

The multilateral trading system has long supported development through openness, cooperation, and predictability. It must now rise to meet the challenges and opportunities of the AI era. This means not only ensuring access for all to AI tools and new AI-related markets, but also addressing the problems arising from fragmented regulation of AI, and leveraging trade policy for responsible and inclusive technology use.

At the WTO, we are working to keep pace with these matters. Members are beginning to discuss AI-related trade issues across various bodies, such as in the Work Programme on Electronic Commerce and in the Committee on Technical Barriers to Trade. Initiatives like the joint WTO and World Bank project, "Digital Trade for Africa", and the forthcoming "Digital Trade for Latin America and the Caribbean", support digital development in dozens of economies. The joint WTO Secretariat–International Trade Centre US$ 50 million Women Exporters in the Digital Economy (WEIDE) Fund is helping women in developing economies use digital tools to trade more and trade better. Recent Aid for Trade projects in areas such as transport, infrastructure and agriculture are already incorporating AI, helping beneficiary economies to optimize logistics and manufacturing processes or to promote sustainable farming. Within the WTO Secretariat, I have established a new Digital Trade and Frontier Technologies Hub to strengthen our ability to monitor developments and support members' needs, and to help contribute to inclusive and forward-looking trade policy.

The AI transition is unfolding rapidly. Whether it becomes a force for convergence or for divergence will depend on the choices we make today. With the right frameworks, trade can play a central role in making AI work for all. The WTO is committed to supporting this effort.

Ngozi Okonjo-Iweala

Dr Ngozi Okonjo-Iweala
Director-General

EXECUTIVE SUMMARY

Artificial intelligence (AI) is beginning to reshape the global economy. Like previous general-purpose technologies, or technological breakthroughs with global impact – such as electricity or the internet – AI has the potential to transform how economies function by altering the ways in which goods and services are produced, exchanged and consumed. However, its future trajectory and impact remain uncertain. In addition, the effects of AI raise critical questions about the future role of trade in supporting inclusive growth, because AI could either foster innovation, boost economic growth, and prompt income convergence between and within economies – or it could deepen existing economic and technological divides.

The *World Trade Report 2025* examines the complex and fast-evolving relationship between AI and international trade, and explores how these forces can shape inclusive growth. The central message of this report is that AI can become a powerful driver of inclusive, trade-led growth – where inclusive growth refers to economic growth that expands market opportunities while ensuring that the gains from trade are widely shared both across economies and within societies – but only if economies invest in the right enabling policies and cooperate to prevent fragmentation of the regulations governing the digital economy. A rules-based multilateral trading system, with the WTO at its core, is essential to ensure that the benefits of AI are widely shared.

AI and trade can be catalysts for more inclusive growth

AI presents new opportunities to reduce trade costs and expand participation in global markets, especially for small companies. AI tools are already enhancing trade efficiency by improving visibility within supply chains, automating customs clearance, reducing language barriers, strengthening market intelligence, improving contract enforcement and helping firms, including micro, small and medium-sized enterprises (MSMEs), to navigate complex regulations. WTO research, based on a joint survey conducted in 2025 with the International Chamber of Commerce (ICC) specifically for this report,[1] finds that among firms currently using AI, nearly 90 per cent report tangible benefits in trade-related activities, and 56 per cent report that it has enhanced their ability to manage trade risks.

AI is also boosting productivity across sectors, which underpins economic growth. Empirical studies show that the use of AI brings about tangible efficiency gains in tasks as diverse as customer support, management consulting and software development, though the extent of these gains can vary by context. One recent estimate, based on research on specific tasks, suggests that AI could add around 0.68 percentage points to annual growth in total factor productivity, which measures how efficiently an economy uses its inputs – typically labour and capital – to generate output (Aghion and Bunel, 2024).

WTO simulations suggest that AI could lead to significant increases in global trade and real income. These simulations are based on an extension of the standard WTO Global Trade Model[2] with AI services and incorporate trade cost reductions, a shift in tasks from labour to AI and productivity gains related to this shift. They suggest that AI could lead to significant increases in trade and GDP by 2040, with global trade projected to rise by 34 to 37 per cent across different scenarios. The largest growth occurs in the trade of digitally deliverable services (42 per cent), including AI services. This trade increase reflects (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.[3] The development and deployment of AI are also projected to generate substantial global GDP increases, ranging from 12 to 13 per cent across scenarios.

The impact of AI on inclusive growth will depend on how the digital divide across economies – which includes disparities in digital infrastructure, capabilities and hardware – is addressed, and on how the technology spreads globally. WTO economists simulated four AI uptake scenarios to capture different degrees of policy and technological catch-up between economies, and the differences between scenarios were substantial. In the benchmark scenario, where low-income economies do not catch up with high-income economies in terms of digital technology and infrastructure, high-income economies see their incomes rise by 14 per cent, compared to 11 per cent for middle-income economies and 8 per cent for low-income economies.[4] However, this gap narrows considerably if digital infrastructure improves in low-income economies, with income growth projected at 11 per cent for low-income economies, and 12 per cent in both middle- and high-income economies. Meanwhile, in a scenario that includes improvements in both infrastructure and broad AI adoption, low-income and middle-income economies are projected to benefit even more, with GDP gains rising to 15 per cent for low-income economies and to 14 per cent for middle-income economies.

Furthermore, AI could contribute to a moderate reduction in income inequality among workers. As a result of the shift in tasks from human labour to AI, the skill premium, measuring the ratio of wages of high-skilled relative to low-skilled workers, could decline slightly. Globally, while the real wages of all labour groups are expected to rise, the skill premium is projected to decline by 3 to 4 per cent across various scenarios. The overall narrowing of the wage premium reflects the fact that the task substitution from human labour to AI is more pronounced for medium-skilled and high-skilled occupations than for low-skilled ones, meaning that the relative demand for medium-skilled and high-skilled labour declines.

Trade contributes to making AI more accessible. Most economies depend on international markets for AI-enabling inputs, from raw materials to semiconductors and high-performance computing equipment, to training data and cloud services. In 2023, global trade in AI-enabling goods – including raw materials, semiconductors and intermediate inputs – totalled US$ 2.3 trillion.[5] Trade also facilitates the delivery of AI-enabled tools – from remote diagnostics to financial inclusion apps, especially in economies with limited domestic capabilities.

Participation in AI value chains opens a range of development opportunities. Some economies are emerging as hubs for upstream inputs, such as critical minerals and energy, while others are positioning themselves as regional centres for data hosting, cloud services or the local adaptation of AI models. Even foundational AI inputs, such as training data, offer entry points for less technologically advanced economies to engage in AI development. Many developing economies are already contributing through labour-intensive activities, including data collection, annotation and moderation; however, ensuring fair compensation and adequate labour protection remains a challenge.

AI-enabled services show potential to create new trade opportunities, as many applications are digital and scalable. Applications such as AI-powered content creation, telemedicine, and data analytics enable firms to scale efficiently and compete globally. While challenges remain, basic digital connectivity may allow economies with limited physical infrastructure to participate more actively in global markets. AI-enabled services create dynamic learning effects and help to accelerate structural transformation, particularly in low-income and middle-income economies.

Trade can facilitate the diffusion of AI innovation, as economies that are more open to trade tend to experience stronger innovation spillovers. Bilateral trade flows in digitally deliverable services are closely correlated with cross-border AI patent citations – i.e., when one patent filed to protect intellectual property (IP) rights references another, a proxy for knowledge flows because they document when one invention builds on another. WTO analysis shows that a 10 per cent increase in digitally deliverable services trade is associated with a 2.6 per cent increase in AI patent citations across borders.

The risk of a widening digital divide

The transformative potential of AI for trade is significant, but it is far from guaranteed. Without targeted investment, inclusive policy frameworks and international coordination, AI could exacerbate existing divides and even create new ones, and this would undermine the development potential of AI.

Global access to AI is highly unequal, and this limits the ability of many economies to participate in AI-driven trade. Digital infrastructure, computing capacity, qualified workers and regulatory readiness are concentrated in a handful of economies. This imbalance is mirrored in trade-related policies: high-income and upper middle-income economies have a much more advanced policy framework for AI and digital trade, and these economies provide significantly more financial support for AI-related production. In contrast, low-income economies have only recently begun to develop regulation regarding data flows and AI. Such disparities constrain the capacity of poorer economies to harness the potential of AI.

AI may shift comparative advantages in ways that reinforce inequality. AI technology favours capital- and data-intensive production, which could erode the competitiveness of economies that rely on low-skilled and low-cost labour. Meanwhile, AI development capacity remains concentrated within a limited number of firms and economies, and it may further raise returns to capital, widening existing divides. WTO simulations show that the rental rate on capital – that is, the cost of using capital inputs – rises significantly relative to wages, by about 14 percentage points. This is mainly because AI services both substitute for labour and rely heavily on capital. As a result, demand for capital increases more than demand for labour, pushing up the rental rate on capital.

While trade can help to diffuse AI, uneven adoption risks reinforcing existing divides. AI uptake is concentrated in large, urban, digitally connected firms. Smaller firms and less-connected regions face a range of hurdles, from infrastructure gaps to compliance costs. The 2025 WTO–ICC survey results show that only 41 per cent of small firms report using AI, compared to over 60 per cent of large firms. Among low-income and lower middle-income economies, fewer than one-third of firms use AI.

Labour market disruptions could compound the risks of a widening divide. AI has the potential to affect the labour market significantly, particularly in services in which digitally delivered trade has offered promising development opportunities for lower-income economies. While certain tasks, such as transcription, translation and support functions, are increasingly susceptible to automation, the overall impact on jobs will depend on how AI complements or substitutes specific tasks, and on the capacity of workers and firms to adapt. In some scenarios, AI may boost the productivity of service workers in developing economies, enhancing their global competitiveness. But without the right policies, these shifts could also narrow export opportunities or intensify reshoring pressures in advanced economies.

The role of domestic policy in creating an enabling environment for more inclusive AI

AI's impact on inclusive growth depends on the design of trade and trade-related policies. Tariffs, export controls, services regulation, and data governance all shape the availability, affordability and diffusion of AI and AI-enabling goods and services. Uneven policy adoption across income groups risks widening structural gaps in AI readiness, especially those linked to the digital divide.

The new WTO AI Trade Policy Openness Index (AI-TPOI) reveals significant variation in AI-related trade policies across and within income groups. The AI-TPOI, compiled by WTO economists (see Annex D), captures three policy areas relevant to AI diffusion: barriers to services trade, restrictions on trade in AI-enabling goods, and limitations on cross-border data flows. On average, lower middle-income and upper middle-income economies tend to maintain the most restrictive policies. While low-income economies appear relatively more open, this may reflect limited regulatory capacity and underdeveloped digital infrastructure rather than deliberate openness. Even among economies with low tariffs, restrictive data localization requirements or export controls can inhibit access to AI tools and markets.

Beyond openness, complementary policies also shape how trade and AI contribute to inclusive growth. Such policies include, among others, IP protection, competition frameworks, infrastructure and energy policies, education systems and government support. These policies, however, remain mostly concentrated in high-income and upper middle-income economies.

IP and competition policies related to AI are expanding rapidly. The number of economies adopting at least one AI-related IP policy rose from 41 in 2017 to 140 in 2024. But significant disparities remain across income groups. In parallel, competition policy measures targeting AI have surged since the release of ChatGPT in November 2022, with 44 new measures recorded. Yet over 80 per cent were in high-income and upper middle-income economies, demonstrating again that the policy uptake is unequal.

Making AI development more sustainable and inclusive would require increasing the already

substantial investments in the energy and digital infrastructure dedicated to AI development. Data centres already consume 1.5 per cent of global electricity, showing the importance of existing infrastructure investments, including in renewable energy, to support AI development. Yet policy activity in support of renewable energy is highly uneven. High-income economies account for 69 per cent of all global renewable energy policies, while low-income economies represent just 1.5 per cent.

Education policy, which helps economies develop the capabilities necessary to benefit from AI, also reflects a global imbalance between higher- and lower-income economies. High-income and upper middle-income economies invest more in education overall, and are increasingly developing AI-specific programmes. In contrast, fewer than one third of developing economies have adopted national AI education strategies, which is likely to widen the skills gap across income groups.

Targeted government support is increasingly playing a role in shaping AI development. The share of global subsidies targeting AI-related products has increased considerably since 2010, exceeding 15 per cent at its recent peak. High-income and upper middle-income economies account for over 98 per cent of these measures, and this demonstrates that there is a substantial risk of further concentration of AI capabilities.

Without concerted action, disparities in policy action risk locking in long-term inequalities. The uptake of AI-targeted policies is highly uneven across income groups, with the major share of such policies being implemented by high-income and upper middle-income economies. International cooperation on such policies could help to narrow disparities, and ensure that trade remains a force for inclusive progress in the AI era.

The role of the WTO in supporting more inclusive approaches to trade and AI

International cooperation on AI is still in its early stages, and remains largely aspirational, with little attention given to trade or trade policy. Most AI-related initiatives primarily involve high-level declarations, broad principles or voluntary guidelines that emphasize the ethical use, safety, transparency and interoperability of AI. Most also make little or no reference to international trade, despite the fact that trade is the "oil" that keeps the AI engine running, as it enables the cross-border flow of essential inputs, from data and infrastructure to the hardware, human talent and services that power AI development and deployment.

Greater international cooperation, and particularly stronger cooperation on AI and trade, could support wider participation in AI development and deployment. Trade cooperation can foster a more stable and predictable environment for AI-related investment and innovation. This can help mitigate issues such as unequal access to technologies, regulatory fragmentation and concentrated market power, that hinder broader and more affordable participation in AI development and deployment.

So far, regional trade agreements (RTAs) have been the main avenue for advancing trade-related AI cooperation among economies. However, such agreements, mostly negotiated by high-income economies, remain limited in both number and scope. They typically recognize the potential of AI to support economic growth or digital transformation, with fewer identifying areas for cooperation, such as research and regulation.

Although not specific to AI, the WTO framework already contributes to AI development and deployment by supporting innovation and enabling more open and predictable trade in relevant goods and services. AI development and deployment rely on access to global markets, cross-border data flows and technological diffusion, areas that are directly impacted by trade policy. In that context, several WTO agreements underpin the global AI ecosystem by lowering hardware costs through the Information Technology Agreement (ITA), promoting regulatory transparency and international standards via the Agreement on Technical Barriers to Trade (TBT), facilitating AI-related services trade under the General Agreement on Trade in Services (GATS), and supporting IP protection and technology diffusion through the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS).

Beyond rules and market access, the WTO can also help broaden participation in AI-related trade through mechanisms that promote transparency, dialogue and capacity-building

on trade-related aspects of AI. For example, the joint WTO-International Trade Centre (ITC)-United Nations ePing alert system, which tracks sanitary and phytosanitary (SPS) and TBT measures,[6] supports stakeholders in tracking trade-related AI developments. Meanwhile, regular discussions in WTO committees allow members to raise concerns, share experiences and learn from each other's regulatory approaches to AI, thereby promoting regulatory alignment. WTO-led initiatives, such as *Digital Trade for Africa*,[7] help developing economies build the infrastructure, regulatory capacity and skills they need to participate more effectively in the digital economy – foundations that are increasingly relevant for AI-related trade. The joint WTO Secretariat-International Trade Centre (ITC) Women Exporters in the Digital Economy (WEIDE) Fund is helping women in developing economies to trade more and better through digital tools. Recent Aid for Trade projects in areas such as transport, infrastructure and agriculture already incorporate AI, helping beneficiary economies to optimize logistics and manufacturing processes or to promote sustainable farming.

Efforts to broaden participation in AI-related trade would also benefit from greater engagement by WTO members. As global AI governance continues to shape up, the WTO could help to guide its development to ensure that trade supports broader access to AI, through improved market access for AI-related goods and services and greater transparency and dialogue on trade-related AI policies. For instance, market access for AI-enabling goods remains uneven, with bound tariffs reaching up to 45 per cent in some low-income economies. Broader participation in the ITA and updated GATS commitments would contribute to making AI more affordable. Striking an appropriate balance between these binding commitments – aligned with each WTO member's implementation capacity – and policy flexibility remains, however, essential to maintain the predictability that credible commitments provide, while promoting more inclusive AI outcomes. The question of AI and inclusive trade has been a key focus of discussions in some WTO bodies, in particular in the context of the Work Programme on e-Commerce and the Informal Working Group on MSMEs.

For trade policy to help broaden economies' participation in AI, deeper collaboration of the WTO with other international organizations and initiatives will be needed. Since many trade-related AI challenges are rooted in broader policy issues, strengthening coherence between trade policy and other public policy areas is essential to address concerns such as the digital divide, market concentration, labour market impacts, and environmental sustainability. While ensuring such coherence depends on national policy choices, increased collaboration among international organizations can play a supportive role by promoting dialogue, encouraging shared approaches and facilitating the pooling of resources to tackle problems. Coordinated international efforts can thus help to support broader global participation in the AI-driven economy through more open, predictable, forward-looking and flexible trade policies.

A moment of strategic choice

The future impact of AI will depend on choices made today. Whether AI becomes a force for inclusiveness both across and within economies or for division will depend on the choices made now. In order to realise its potential, investment in digital infrastructure, workers' skills and competitive ecosystems will be required, as well as domestic reform, international cooperation and institutions capable of adapting to fast-moving technological change, underpinned by a commitment to openness, inclusivity and shared prosperity.

The WTO can play a central role in ensuring AI supports inclusive trade-led growth. This means not only advancing trade openness and rule-making, but updating the functions of the WTO itself, promoting transparency and interoperability, and continuing to provide a trusted forum for members to align trade policy with responsible, inclusive digital transformation.

This is a moment of strategic choice for shaping how AI will influence trade and growth. With the right frameworks in place, supported by investment, domestic reform and international cooperation, AI could expand opportunities and strengthen the multilateral trading system. But without deliberate action to close capacity gaps, update trade rules and foster regulatory alignment, the risks of AI may be compounded, and its benefits may remain concentrated among the few.

Endnotes

1 The survey will be published shortly after this report. It will be made available on the websites of the WTO and ICC.

2 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 (Bekkers et al., 2025).

3 This contrasts with the 2024 WTO report on trade and AI, *Trading with Intelligence* (WTO, 2024a), which projected trade growth of 14 per cent by 2040, under a scenario of larger productivity gains and more uniform adoption of AI across economies. This difference arises because the model used for this report incorporates additional channels of reduced operational trade costs, a highly tradable AI services sector with strong projected growth, and higher productivity growth.

4 Income groups in this report are based on the World Bank classification by income level for 2024–2025, available at https://blogs.worldbank.org/en/opendata/world-bank-country-classifications-by-income-level-for-2024-2025.

5 An illustrative list of AI-enabling goods is provided in Annex A.1.

6 See https://www.epingalert.org/en.

7 See https://www.wto.org/english/tratop_e/serv_e/serv_2502202416_e/serv_2502202416_e.htm.

A Introduction

The development and deployment of artificial intelligence (AI) have accelerated in the last few years, and its applications hold the potential to revolutionize human society and economic activities. This chapter sets the context for the current AI landscape and discusses why it is timely and important to examine how trade can be a vehicle for the development and dissemination of AI, and how AI can help trade to continue to be a force for good by extending the benefits of trade to more economies, firms and individuals.

AI has ushered in a new era of growth potential, but it can also reshape the distribution of wealth and income both across and within economies. As discussed in the *World Trade Report 2024*, trade-led growth has lifted billions of people out of poverty over the past decades, but some individuals, regions and economies have not been able to benefit to the same extent from trade. At this juncture, critical questions arise: in the age of AI, will similar opportunities for income convergence persist, or even further improve – or will they diminish? And how can trade and trade policy be part of the solution to make trade and the global economy more inclusive?

The *World Trade Report 2025* explores how trade and AI could reinforce each other to promote inclusive growth in all economies. Expanding on a WTO study released in November 2024 (WTO, 2024a), this report will examine how AI could promote inclusive trade and growth, and how trade could contribute to the development and deployment of AI, even against a backdrop of increasing geopolitical tension and rising protectionist measures.

1. What is AI?

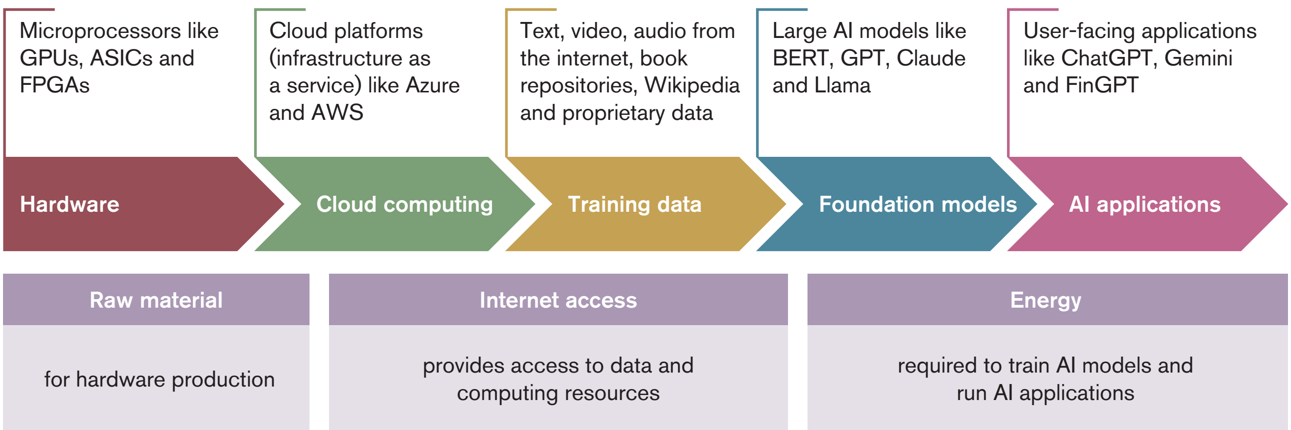
AI refers to systems that process data to perform tasks, often with various degrees of autonomy and adaptability. Although there is no universally accepted definition of AI, a common understanding is that AI systems generate outputs – such as recommendations, content or decisions – based on data inputs, with varying levels of human involvement. These systems are designed to learn, adapt and evolve over time, making them distinct from traditional programmed software (OECD, 2024).

AI has a long history, but recent breakthroughs have driven its widespread application. Although AI research began in the 1950s, early progress was slow and was followed by a period of stagnation (referred to as "AI winters"). Since the 2000s, however, innovations in machine learning and neural networks, combined with unprecedented advances in computational power and the generation of huge amounts of data, have significantly accelerated AI development. With the launch of ChatGPT in November 2022, AI, and in particular generative AI – capable of generating high-quality text, images and other content based on the data on which it is trained – entered public consciousness and has been experiencing rapid adoption ever since (see Annex B for a glossary of key AI-related terms).

Today, AI is increasingly used in daily life and across industries, particularly in advanced and emerging economies. A recent development is the emergence of agentic AI – systems capable of autonomously pursuing goals, making decisions and taking actions in complex environments – which is raising new questions about control, accountability and the distribution of economic gains. As argued in the WTO report *Trading with Intelligence: How AI shapes and is shaped by international trade* (WTO, 2024a), contemporary advances in AI render it distinct from other technologies in several key ways: it is a general-purpose technology, i.e., it has multiple applications across a range of different industries; it is dependent on large datasets to improve its performance and accuracy; its functions and efficiency can evolve rapidly; and it is inherently complex and opaque. Moreover, AI development and adoption are increasingly structured along a value chain (see Figure A.1).

AI is increasingly recognized as a general-purpose technology with far-reaching applications and implications. Generative AI, in particular, exhibits the defining characteristics of general-purpose technologies: i) pervasiveness, ii) continuous improvement over time and iii) innovation-spawning (Calvino, Haerle and Liu, 2025). Notable for its flexibility, AI can be used across virtually all sectors and tasks (Suleyman and Bhaskar, 2023). It powers applications in language processing, image recognition and multimodal systems. However, this broad utility also raises concerns, as the same technologies can be used, for example, for surveillance, misinformation or military purposes, highlighting the need for ethical oversight and strong regulatory frameworks.

Figure A.1: The AI value chain comprises interconnected segments



Source: Adapted from Gambacorta and Shreeti (2025).
Note: GPU: graphics processing unit; ASIC: application-specific integrated circuit; FPGA: field-programmable gate array.

Data fuel AI, and data governance is crucial for the trustworthy development and deployment of AI.[1] AI systems rely on large volumes of data not only for their creation and deployment, but also to sustain their constant learning and improvement. As important as data quantity are data quality and diversity, which are also essential for determining how well an AI model performs. Data sources can be open or proprietary, and access to high-quality data is often uneven across firms and economies. As data usage grows, regulations are increasingly important to ensure privacy, protect intellectual property (IP) and enable safe data flows within and across borders.

AI evolves quickly, requiring constant adaptation by policymakers and institutions, in particular as the capabilities of AI systems advance. AI's capabilities improve rapidly due to advancements in algorithms, data availability and computing power, and the resources needed to train AI models are growing exponentially. As some systems increasingly become autonomous (including in the form of agentic AI systems that are now being deployed in various domains), they raise new questions about the appropriate levels of human oversight depending on their specific use. Regulatory approaches need to be flexible and forward-looking rather than relying solely on past models.

The complexity and opacity of AI systems pose significant challenges for transparency and accountability. Many AI models – particularly deep learning models – and the systems that incorporate them operate as "black boxes", meaning that it is difficult to understand how they reach decisions. This lack of transparency raises ethical concerns, and can amplify risks of misinformation and systemic bias. It also complicates efforts to assign liability and seek redress should harm be caused by AI-enabled products. Addressing these challenges requires the development of explainable AI (i.e., AI systems whose decision-making processes are transparent and understandable to humans), improved data practices, continuous evaluation and verification, and enhanced digital literacy.

The AI value chain comprises a series of interconnected segments that underpin the development, production and adoption of AI technologies. As shown in Figure A.1, the main components of this supply chain include: (i) computing hardware; (ii) cloud computing infrastructure; (iii) training data; (iv) foundation models; and (v) user-facing AI applications. Supporting this value chain are critical raw materials used in AI hardware, reliable internet access to enable data storage, access and transmission, as well as the substantial energy required to power various stages of AI training and deployment. These foundational inputs are essential to the functioning and scalability of the entire AI ecosystem.

Throughout this report, a clear distinction has been drawn between AI development and AI adoption. This distinction is important because AI activities occur along a spectrum. At one end is AI development, which involves creating and training new foundation models – a process that demands massive computational power, vast datasets and substantial capital investment. In the middle of the spectrum is adaptation, which entails refining algorithms and customizing existing or foundation models – such as by fine-tuning open-source or pre-trained models – to meet the needs of specific tasks, domains or local contexts. At the other end is adoption, which involves the integration of AI tools and applications into existing processes, products and services across industries and economic sectors. For developing economies, the greatest immediate opportunities lie in these latter stages: leveraging pre-trained models and open-source tools to build AI solutions tailored to their economic, linguistic and social contexts, enabling them to adopt AI to improve people's well-being and productivity without having to make the substantial investments required for foundation model development.

In this context, the report distinguishes between the terms "AI-enabling" and "AI-enabled". AI-enabling goods and services encompass the raw materials, intermediate inputs, products and services that support the development and production of AI technologies (see Annex A.1 for an illustrative list of AI-enabling goods). In contrast, AI-enabled sectors have adopted and are applying AI in their operations. The adoption of AI is likely to be more concentrated and intensive in certain sectors, such as in media, telecommunications or IT services, than in others (see Annex A.2 for a list of the AI-intensity of different economic sectors), even though AI, as a general-purpose technology, is expected to have wide-ranging applications across the economy generally.

2. AI and the future of trade-led growth

Inclusive growth refers to strong and sustainable economic growth that benefits a broad range of economies and that is widely

shared within economies. It encompasses two key dimensions: reducing disparities between economies, and ensuring that the gains from growth are shared broadly within societies. Inclusive growth therefore involves expanding market opportunities and enabling greater participation in global trade, particularly for lower-income economies and smaller firms. At the same time, it requires addressing adjustment challenges and protecting workers who may be displaced or disadvantaged by structural change.

Over the past three decades, average income levels in low-income and middle-income economies have converged significantly with those of high-income economies. As argued in the *World Trade Report 2024* (WTO, 2024b), international trade has played a central role in fostering income convergence over the last 30 years, lifting billions of people out of poverty and reshaping the global economic landscape. Trade in goods and services and the exchange of ideas facilitated by trade-related IP rights have allowed economies to specialize, scale up production and integrate into global value chains. Yet, some individuals, regions and economies have been left behind by not being able to benefit to the same extent from trade. While the *World Trade Report 2024* analysed how trade and trade policy can be part of the solution to make trade and the global economy more inclusive, this report explores how trade and AI together could reinforce one another to promote inclusive growth across all economies.

AI has the potential to boost international trade and global economic growth significantly, particularly in services. By enhancing productivity across sectors, streamlining supply chains and reducing the costs of cross-border transactions, AI could lower traditional barriers to trade. For example, language translation tools and automated logistics management could reduce obstacles in global commerce. Moreover, AI may create entirely new services or make services more tradable via the internet (e.g., remote AI diagnostic services in healthcare), thereby enabling firms in both developed and developing economies to participate more efficiently in international markets (WTO, 2024a).

However, without deliberate efforts by policymakers to broaden access and opportunity, the gains from AI may still be unevenly distributed. A key concern is whether AI-enhanced trade will deliver broadly shared economic benefits or mainly benefit a small number of technologically advanced economies and large firms. As with previous waves of technological change, early adopters of AI with access to data, computing power and skilled labour may capture a disproportionate share of the value created. This could entrench existing disparities between economies and deepen inequalities within economies, particularly where small firms or certain workers are unable to adapt or compete. The complexity and uncertainty of AI's impact on economies, jobs and wages underscore the importance of policies that support adaptation and inclusive participation.

Throughout history, technological change has brought economic restructuring and periods of rising inequality. Since the Industrial Revolution some 200 years ago, economic development has progressively widened, deepened and accelerated, in part due to the interplay of technological innovation and global integration (WTO, 2017b). Yet the Industrial Revolution also posed significant challenges for workers. In early 19th-century England, for example, output per worker increased due to the introduction of new technologies, but real wages remained stagnant. While automation lowered the cost of consumer goods and eventually spurred the emergence of new industries, these long-term benefits offered little immediate relief to those displaced by technological change. It was only in the latter half of the century that wages began to rise in line with productivity, among other reasons because an expanding capital stock enabled productivity gains to translate into real income growth (Allen, 2009; Kurzweil, 2024).

The implications of AI for the future of trade-led growth have yet to be fully understood. While AI could open new paths for exports in digitally delivered services or allow firms to leapfrog traditional infrastructure bottlenecks, it could also displace labour-intensive production or reduce incentives to offshore certain tasks. These trends raise critical questions: will AI reduce or reinforce the advantages of scale and agglomeration? Will it create new entry points for developing economies or fortify the dominance of current market leaders? How can policies ensure that gains from AI-driven trade are more widely distributed? These questions are crucial, yet remain underexplored in current research and policy debates.

This report aims to contribute to a better understanding of the mechanisms by which

the benefits of trade and AI can be broadly disseminated both across and within economies. It examines the types of domestic, regional and multilateral policies needed to foster inclusive development, enable the diffusion of AI, and support trade-led inclusive growth, while addressing the challenges that AI presents. However, in a context of rising geopolitical tensions and a fragmented global trading system, the gains both from trade and from AI risk being reduced, and any remaining gains risk being accessible to fewer economies, firms and individuals.

The future of AI is marked by profound uncertainty, both in how the technology itself will develop and how governments and policymakers around the world will respond. Some experts predict the advent of artificial general intelligence (AGI) – a type of AI system that possesses a broad range of capabilities that matches or outmatches those of humans (see Annex B for key AI terms) – within a few years, leading to a significant reduction in the demand for workers. Others, however, anticipate a more incremental path in which AI continues to assist with specific, narrowly defined functions. This uncertainty is mirrored in the fragmented policy landscape. Some governments are actively promoting AI adoption as a driver of national competitiveness and economic growth, investing in research, infrastructure and public-private partnerships. Others are taking a more cautious stance, prioritizing regulation to manage the risks associated with AI. Meanwhile, most low-income countries have yet to implement any AI-specific policies. Compounding these challenges is the increasingly fraught geopolitical environment in which AI is developing.

3. The structure of this report

This report pursues four main objectives. First, it examines the conditions under which AI could broaden the benefits of trade – both across and within economies – by lowering trade costs and enhancing productivity. Second, it assesses the potential of trade to expand access to productivity-enhancing AI technologies and essential services, while also identifying the associated risks. Third, it analyses how trade and complementary policies may enhance the inclusiveness of AI development and deployment and ensure that its benefits are widely shared. Finally, it explores pathways for international cooperation and the role of the WTO in supporting inclusive and trustworthy AI development, while addressing emerging risks. The report discusses various dimensions of inclusiveness within economies, including the labour market effects of AI and the opportunities and challenges that AI raises for small businesses. Gender issues are addressed indirectly through the discussion on small businesses, as women are more likely to lead small firms or newly founded businesses than large, well-established firms.

Chapter B explores the economic characteristics of AI and the conditions under which it might generate trade-led growth opportunities that could be more widely shared. It presents simulation results illustrating the potential impact of AI on trade and global growth, and highlights the role of trade in improving access to AI technologies and services. **Chapter C** provides an overview of the evolving policy landscape, focusing on both trade policies and complementary trade-related policies that influence the inclusiveness of AI adoption. **Chapter D** turns to international cooperation, examining opportunities for collective action and the role of the multilateral trading system in fostering a more open and trustworthy AI-enabled global economy.

Endnote

1 Trustworthy AI is understood as AI that is lawful, ethical, robust, transparent, fair, respectful of privacy, and accountable across its entire lifecycle (High-Level Expert Group on AI, 2019; US National Institute of Standards and Technology, 2022).

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.

Contents

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 Studio[1] 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.

Disclaimer

Case studies are the sole responsibility of their authors. They do not necessarily reflect the opinions or views of WTO members or the WTO Secretariat.

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.

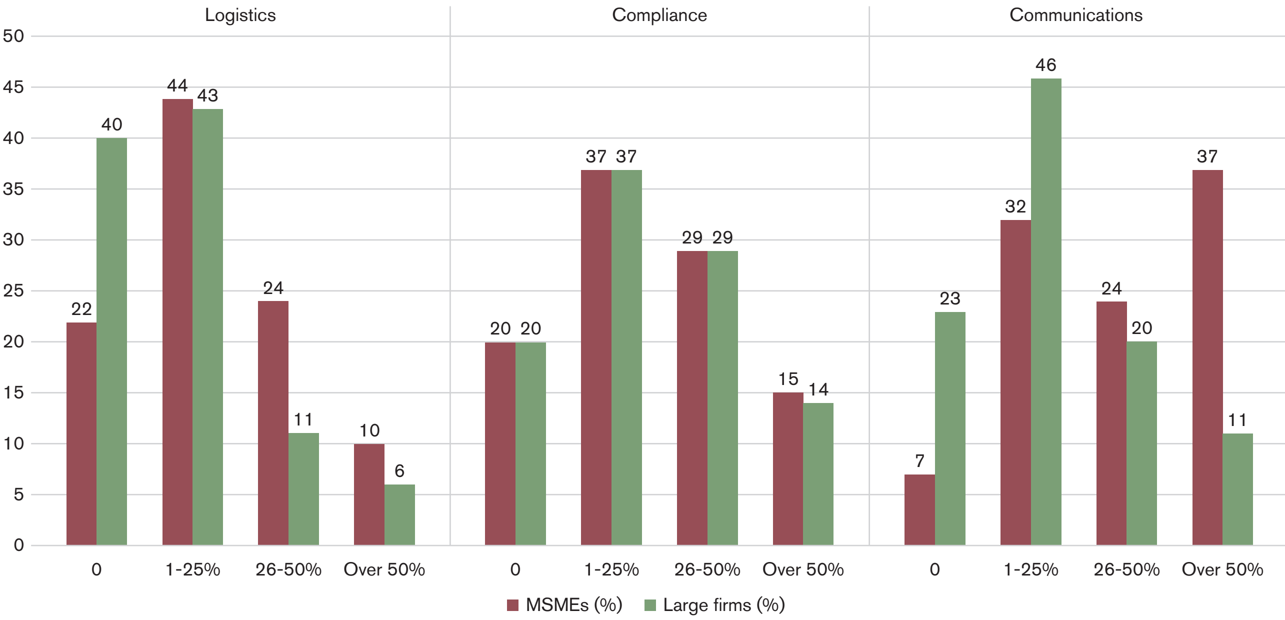
AI has the potential to increase participation in global value chains by enhancing their overall efficiency. It can improve coordination among suppliers, reduce lead times and minimize the need for inventories. AI tools used in predictive maintenance and just-in-time delivery systems can substantially 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.

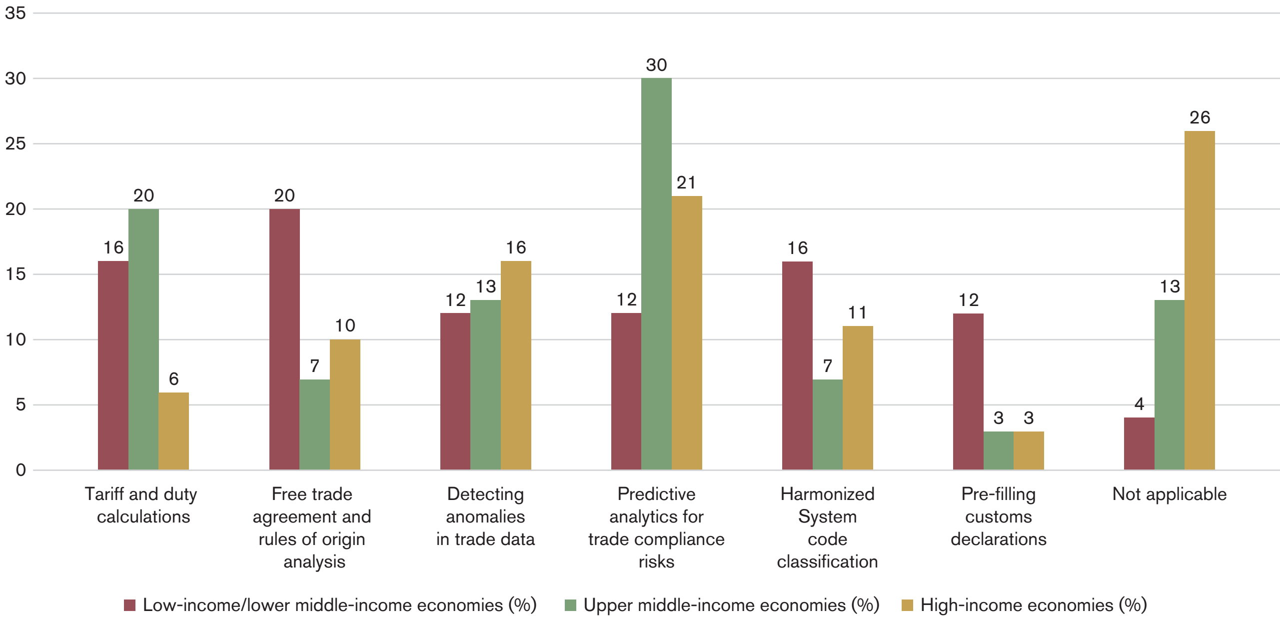
The survey shows how AI may help firms to navigate complex trade rules and benefit from trade agreements. Three-quarters of firms that currently use AI responded that they were using AI for customs-related applications. When the results by income level were examined, as shown in Figure B.2, it was observed 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

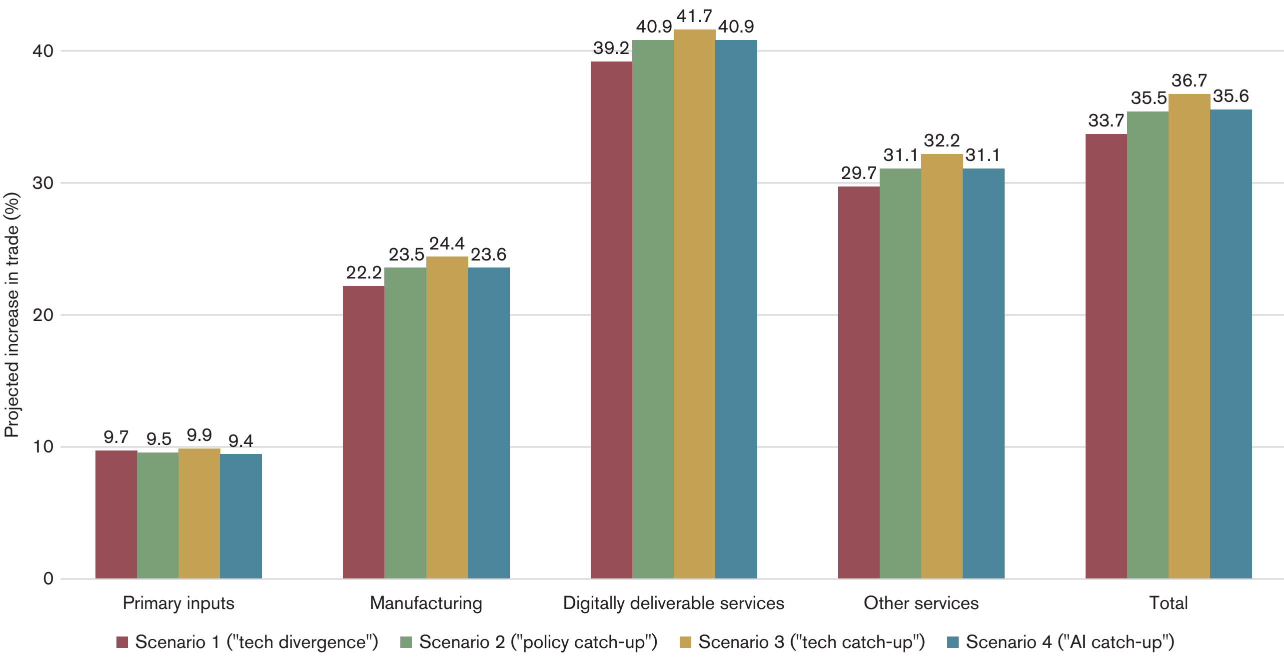
gains associated with this shift. Trade cost changes are calibrated based on gravity regression and consider reduced trade costs related to regulatory compliance costs, language barriers (in terms of translation and ease of communication), logistics costs (in terms of timeliness of shipments), contract 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).

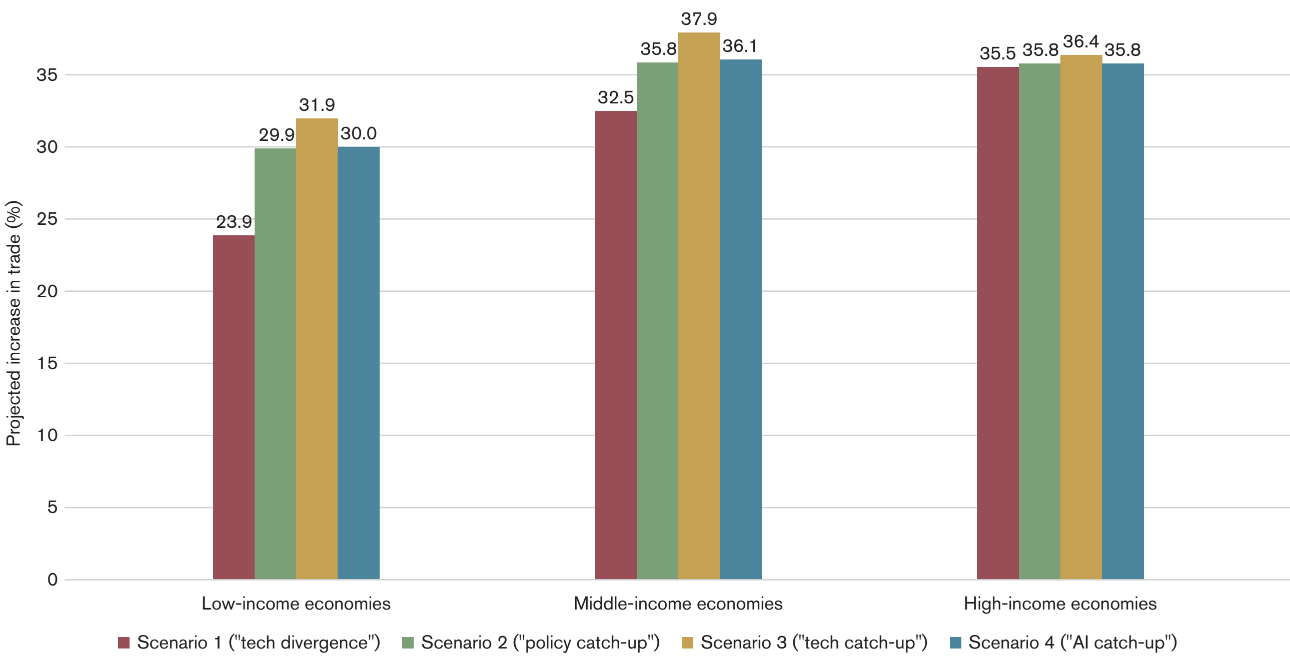
(b) Under the right conditions, AI can enable more inclusive growth through trade

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

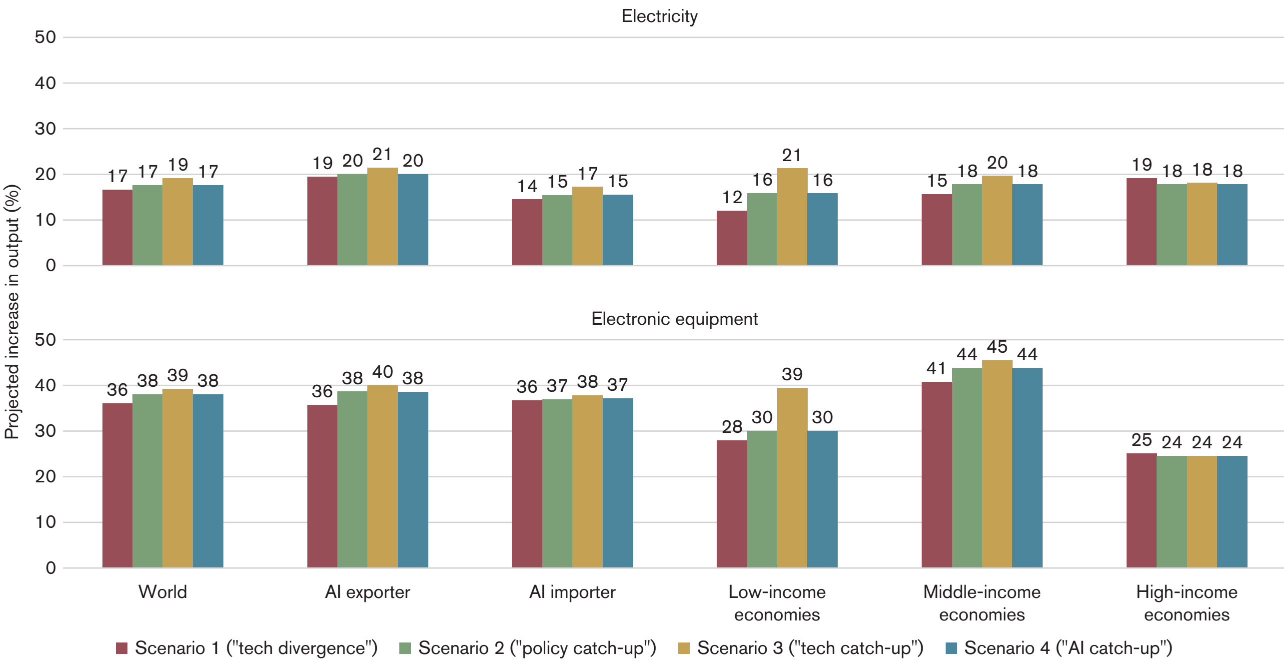
AI can contribute to development both by improving public services and by opening up new trade opportunities. Directly, AI can enhance the quality and affordability of public services, streamline bureaucratic processes and improve

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

By Amandeep Singh Gill

United Nations Under-Secretary-General and Special Envoy for Digital and Emerging Technologies

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.

Disclaimer

Opinion pieces are the sole responsibility of their authors. They do not necessarily reflect the opinions or views of WTO members or the WTO Secretariat.

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.

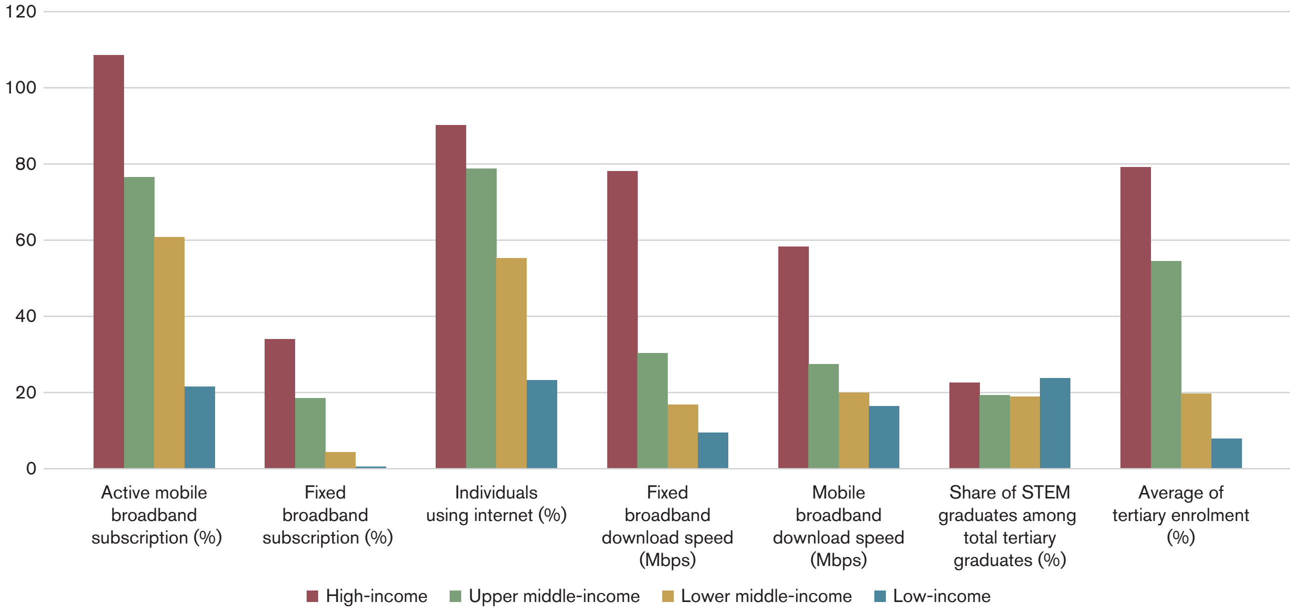
Investment in digital infrastructure and workforce skills is increasingly recognized as a key driver of comparative advantage in the emerging AI-driven global economy. Expanding broadband access, cloud computing and data infrastructure enhances an economy's capacity to enter and scale in AI-intensive 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).

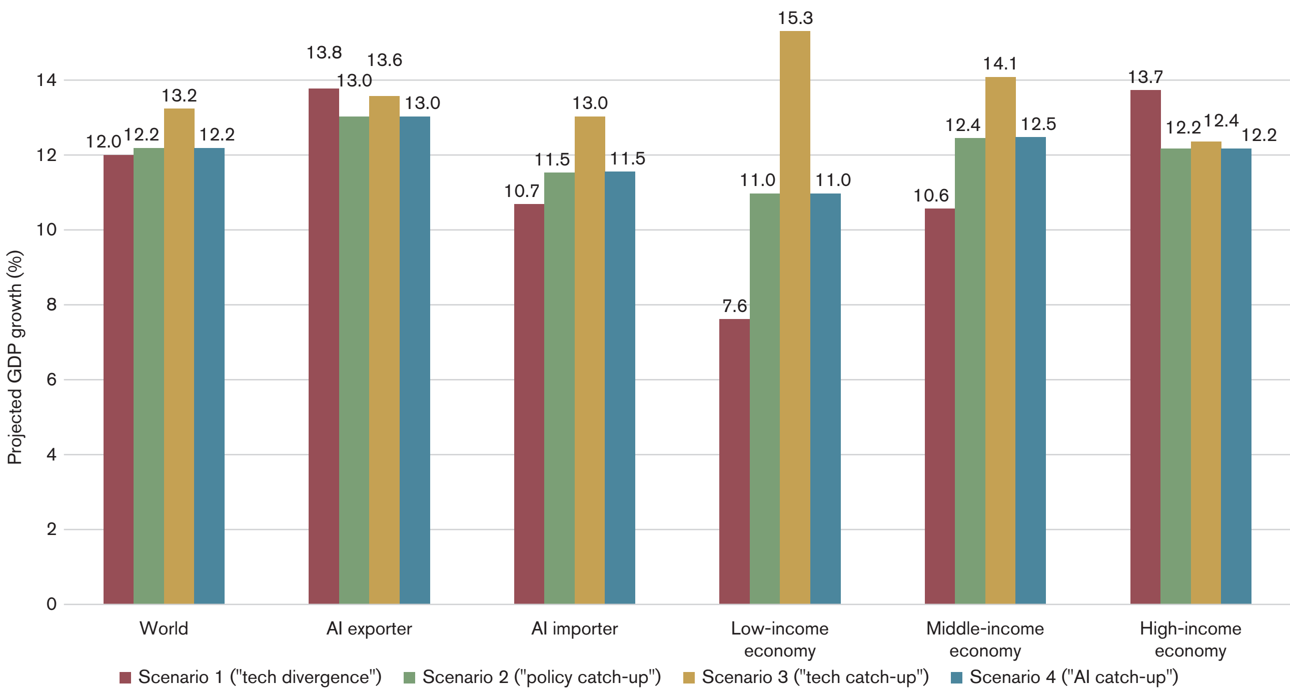
The availability of skilled labour and the development of a local AI ecosystem present major challenges. Successful AI research and commercialization often depend on strong academic institutions, well-funded research laboratories, and high levels of venture capital investment – resources that are frequently 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 Copilot[11] 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.

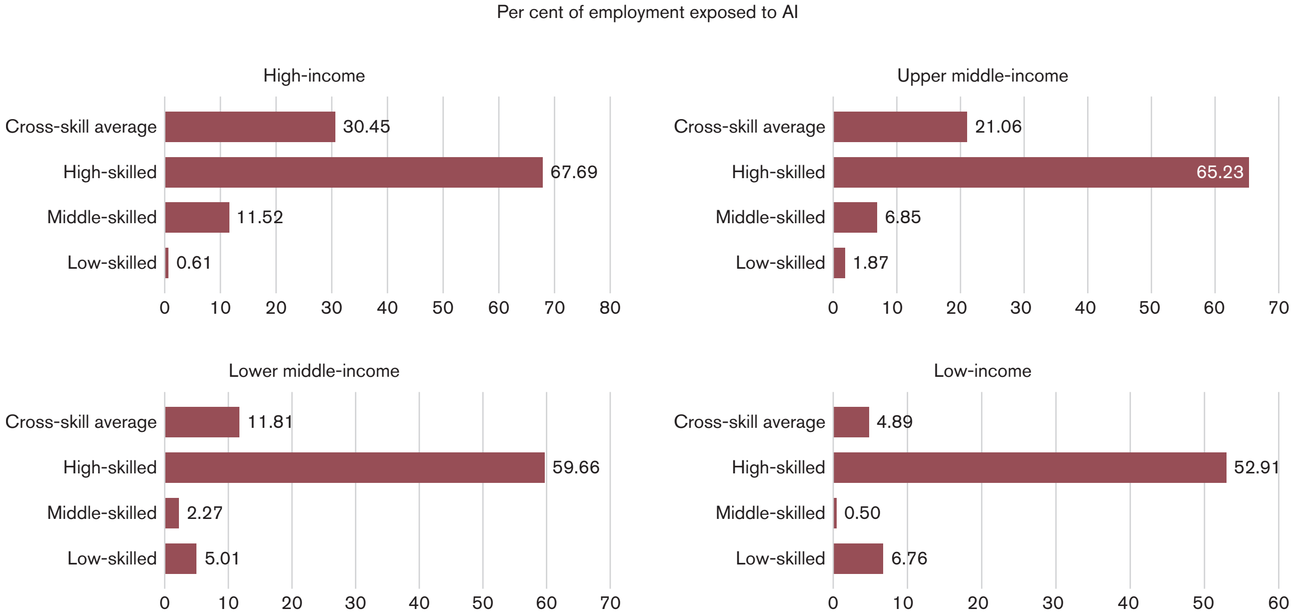
A task-based approach, rather than economy-wide assessment, may thus provide a more accurate understanding of how AI reshapes the nature of work across different industries. According to the AI Occupational Exposure Index developed by Felten et al. (2021), broadly defined managerial and professional 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

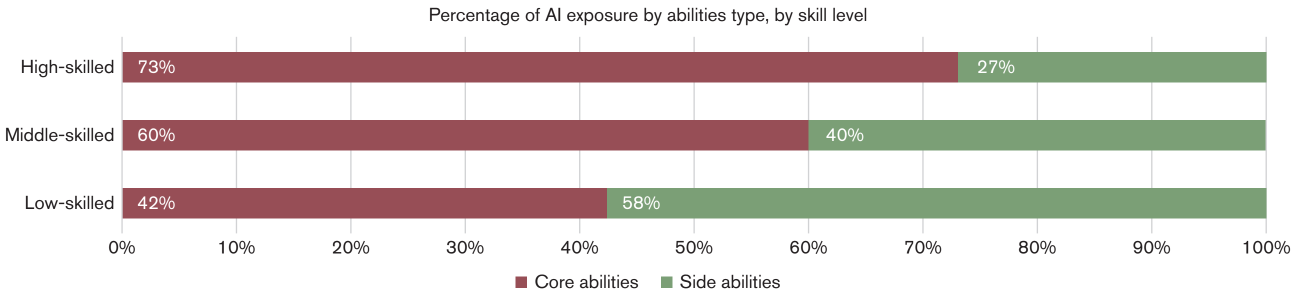


Source: WTO Secretariat calculations based on AI exposure measure based on Felten et al. (2021) and global employment data for 118 countries using ILO Harmonized Microdata.

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).

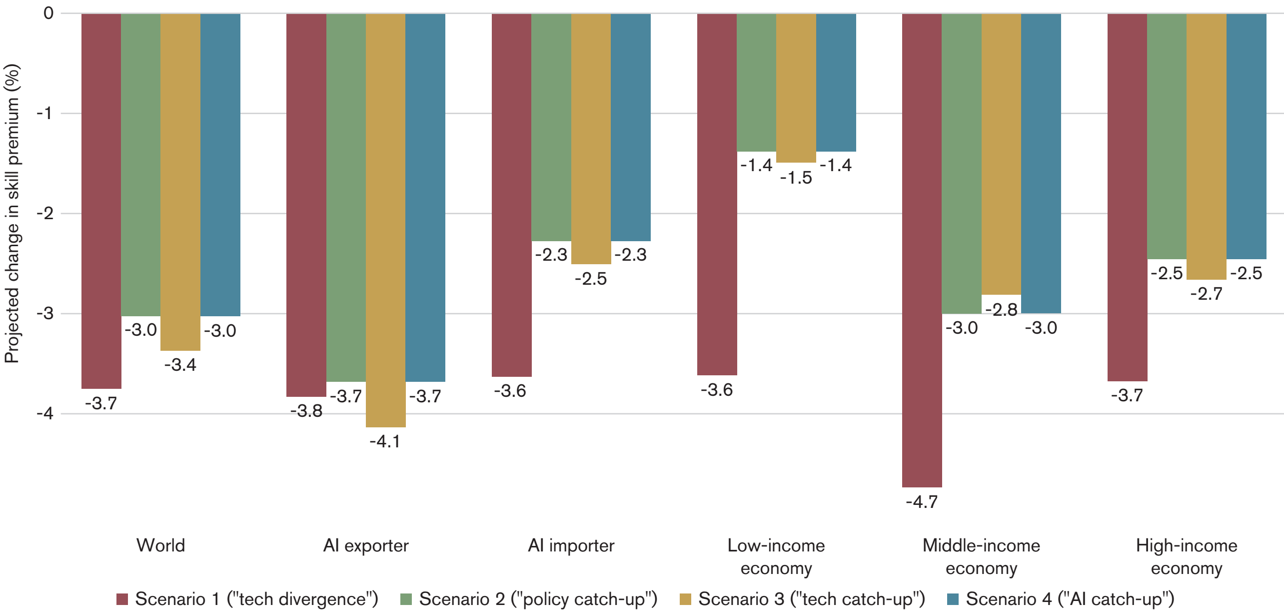
Two main forces shape the impact of AI on employment across skill groups. On the one hand, higher productivity raises output and, in turn, increases demand for human labour. On the other hand, some tasks previously performed by human labour are expected to be automated, which reduces the demand for human 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)



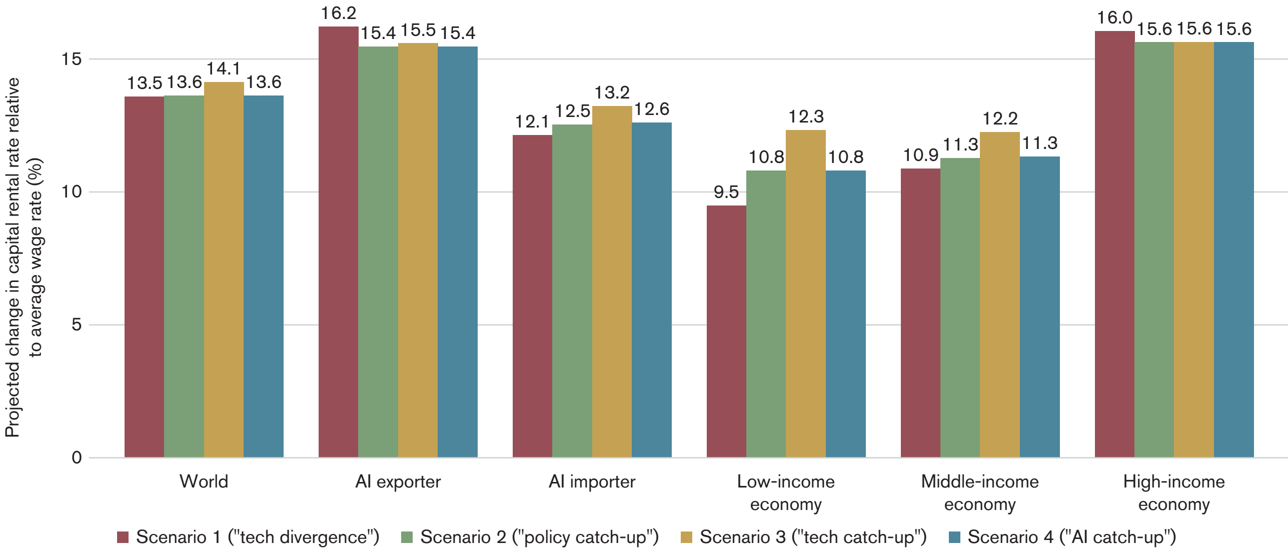
Source: Simulations using the WTO Global Trade Model.
Notes: The figure displays the change in the skill premium, i.e., the ratio of wages of high-skilled workers relative to low-skilled workers, for four scenarios in deviation from the baseline, both globally and for aggregate regions, split by level 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 Intelligence[16] 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.

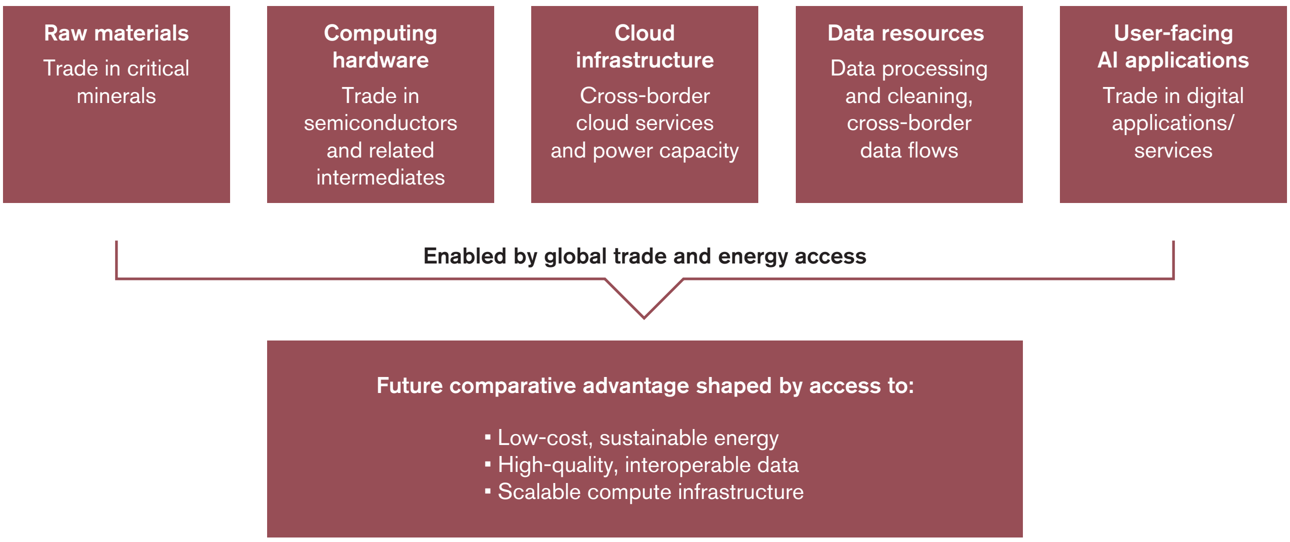
The key components of the AI supply chain include raw materials, computing hardware, cloud infrastructure, training data, foundation models and user-facing AI applications. As illustrated in Figure B.12, each of these segments is enabled and amplified by the cross-border movement of physical components,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

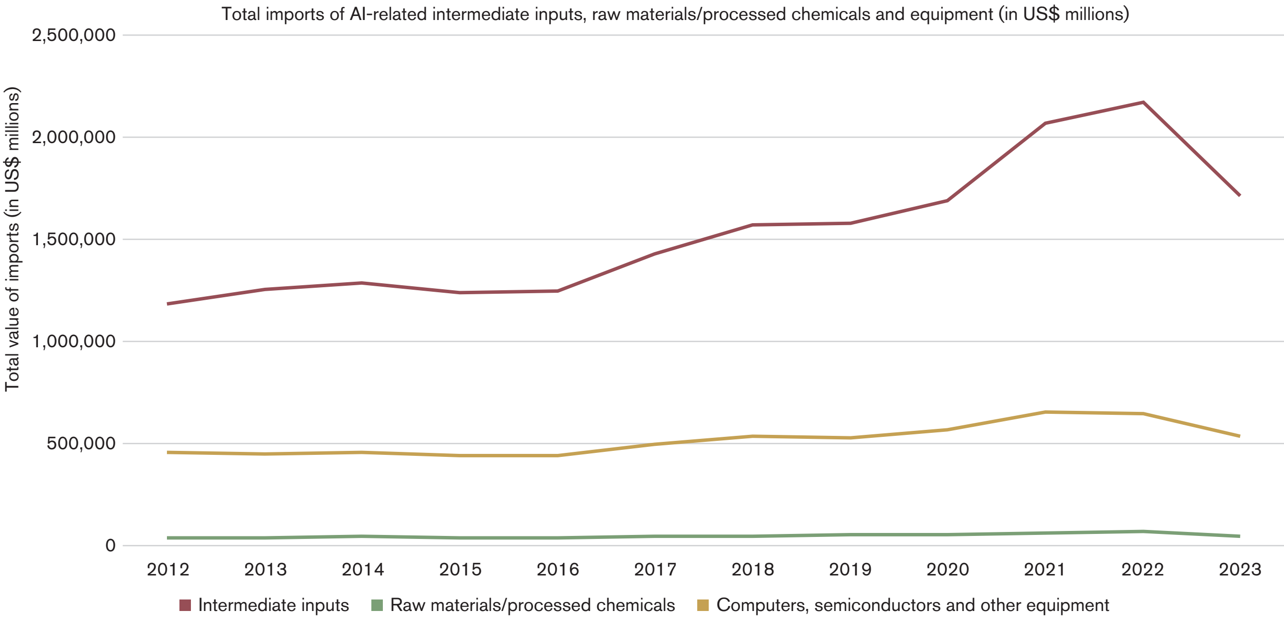
(i) AI-enabling raw materials and equipment

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

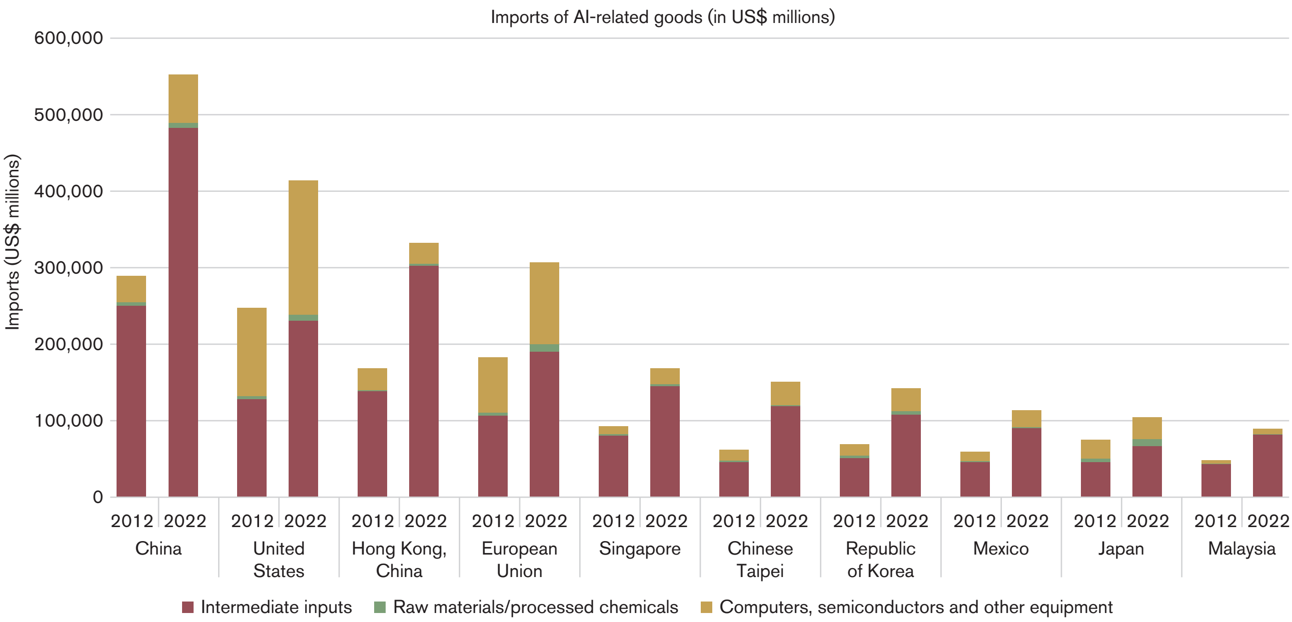


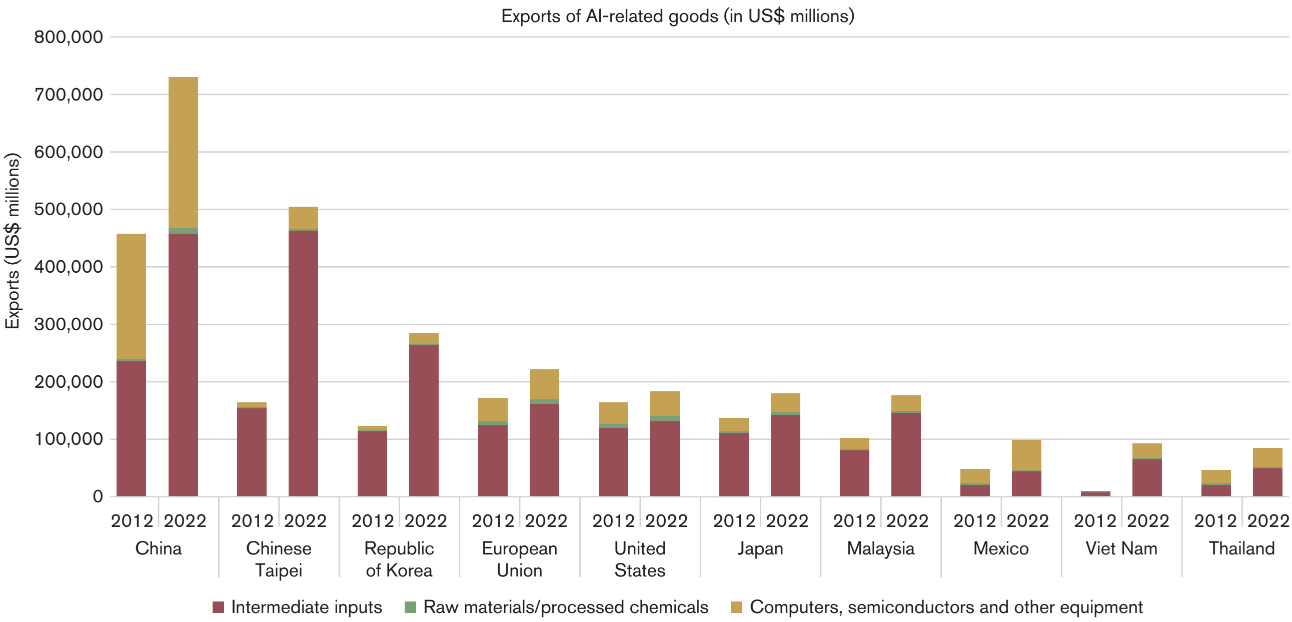
Source: WTO Analytical Database.
Note: The product categories shown are based on a non-exhaustive list of HS codes, and may include items not exclusively used in the AI value chain. The classification reflects indicative groupings of goods that enable AI development and deployment. The list of AI-enabling 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.

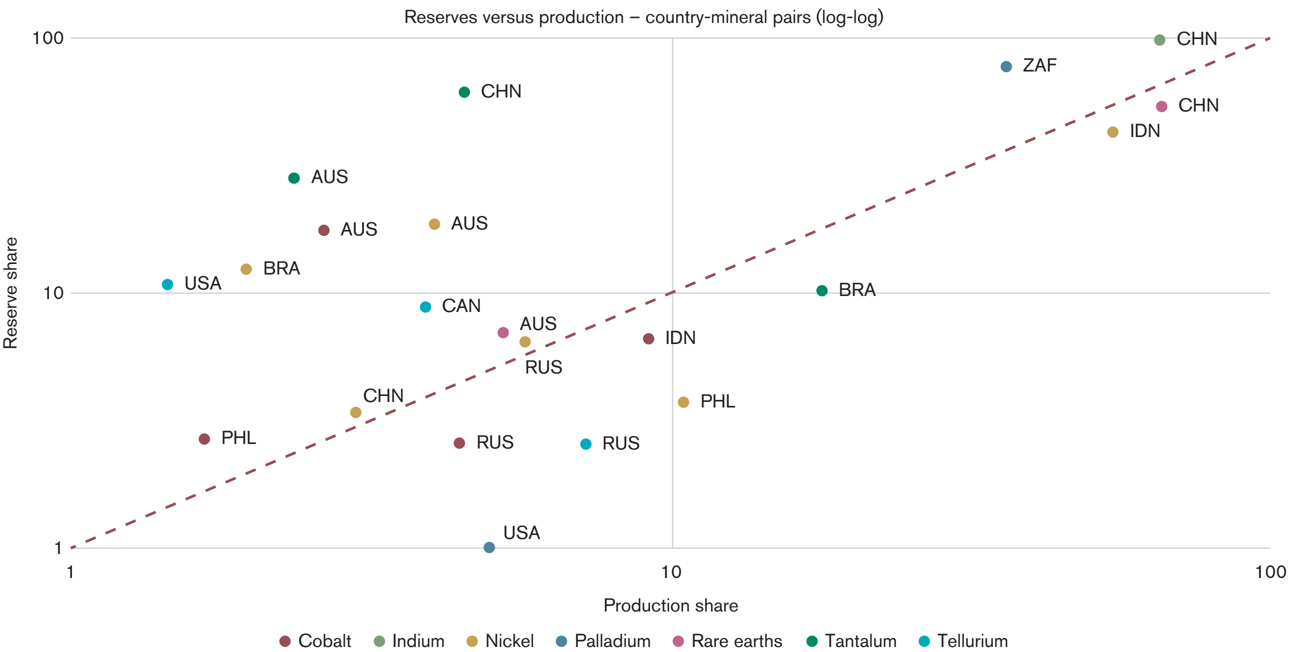
While the European Union, the United States and Japan remain major exporters of AI-enabling intermediate inputs and equipment, growth of these exports has been more modest. Emerging manufacturing hubs such as Malaysia, Mexico, Viet Nam and Thailand have also increased exports of AI-related intermediate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

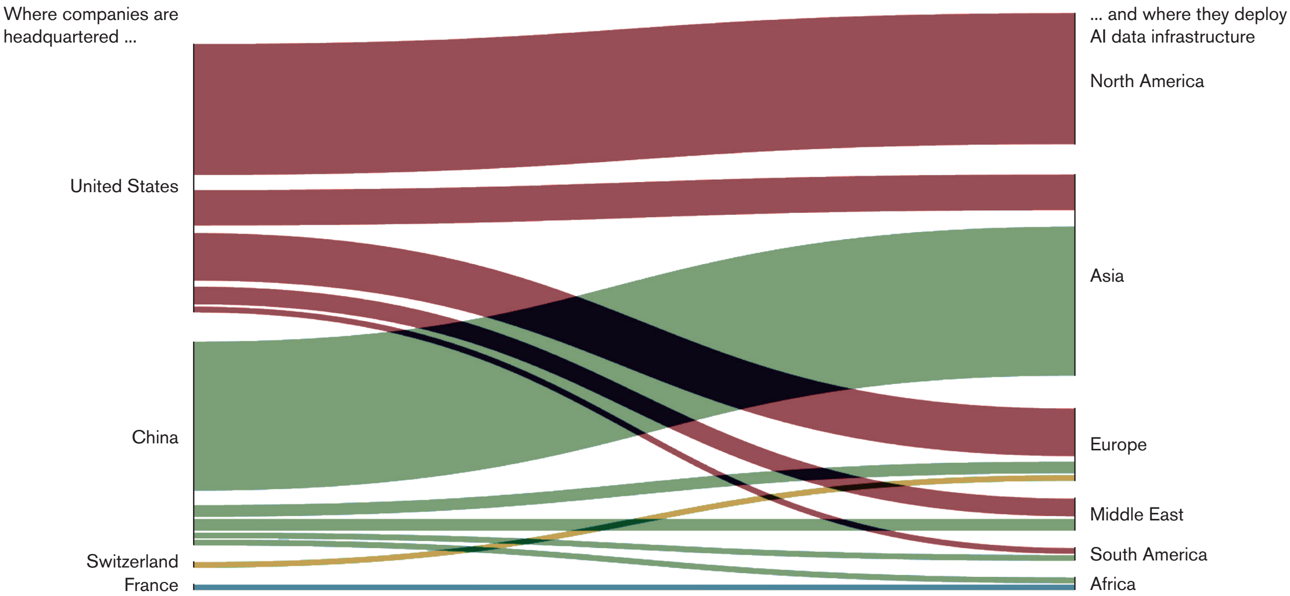
Investment in renewable power infrastructure to meet AI's growing energy needs remains important. Economies with abundant renewable energy and digital connectivity can gain a trade advantage in the AI value chain by hosting data centres that serve regional or global markets. Developing economies in sun-rich 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.

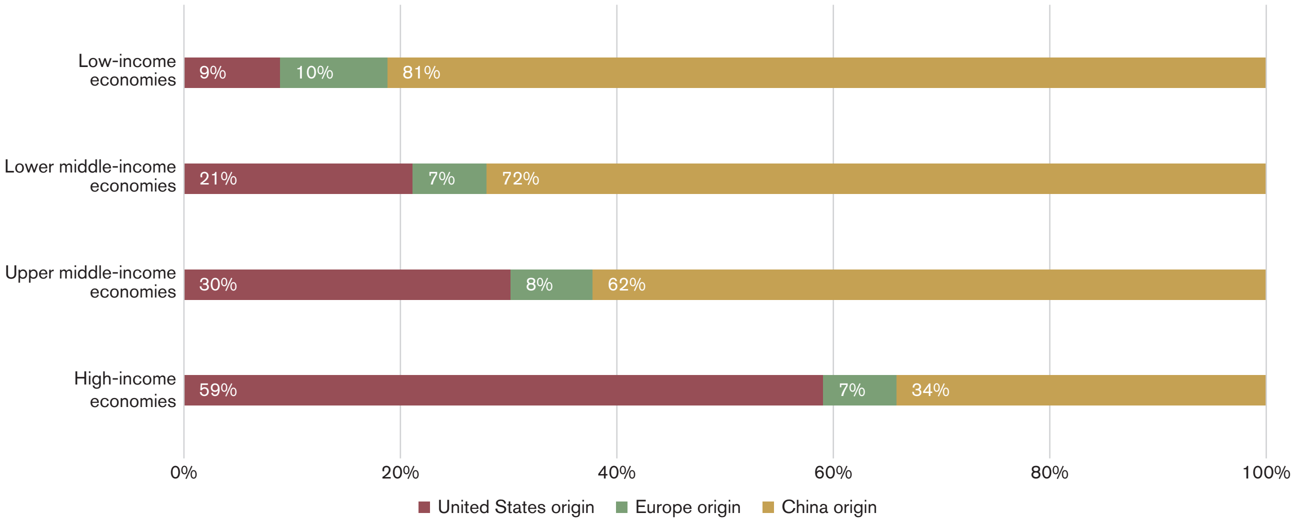
One way for resource-constrained economies to leverage AI is by adapting open-weight models. A notable example is Singapore's Infocomm Media Development Authority (IMDA)'s GPT-Legal, an AI-powered legal research tool launched by Singapore's legal resource database and built on Meta's Llama model. Fine-tuned 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).

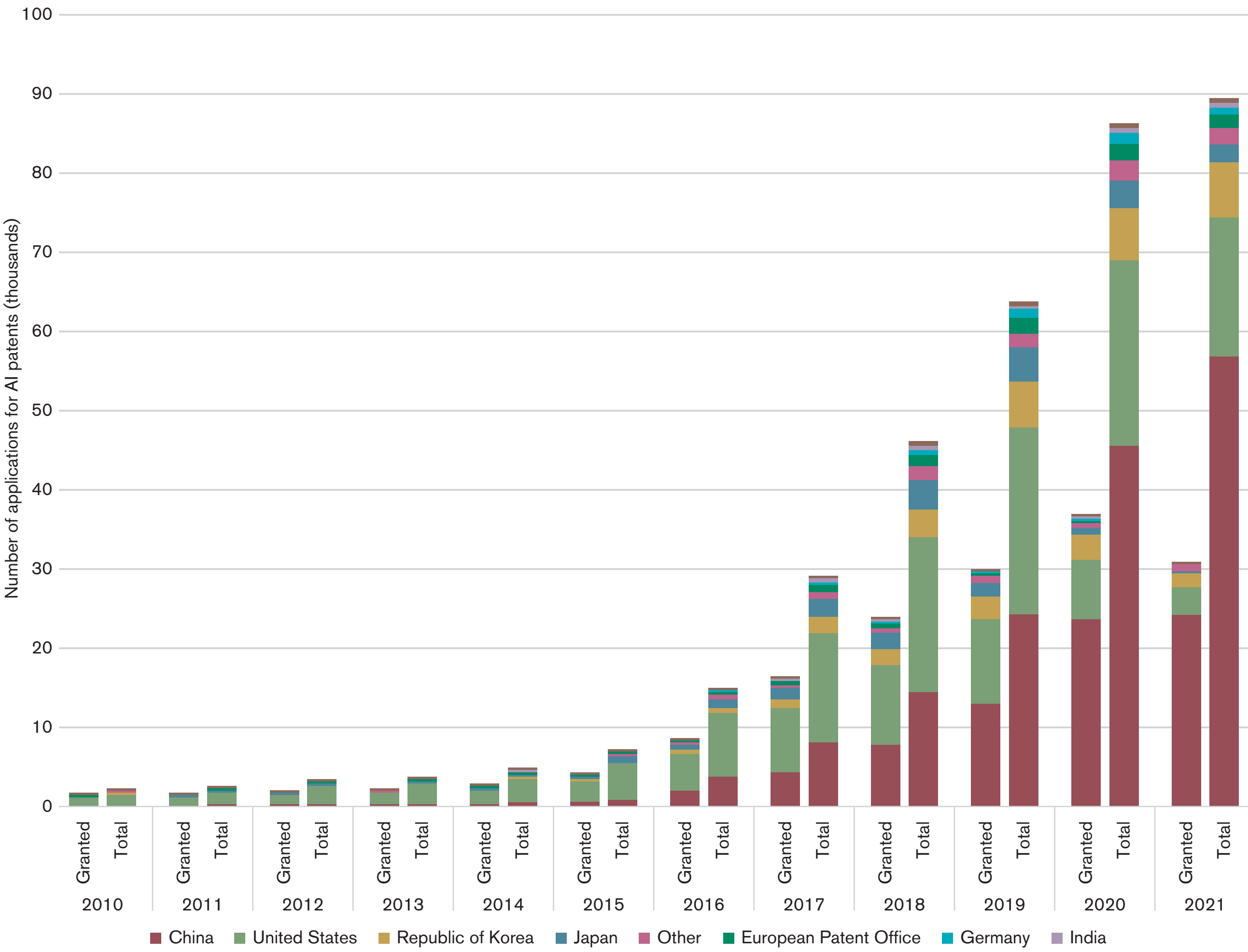
One widely used measure of knowledge and innovation is the number of patents. In this context, a patent is a legal right granted by a government to an inventor, giving them exclusive rights to use, produce or sell their invention for a certain period of time, typically in exchange for publicly disclosing 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.

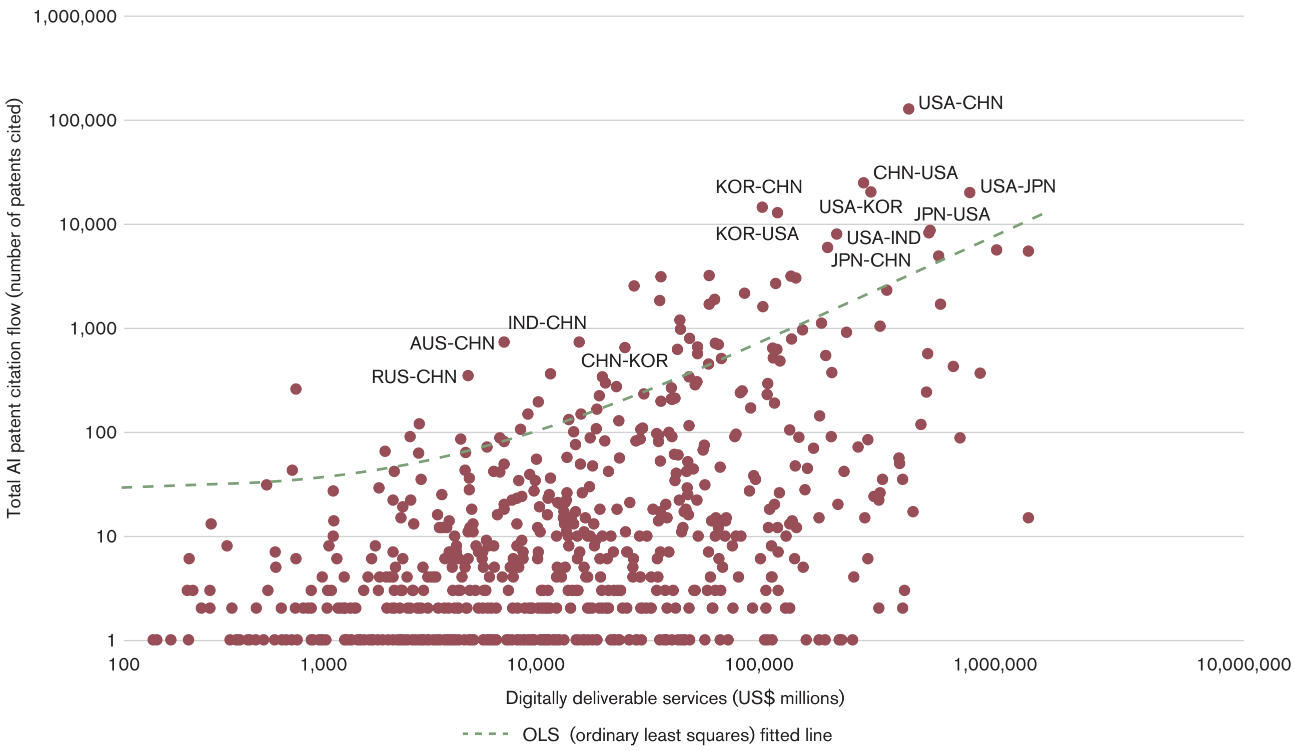
The global diffusion of AI models depends heavily on international data flows and services trade. Trade, particularly in digitally deliverable services, underpins the cross-border dissemination of AI technologies and capabilities. Adoption patterns suggest that the development of digital infrastructure, 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://ixafrica.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 userled 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.

C How domestic policies can shape the trade and AI relationship to favour inclusive economic growth

Trade policies are a necessary part of any relationship between trade and AI that results in inclusive economic growth. Trade policies affect the availability and price of the products that enable AI, from critical minerals to IT services. They also regulate how data – the key input for AI models – flow across borders. They maintain an open and predictable trading system, which is key to unlock the benefits of AI for growth. Other trade-related and complementary policies, including those regulating intellectual property, competition, infrastructure and labour markets also affect how AI will develop and interact with trade. However, these policies must ensure that the benefits from AI are dispersed widely if inclusive trade-led growth is to be achievable but, as this chapter shows, there is a clear divide in policy rollout that risks widening the structural divide between higher-income and lower-income economies.

Contents

Key points

- A predictable trade policy environment that ensures low trade costs, in combination with trust-building standards, is necessary if AI is to boost trade-led inclusive growth, and trade policies need to be embedded in a coherent policy framework to be effective.

- AI-enabling goods, such as semiconductors, face relatively low tariffs, but are increasingly targeted by non-tariff measures, including antidumping duties and export restrictions. AI development and diffusion is also being held back by the relatively high trade costs imposed by regulations on services trade and data flows. Such trade restrictions could jeopardize the global dissemination of AI.

- Key policy areas that need to work together with trade policy for AI to be beneficial are intellectual property and competition policies, infrastructure and labour market policies, and industrial policy.

- High-income and upper middle-income economies have a substantial lead in regulating AI and and adopting trade-related complementary policies, and this risks widening the structural divide across income groups.

- Legitimate policy objectives, such as protecting data privacy, can come into conflict with objectives to further open cross-border flows of products and data. Policymakers face complex challenges as they aim to achieve policy objectives without compromising inclusive growth through AI and trade. International cooperation can be an important avenue to address such challenges.

1. Trade policy is critical for inclusive growth driven by AI

Tariffs and non-tariff measures on goods, services and data flows determine the extent and inclusiveness of the growth that AI can generate. AI could reshape comparative advantage and allow for much larger-scale production. Trade policy determines who has access to such production, and at what cost. Moreover, trade policy is a key lever to shape AI development and diffusion. Restrictions on key inputs for AI development can deny certain economies access to the benefits of AI. Yet concerns about data privacy, security or fiscal space can lead to legitimate policy interventions. For instance, for governments with weak tax enforcement capabilities, it may not be possible to forego tariff revenue on AI-related goods without other sources of revenue. Thus, the AI revolution is bringing with it numerous opportunities, but also challenges, that policymakers will need to manage.

(a) Trade-opening can accelerate the development of new sectors

Trade policy plays a crucial role in shaping innovation, and influences the global diffusion of knowledge and technology. There is a large body of literature that shows how trade policy can affect incentives for innovation and learning. The theoretical foundation builds on the influential idea that knowledge is a cumulative and non-rival good, so new knowledge builds on existing ideas without diminishing their value (Romer, 1990; Grossman and Helpman, 1991). Trade and investment policies, if they encourage the exchange of products and personnel, are important conduits for cross-border knowledge flows. Empirical work shows that open trade policies can magnify the positive impact of foreign research and development (R&D) on domestic productivity (Coe and Helpman, 1995; Keller, 2004; Nishioka and Ripoll, 2012). Moreover, trade policies that give access to cheaper, higher-quality or more varied inputs boost profitability and incentives to invest in R&D (Bøler, Moxnes and Ulltveit-Moe, 2015). They also enhance firm-level productivity and promote technology diffusion (Amiti and Konings, 2007; Bloom, Draca and Van Reenen, 2016; Harding and Javorcik, 2012). Importantly, the link between trade policy and innovation is not limited to advanced economies. In developing economies, trade openness and participation in global value chains can support technological catch-up and capability-building (UNCTAD, 2021; Pietrobelli and Rabellotti, 2011; Rodrik, 2004).

Sectoral development often relies on targeted trade measures that influence firm behaviour and shape the structure of domestic production. Exporters and importers tend to be more productive and innovation-intensive, while multinational corporations act as important vectors for technology transfer. A growing body of firm-level evidence shows that trade-opening can foster innovation by improving access to foreign inputs. For example, tariff reforms in India in the early 1990s enabled domestic firms to access a larger variety of inputs, accounting for 31 per cent of new product introductions (Goldberg et al., 2010). In Colombia, tariff reductions on inputs spurred innovation by lowering production costs and encouraging firms to source more efficiently from abroad (Fieler, Eslava and Xu, 2018). Firm-level studies from Argentina, Chile, Hungary and India confirm that better access to foreign intermediate inputs increases plant productivity (Topalova and Khandelwal, 2011; Gopinath and Neiman, 2014; Halpern, Koren, and Szeidl, 2015). In AI-related sectors, lower input tariffs on computing hardware have helped to build technological depth and enhance participation in global value chains (Freund, Mulabdic and Ruta, 2022; Cherif and Hasanov, 2019). Trade-opening in services sectors can have similar effects, improving the productivity of downstream manufacturing firms by raising service quality and reducing input costs (Arnold et al., 2015; Arnold, Javorcik and Mattoo, 2011).

Export restrictions have sometimes been used by governments as a tool for strategic sectoral upgrading, although outcomes have often been unsatisfactory. Such measures aim to redirect inputs, such as raw materials, from export markets to domestic processing industries, with the goal of building value-added capacity and climbing the technology ladder. While this strategy can help to nurture infant industries, its short-term costs can be significant: upstream producers may face lower returns, and incomes are redistributed across sectors. Moreover, evidence relating to critical minerals and rare earths suggests that these policies can trigger unintended effects by stimulating innovation abroad. For example, China's rare earth export restrictions in the early 2010s led to a global surge in innovation and exports in rare-earth-intensive downstream sectors outside of China, driving down demand for Chinese rare earths permanently (Alfaro et al., 2025).

High-income economies have also sometimes turned to restrictive export measures, particularly to retain technological leadership in sensitive sectors. Recent export controls on semiconductors, for instance, have sought to slow the diffusion of high-performance chips and AI components to strategic competitors. While such measures may have legitimate objectives, they risk fragmenting global innovation ecosystems and often face significant enforcement challenges. Emerging evidence suggests that overly restrictive controls can produce the opposite effect. Rather than curbing technological advancement, they may incentivize greater self-reliance in targeted economies by accelerating domestic R&D and investment abroad (Clayton et al., 2025). The broader literature on sanctions finds that unilateral measures often underperform, especially in more recent years, as complex supply chains increasingly complicate enforcement (Felbermayr et al., 2020). Coordinated sanctions by a coalition may reduce the average welfare loss for each coalition member and amplify the impact of sanctions. Yet sustaining such coalitions remains politically and economically costly, as the burden is often unevenly distributed among its members (Chowdhry et al., 2024).

Overall, the effectiveness of trade policy in fostering innovation and sectoral development depends on its alignment with domestic capabilities and institutional contexts. There is no one-size-fits-all model, as successful trade policies for innovation and technology diffusion tend to be adaptive, targeted and embedded within broader national development strategies (Lee, 2013). For example, coordinated trade and industrial policies can enable firms to gradually integrate into global value chains while building local technological capabilities (Rodrik, 2004; Hausmann, Hwang and Rodrik, 2007). This is particularly relevant in the context of AI, as economies must simultaneously integrate into global digital markets and develop domestic capacities to ensure inclusive benefits from technological progress.

(b) Tariffs on AI-enabling goods are low but non-tariff measures are on the rise

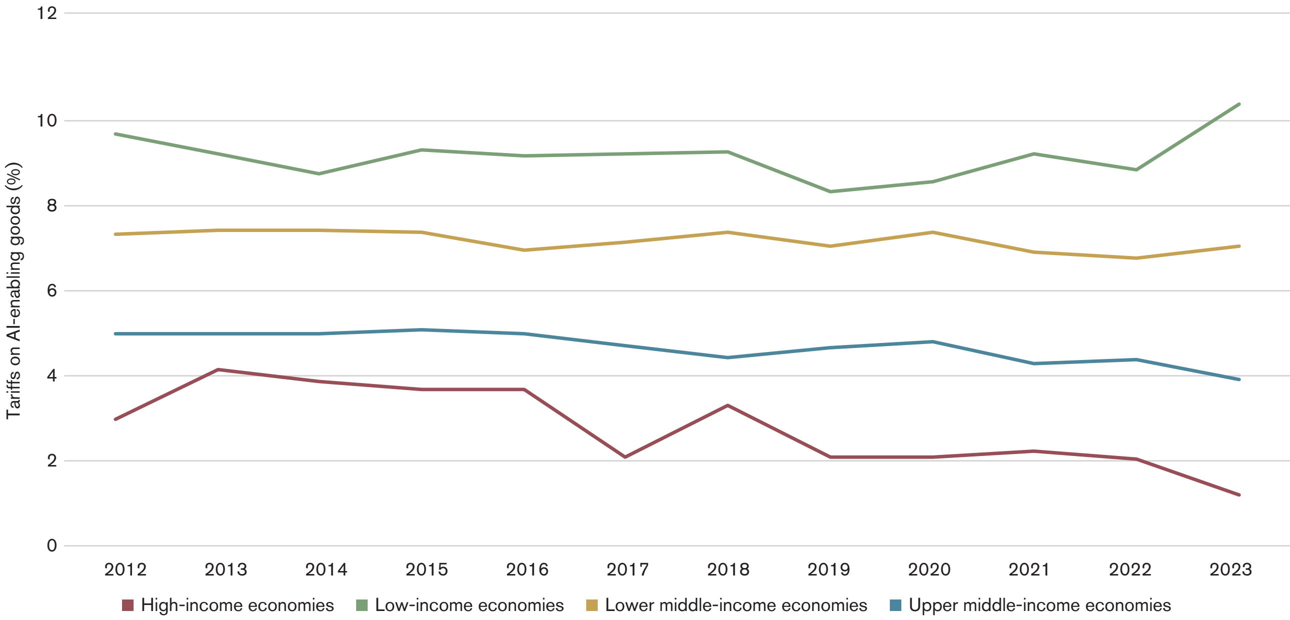
There is a large set of border measures in the toolkit of policymakers trying to regulate the AI ecosystem. These range from the use of tariffs to import and export restrictions, including full bans or licensing systems. Reasons for relying on these measures are diverse. They cover both economic and non-economic considerations, including environmental and national security concerns, not least since many of the relevant AI products are so-called "dual-use items", i.e., adaptable both to civil and to military use. This section provides an overview of these measures to show some of the potential roadblocks to the international trade of AI and to its role for inclusive trade-led growth.

Tariffs are the most prevalent tool for policymakers, and applied duties on AI-enabling goods are generally low.[1] Figure C.1 shows that simple average tariffs were consistently low between 2012 and 2023, not exceeding 11 per cent for any income group. Tariffs were lowest among high-income economies, having dropped from around 4 per cent in 2013 to just 1 per cent by 2023. Many high-income economies are members of the WTO's Information Technology Agreement (ITA) and its 2015 Expansion,[2] and many of the tariff lines relevant to AI are covered by these agreements, resulting in generally lower tariffs (see Section D.1). For the other income groups, however, tariffs are generally higher, and they are highest of all for the low-income group, with a recent uptick in 2023.

Trade remedies can have restrictive effects on AI-enabling goods in economies with low tariffs. While average tariffs provide a useful snapshot, they only tell part of the story when it comes to the trade barriers faced by AI-enabling goods. Trade remedies such as anti-dumping duties, countervailing duties or safeguards often complement regular applied tariffs. The Digital Trade Integration Index (DTI),[3] an indicator assessing the restrictiveness to digital trade of different policies, compiled by the Digital Trade Integration Project (see Ferracane, Ugarte and Rogaler, 2025), suggests that such measures are mainly used by economies with low tariffs. In fact, trade remedies are strongly negatively correlated with tariffs, according to the DTI. As a result, they partly offset the market access provided by low tariffs. These measures are almost exclusively used by the high-income group, so the overall level of protection is higher than what might be concluded from tariffs alone.

A growing set of quantitative restrictions, such as import and export quotas, licensing

Figure C.1: Tariffs on AI-enabling products are consistently low



Source: WTO Secretariat calculations based on WTO Tariff & Trade Data platform.
Note: Figure C.1 contains simple average most-favoured-nation (MFN) tariffs for AI-enabling products aggregated by income group. AI-enabling products are defined in Annex A.

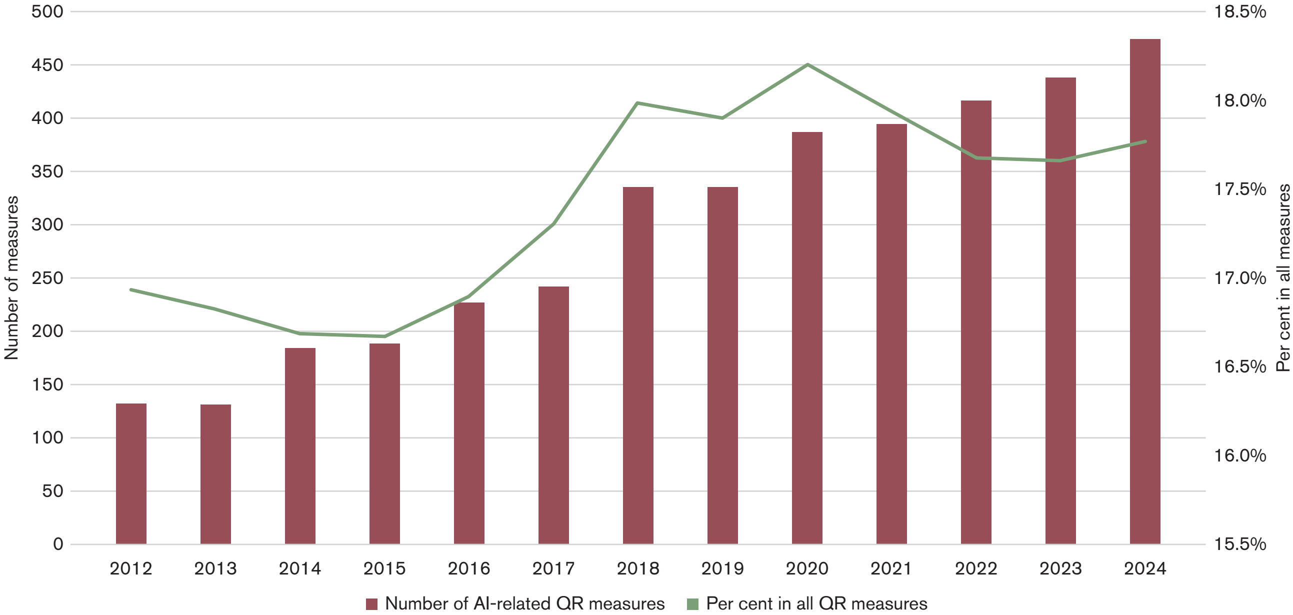
requirements, and even bans, are increasingly shaping trade in AI-related products. Figure C.2 illustrates the number of quantitative restrictions (QRs) applied to AI-enabling goods, based on data from the WTO's Quantitative Restrictions Database. QRs applied to AI-enabling goods have climbed sharply over time, reaching nearly 500 in 2024. In relative terms, the share in total QRs applied to AI-enabling goods has also shown an increase since 2015, reaching almost 18 per cent in 2024. However, gaps in the notification of these measures to the WTO remain significant, with only about half of WTO members complying with the obligation to notify their QRs, meaning the true number of restrictions could be considerably higher.

QRs are typically, but not exclusively, applied to dual-use goods, reflecting the fact that these goods may potentially have both a civil and a military use. The products most frequently covered by these restrictions include nitrogen function compounds, ethers, inorganic acids and non-metallic oxygen compounds, hydrides and other chemicals. These substances play a key role in the production of AI technologies, but they also have applications in the manufacture of explosives and military equipment, a dual potential that often prompts stricter regulation by WTO members. Other products frequently covered are telephones, routers and other cell phone hardware, and data storage, which have predominantly civil uses.

If the share of QRs that is export-related is examined, the proportion of AI-related QRs is consistently higher than other types of QRs. For instance, in 2024, 43 per cent of QRs on AI-enabling goods targeted exports, compared to just 38 per cent for QRs on all other goods. This pattern could be an indication that WTO members are more concerned about regulating the outflow of AI technologies, possibly to prevent their use in sensitive or strategic applications abroad. Such concerns could reflect growing awareness of the dual-use nature of many AI-related goods, as well as the geopolitical, economic and ethical implications of their deployment outside domestic jurisdictions.

AI-enabling goods are increasingly affected by technical barriers to trade. Under the WTO Agreement on Technical Barriers to Trade (TBT), members are encouraged to ensure that technical regulations, standards and conformity assessment procedures do not create unnecessary obstacles to international trade. Although such measures may be justified on legitimate grounds, they must be non-discriminatory, transparent and based on international

Figure C.2: The number of quantitative restrictions on AI-enabling goods is rising



Source: WTO Secretariat calculations based on WTO Quantitative Restrictions Database.
Note: Some quantitative restrictions are both import and export measures, and are thus counted twice.

standards where available. According to the WTO's ePing database,[4] the number of TBT notifications for AI-enabling goods has slightly increased since 2012. However, overall numbers remain small in terms of TBT measures for these goods when compared to other goods. This suggests that, while awareness and regulation of AI are on the rise, AI-specific TBT measures still represent a niche area within the broader framework of technical regulation and trade policy.

(c) Trade in AI-related services is limited by restrictive regulations

Trade in services is key both to leverage the benefits of AI and to accelerate its global development and diffusion, but restrictive regulations limit this potential. Trade in services growth has been outpacing the growth of trade in goods for at least two decades. AI is expected to accelerate this divergence, as it is likely to increase the productivity and tradability of services (see Section B.1). However, the potential for AI-driven services trade is not without friction. Despite technological readiness, many of the sectors most exposed to AI face persistent regulatory and policy barriers.

Evidence suggests that AI-intensive services face significant restrictions to trade. Combining the World Bank-WTO Services Trade Restrictions Index with the classification of AI-intensive sectors by Calvino et al. (2024) (see also Annex A.2) reveals high barriers across key AI service sectors. In the context of General Agreement on Trade in Services (GATS) mode 1 of supplying services (i.e., the cross-border supply of services),[5] sectors such as accounting, auditing, television services, insurance, telecommunications and commercial banking exhibit some of the highest levels of restrictions. In the case of services trade through GATS mode 3 (i.e., when a foreign company establishes a presence in another economy to provide services), the most restricted sectors are accounting, auditing, legal services and television services. Trade through mode 3 is, however, on average significantly more open than trade through mode 1. Regulation of services trade, ranging from foreign equity limits to restrictions on the legal form of entry or quantitative restrictions, can significantly constrain the flow of services. Potential reasons for higher trade restrictions on certain services can be regulatory oversight, consumer protection or national security. Since services like accounting, banking and telecommunications involve sensitive data or systemic risks, many governments prefer providers to operate under direct domestic supervision rather than across borders.

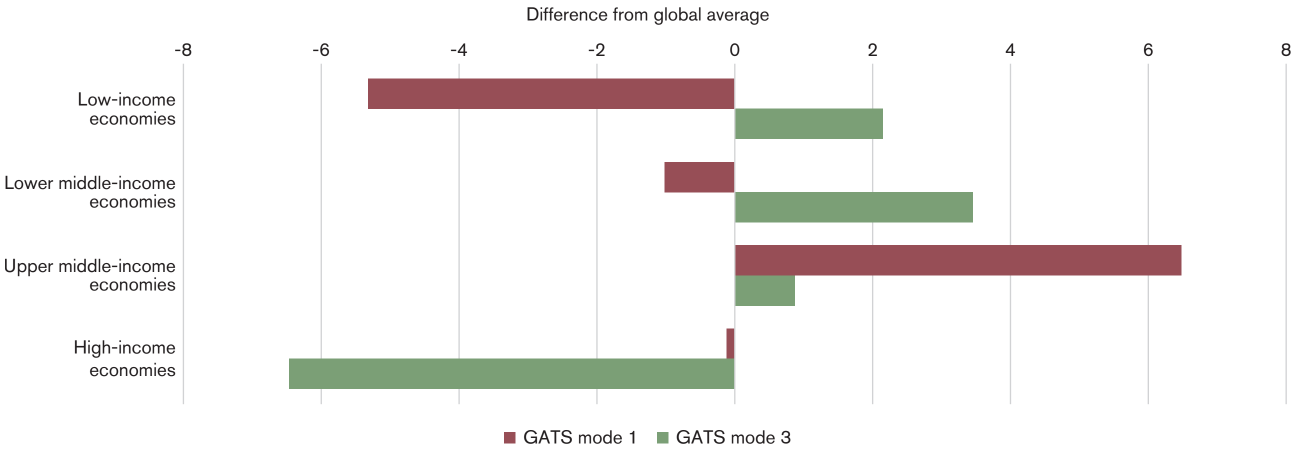
The level of services restrictions in different economies differs according to income and across modes of supply. As illustrated in Figure C.3, the cross-border supply of services (GATS mode 1) tends to be less regulated in low-income economies, and the highest levels of restriction are observed in upper middle-income economies. In contrast, for commercial presence (GATS mode 3), the pattern is reversed: low-income economies exhibit the highest restrictions and high-income economies impose the lowest. This finding aligns with the tariff analysis demonstrated in Figure C.1, which shows that low-income economies maintain higher levels of protection. However, trade barriers for mode 1 present a contrasting picture, with lower levels of protection in low-income economies. The application and integration of AI technologies in facilitating international service delivery are more limited when restrictions are high, suggesting that, while AI could enhance efficiency and connectivity in global services trade, its transformative role could be uneven across sectors depending on the prevailing regulatory environment. Since these regulations can have important and legitimate objectives, policymakers may need to make more conscious trade-offs between these objectives and facilitating AI development and diffusion.

(d) Fragmented regulation of cross-border data flows is a risk to inclusive AI development

Data are a key input of AI, and regulatory approaches to data are critical for AI development and diffusion. Open, low-cost access to diverse datasets supports innovation, quality and the scale-up of AI applications. AI models can provide more accurate predictions that are not susceptible to bias if the data on which they are trained is accurate and representative. To enable this, data regulation could facilitate the access of AI developers to such high-quality datasets. Recent evidence suggests that economies with a more liberal policy environment for digitally enabled trade, including data regulation, export relatively more in AI-intensive industries (Bonfiglioli et al., 2025).

At the same time, concerns around privacy and security have led to increased scrutiny of how data are collected, transferred and used. The increasing importance and value of data to companies training AI models have resulted in privacy and IP violations. There have also been issues with improperly trained AI models, with numerous examples of AI-created outputs that have been biased, for example in terms of gender or race (UNESCO and International Research Centre on Artificial Intelligence, 2024). Disputes on the unauthorized use of copyrighted data to train AI

Figure C.3: The Services Trade Restrictions Index for highly AI-intensive sectors depends on income and mode of supply



Source: WTO Secretariat calculations based on the World Bank-WTO Services Trade Restrictions Index.
Note: The Services Trade Restrictions Index, developed by the World Bank and the WTO, is a measure of the restrictiveness of an economy's regulatory and policy framework with respect to trade in services. Highly AI-intensive sectors that were identified were accounting, auditing, audiovisual services, commercial banking, computer services, fixed-line and mobile telecommunications, legal services and non-life insurance.

models are frequent. Hence, regulatory choices on data use play a central role in shaping not only how economies benefit from AI, but also in balancing this benefit with the need for trust and accountability in digital systems.

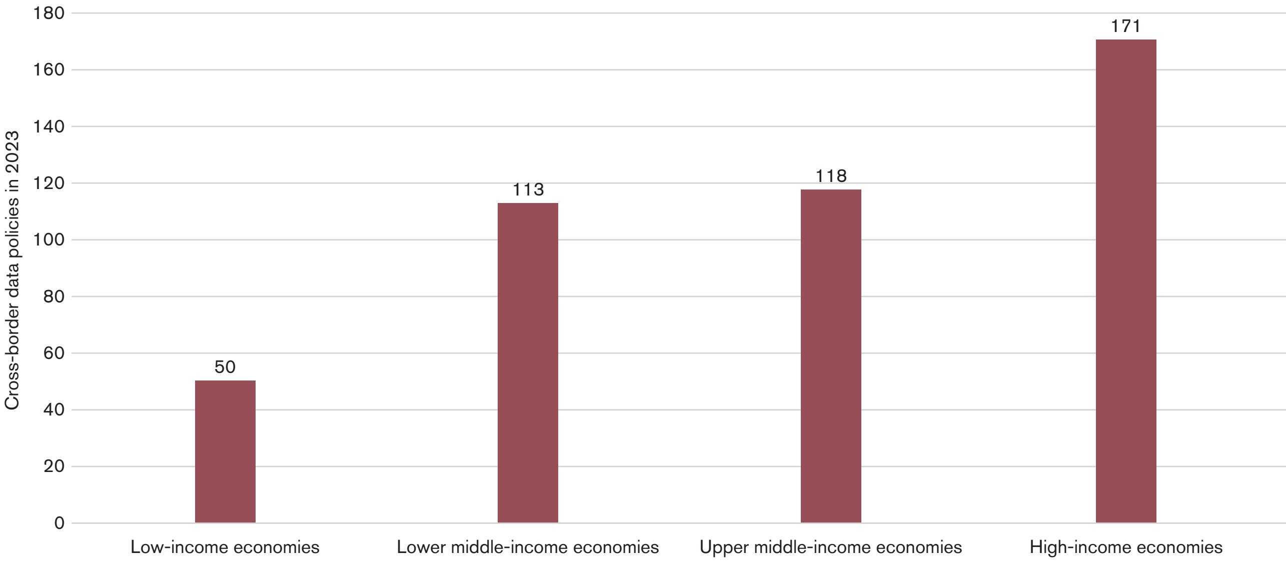
Even well-intended and well-crafted data regulation can hinder AI diffusion if rules are fragmented rather than coordinated across jurisdictions. A multiplicity of diverging data regimes leads to an increasingly complex and fragmented regulatory landscape for cross-border data flows (OECD, 2023a). This can make it difficult to import or export data, which is especially problematic for firms in low-income and lower middle-income economies (Chander and Le, 2015; Casalini and López-González, 2019). Without access to global data, these firms are often excluded from collaborative R&D, cloud-based AI tools or real-time analytics that drive innovation (Schweitzer, Saccomanno and Saika, 2024; Cui, 2025). Moreover, complex or fragmented data governance frameworks can impose high compliance costs. For small firms with limited legal and technical resources, this can act as a disincentive to adopt AI technologies (Aaronson, 2024; van der Marel and Ferracane, 2021). Data localization can be particularly counterproductive in economies where insufficient data infrastructure undermines the intended benefits of domestic control of data, and this may, in turn, slow AI deployment. A recent study finds that AI-powered apps reach substantially more foreign users than apps without AI, but that the effects are halved in economies with strict limitations on cross-border data flows (Sun and Trefler, 2023). Simulations by the Organisation for Economic Co-operation and Development (OECD) and the WTO suggest that, in a scenario in which all economies fully restricted cross-border data flows, global gross domestic product (GDP) losses would reach 4.5 per cent, and reductions in exports would amount to 8.5 per cent (OECD and WTO, 2025).

An absence of data regulation would be equally costly because it would undermine trust in economic transactions requiring data-sharing. Fragmented approaches to data regulation are costly, but so is a lack of regulations. Consumers and businesses need to trust their counterparts in economic transactions if they are to send their data and grant authorization to use those data for AI applications. To enable the scale that is needed to fully exploit the benefits of AI for trade, and *vice versa*, such trust must extend beyond national borders. Concerns about unauthorized data use tend to be particularly prevalent where foreign jurisdictions are concerned. Hence, policymakers are tasked to develop data regulation that provides for the movement of data across jurisdictions, but also guarantees that those data are protected and safeguarded. In fact, the simulations by the OECD and WTO also suggest that, in a scenario where all economies removed their data flow regulations, global GDP would fall by nearly 1 per cent and global exports by just over 2 per cent. In these scenarios, the negative impact on trust would outweigh reductions in compliance costs (OECD and WTO, 2025).

The last decade has seen a rapid rise in data regulation, much of which restricts the flow of data. While data-related regulation dates back to as early as the 1970s, the number and scope of policies has accelerated in the digital era, with many economies updating their regulatory framework to keep pace with technological change. According to the Digital Trade Integration Project, 452 cross-border data policies were recorded in 2023 (Ferracane, Ugarte and Rogaler, 2025). In particular, data localization measures, which regulate instances in which firms are allowed to transfer data across borders, have seen important increases in recent years (Del Giovane, López González and Ferencz, 2023). However, the DTI also records more than 50 enabling measures among the 452 policies, highlighting that policymakers remain aware of the need for cross-border data flow for inclusive and rapid development of AI.

While data regulation is increasingly ubiquitous, regulatory asymmetries remain visible across income groups. As shown in Figure C.4, DTI data indicates that a large number of cross-border data regulations were in place in all income groups in 2023. However, high-income economies have introduced significantly more cross-border data-related policy measures than middle-income economies, which in turn have more policies in place than low-income economies. These differences reflect unequal regulatory capacity, as well as disparities in the scale and speed of AI adoption. DTI also provides a breakdown of policies into enabling versus restrictive measures, which shows that more than 80 per cent of enabling measures were introduced by high-income economies, usually as part of trade agreements covering cross-border data flow commitments. Due to these enabling measures, the average DTI cross-border data policy

Figure C.4: Cross-border data regulation increases with income



Source: WTO Secretariat calculations based on the Digital Trade Integration Project by Ferracane, Ugarte and Rogaler (2025).

restrictiveness index for high-income economies is 0.25, much lower than for middle-income economies, with values at 0.35 and 0.36. Low-income economies have an average index value of 0.29 – a relatively liberal policy environment, but this is due to the absence of regulation rather than to any particular enabling measure.

The scope of data regulation is substantially more comprehensive in high-income and middle-income economies. According to UNCTAD's Global Cyberlaw Tracker, only 42 per cent of low-income economies have established data protection and privacy laws, compared to 92 per cent of high-income economies, and only 50 per cent of low-income economies have adopted online consumer protection legislation, compared to 78 per cent for high-income economies. OECD data on data localization measures indicates that both middle-income and high-income economies regulate a broad set of different types of data, including health, financial, payment, insurance and telecommunications data, as well as business records. In contrast, regulation in low-income economies is so far limited to personal and public sector data (Del Giovane, López González and Ferencz, 2023). This discrepancy means that businesses have more legal certainty regarding different types of data in high-income and middle-income economies. However, since many of these regulations are trade-restrictive, they also impose high costs and contribute to a fragmentation of data access.

Overall, it appears that the evolving regulatory landscape of cross-border data flows is necessary to instil trust, but that, in its current form, it is dominated by unilateral measures that prevent equal access to data. The evidence reviewed shows that there is a growing number of restrictive measures for cross-border data flows in place. This is particularly costly for low-income economies and micro, small and medium-sized enterprises (MSMEs) that typically lack access to large high-quality datasets. Given the importance of such datasets for AI, this implies a significant inequality in opportunities to benefit from AI due to trade measures. However, since such measures might serve legitimate objectives, the challenge is to design them in a way that minimizes barriers to inclusiveness. As Chapter D will discuss, this can be best achieved through international cooperation.

Unlocking AI for all: a Global South perspective

By Kate Kallot

Founder and CEO, Amini[6]

At its heart, inclusive AI is not just a technical concept; it is a vision for a future where AI serves everyone, not just a privileged few. As the AI market explodes in value, from US$ 400 billion today to an estimated US$ 1.81 trillion by 2030, it represents an extraordinary opportunity for entrepreneurs and innovators to build AI solutions tailored to their unique local contexts and needs. However, realising this potential requires intentional trade policies to regulate cross-border data flows, equitable access to essential AI infrastructure, and the rising tide of digital protectionism.

AI is fundamentally reliant on data. While data availability exploded across the Global North throughout the 2010s, this critical fuel for AI development has remained inaccessible in the Global South due to poor data infrastructure. Despite this gap, growing recognition of the importance of data has prompted governments to develop a patchwork of data protection legislation and AI policies. This fragmented landscape creates barriers to cross-border data flows for an already limited resource in the Global South. Startups must navigate complex, expensive regulatory mazes, characterized by burdensome procedures and limited resources in regulatory bodies, which severely limit the scalability and impact of AI solutions.

The challenge is intensified by data localization requirements mandating domestic data processing and storage. With less than 2 per cent of the world's data centre supply available on the African continent, blanket localization could cut it off from the AI revolution before that revolution even begins.

Yet within this challenge lies opportunity. Digital policies focused on ensuring that AI models are fine-tuned for national contexts can benefit emerging economies when implemented strategically. By investing in data infrastructure that makes critical, non-sensitive datasets, from agriculture to demographics, accessible, governments can unlock the untapped potential of applied AI innovation. Our young, digitally native populations are well-positioned to develop solutions that address local challenges, from supply chain transparency to financial inclusion. This not only creates significant local economic value and improves market access, but also benefits the global economy through more efficient, transparent and fair trade. Building critical infrastructure for a country today means building data infrastructure, not just roads and hospitals.

Further opportunity lies in regional approaches that harness shared resources. Rather than isolated national policies, we need regional consensus on our shared future. While initiatives like the African Union Data Policy Framework and the US$ 60 billion Africa AI Fund announced in Kigali, Rwanda in April 2025 are promising, we must go further by operationalizing the regional pooling of key resources in order not only to protect, but also to accelerate, AI development.

Creating regional frameworks that support open data, distributed computing (i.e., linking multiple computers together to solve complex problems) and talent development enables full participation in the AI revolution and allows people to move beyond fear-based barriers to active creation. We can shift from being mere technology consumers to becoming global contributors and creators.

For governments seeking to empower local innovators, the focus should be on creating enabling environments through small but critical policy changes. Sensible import duties on AI hardware to reduce infrastructure costs, streamlined patent registration and regulatory stability will enable entrepreneurs to invest in local research and talent while accessing global markets.

Achieving inclusive AI requires collaborative trade policies that balance protection with openness. By facilitating secure data flows, ensuring affordable hardware access and strategically leveraging digital sovereignty, nations can build an equitable global AI ecosystem.

AI's true potential is realised not through isolation, but through interconnectedness that preserves local agency while enabling global participation.

Disclaimer

Opinion pieces are the sole responsibility of their authors. They do not necessarily reflect the opinions or views of WTO members or the WTO Secretariat.

(e) Measuring AI trade policy openness: the AI Trade Policy Openness Index

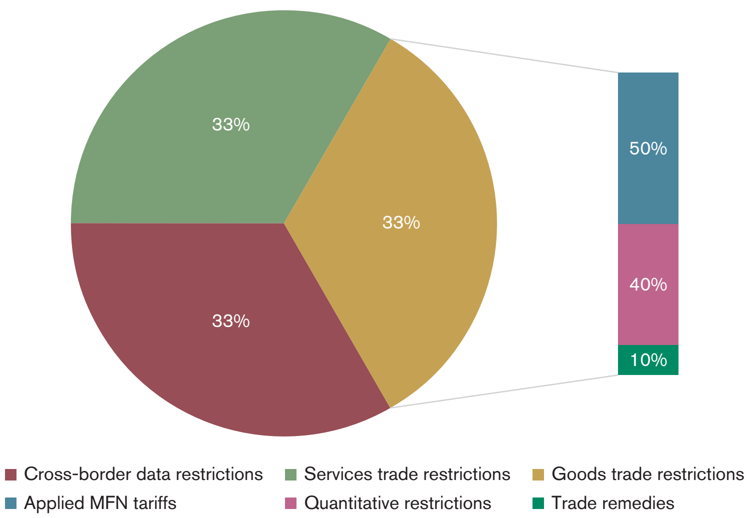
Trade and regulatory policies play an important role in shaping the international diffusion of AI technologies. As AI advances, its deployment increasingly relies on the openness of economies to flows of AI-related goods, services and data – key channels through which AI capabilities are exchanged and scaled. To provide a systematic overview of how trade policy measures interact with AI readiness, the AI Trade Policy Openness Index (AI-TPOI), compiled by WTO economists for this report, combines data on key trade policies (see Annex D for more information on the AI-TPOI). Covering 108 economies, the index aggregates policy data for goods trade, services trade and cross-border data flows. Scores closer to one indicate less openness, greater restrictiveness and potential barriers to AI-related trade.

The AI-TPOI consists of three equally weighted pillars, each reflecting a policy domain relevant to AI diffusion. These are: (i) barriers to services trade, based on the World Bank–WTO Services Trade Restrictiveness Index (STRI); (ii) restrictions affecting AI-enabling goods trade, drawing on average applied tariffs from the WTO Tariff & Trade Data (TTD) platform, as well as quantitative restrictions and trade remedies from the Digital Trade Integration (DTI) database[7] (Ferracane, Gonzalez Ugarte and Rogaler, 2025); and (iii) cross-border data flow restrictions, using regulatory indicators from the DTI database (see Figure C.5). Together, these components capture policy instruments that influence economies' ability to access, develop and export AI or AI-related goods and services. The composite index aggregates these elements to provide a standardized measure of AI-related trade policy openness. Annex D of the report provides a detailed account of the methodology used to construct the index.

Patterns of openness across economies suggest that overall policy openness to AI-related trade is not solely determined by income levels. On average, lower middle-income and upper middle-income economies exhibit the highest restrictiveness, while high-income and low-income economies tend to be more open (see Figure C.6). However, there is substantial variation within each income group. Upper middle-income economies, in particular, show considerable dispersion, pointing to divergent regulatory approaches. For instance, Costa Rica, Jamaica, Namibia and Peru belong to the most open economies. Moreover, low-income economies generally record lower AI-TPOI scores, but this lower number of formal barriers also reflects the fact that low-income economies often have limited governance capacity and underdeveloped digital infrastructure.

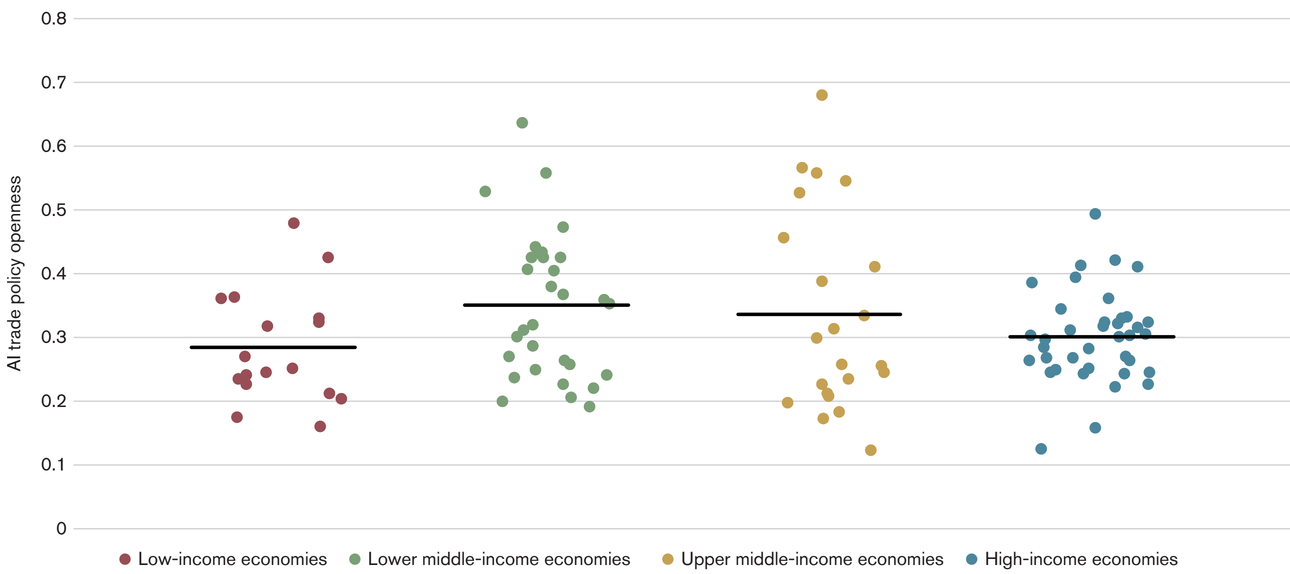
Clearer patterns across income groups emerge when disaggregating the AI-TPOI into its three components. High-income economies exhibit higher restrictiveness in goods-related trade

Figure C.5: Composition of the AI Trade Policy Openness Index



Source: WTO Secretariat, representation of the composition of the AI Trade Policy Openness Index.
Note: Data for the AI Trade Policy Openness Index stem from the WTO's Tariff & Trade Data platform, the Digital Trade Integration (DTI) index and the World Bank–WTO Services Trade Restrictiveness Index (STRI).

Figure C.6: Variation in AI trade policy openness within income groups



Source: WTO Secretariat calculations based on the World Bank–WTO Services Trade Restrictiveness Index (STRI), the WTO Tariff & Trade Data (TTD) platform and the Digital Trade Integration (DTI) database.
Note: Each dot represents the AI-TPOI score for an economy, grouped by income level. Lower scores indicate greater openness, while higher scores indicate greater restrictiveness. Horizontal lines denote the average AI-TPOI value within each income group.

measures, despite generally applying lower average tariffs. This may reflect the use of non-tariff barriers and recent export control measures targeting advanced technology products, particularly along semiconductor value chains. In contrast, lower middle-income economies and upper middle-income economies tend to exhibit greater restrictiveness in services trade and cross-border data flows, driven by localization requirements, data sovereignty concerns and efforts to promote domestic digital industries. Low-income economies generally display lower restrictiveness across all three dimensions, although this often reflects limited regulatory capacity rather than deliberate openness. Substantial variation within each income group also highlights the diverse strategic priorities and institutional approaches shaping AI-related trade policies across economies.

2. AI, trade-related and complementary policies are necessary for AI and trade to work together for inclusive growth

Trade-related and complementary policies are key to ensure both that AI supports inclusive trade-led growth, and that trade can support AI development and diffusion. While tariffs and non-tariff measures can drive down the prices and increase the availability of both AI-enabling and AI-enabled products, they can only be effective in a policy environment that stimulates widespread AI adoption. Such an environment requires intellectual property (IP) policies that incentivize innovation while allowing for knowledge diffusion and competition policies that prevent excessive market concentration. It requires education and labour market policies that foster talent and leave no one behind, as well as investment in data infrastructure and regional policies to allow for the inclusive adoption of AI, and government support, through subsidies and public procurement, that does not exclude fiscally constrained economies from AI benefits. These policies typically tend to apply to domestic and foreign firms alike, but policy design can lead to discriminatory effects that prevent AI diffusion and inclusive trade.

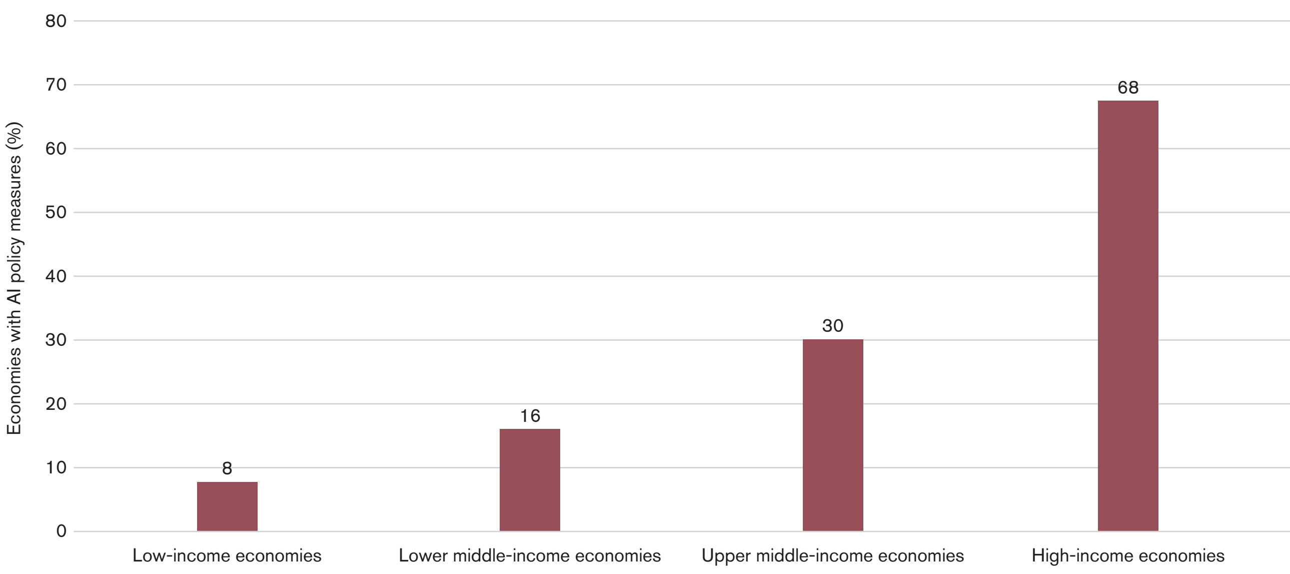
Governments are increasingly launching comprehensive AI strategies and AI-related policies to provide a stimulating environment for AI development and adoption. According to the OECD.AI Policy Observatory, more than 70 economies – including all 38 OECD members – have introduced national AI strategies and policies (OECD.AI, 2025). Such approaches address key elements for AI, such as data regulation, competition policy, infrastructure investment or skills development. They can build trust in the new technology and ensure that the benefits of AI accrue in an inclusive fashion. For instance, the European Union AI Act,[8] which entered into force on 1 August 2024, requires that an AI office and member states assess and mitigate the negative impacts of AI systems on vulnerable groups. Beyond such comprehensive AI approaches, numerous measures have been introduced that touch upon AI regulation, with the OECD currently listing more than 1,300 such policies (OECD.AI, 2025).

High-income and upper middle-income economies are leading in terms of AI regulation. Only 36 per cent of economies globally have adopted AI policy measures. Most of these measures are implemented either by high-income or upper middle-income economies, which together account for 92 per cent of the policies registered in the OECD Artificial Intelligence Policy Observatory. AI regulation is also substantially more pervasive among high-income economies, of which 68 per cent have AI policies in place, compared to only 16 per cent in lower middle-income economies and 8 per cent in low-income economies (see Figure C.7). The data reveal differences in both the scale and scope of regulation. Whereas many AI policies of low-income economies are limited to data regulation, the policies of high-income and upper middle-income economies cover a broad range of issues including skills, ethical AI and risk management (OECD.AI, 2025).

High-income and upper middle-income economies started to adopt AI policies substantially earlier than lower-income economies. Several high-income economies were developing comprehensive AI strategies and policies as early as the mid-2010s (Maslej et al., 2025). Across all high-income economies, more than 100 AI policies had already been implemented by 2015. The same threshold was crossed by upper middle-income economies in 2018. In contrast, both low-income and lower middle-income economies have yet to reach this threshold, although some lower middle-income economies, such as India, were early movers in this area (OECD.AI, 2025).

The differences in the scale, scope and timing of AI regulation may allow high-income and upper middle-income economies to move faster towards an optimal AI policy environment. Although knowledge about the effects of different policies on AI development is limited, these differences in the scale, scope and timing of AI regulation do provide high-income and upper middle-income economies with valuable experience and space to experiment. This is likely to allow these economies to develop a policy mix appropriate to exploit the benefits of AI more quickly than low-income and lower middle-income economies. It may also lead to lock-in

Figure C.7: Economies that have adopted AI policy measures, by income level (%)



Source: WTO Secretariat calculations based on the OECD.AI Policy Observatory (2025).

effects for these economies when compliance costs for domestic firms are too high to allow for alternative policy approaches to those in high-income markets.

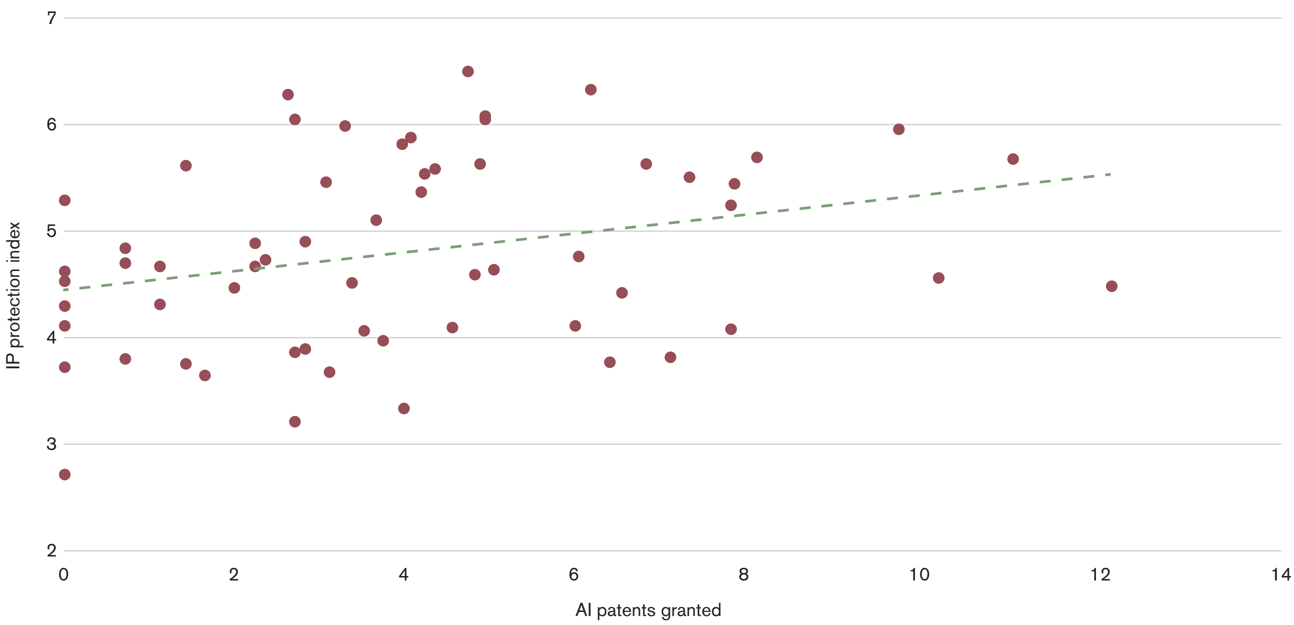
Beyond AI strategies and targeted AI policies, various policy areas affect whether AI and trade can jointly support inclusive growth. Labour market policies can help workers to become more agile and regions to become more resilient in order to respond to the changes that the interaction of trade and AI will bring. IP and competition policies are needed to balance incentives for innovation with risks that may arise as a result of extreme concentration in AI-enabling and AI-enabled products. Infrastructure and education policies can help to prevent a widening of the digital divide. Industrial policy can accelerate the development and diffusion of AI. The remainder of this subsection looks at these policy areas in turn.

(a) IP policies should help stimulate innovation and facilitate technology diffusion

Trade-related IP rules play a critical role in shaping how technologies are shared across borders, with important implications for inclusive innovation. While comprehensive studies on the impact of IP protection on inclusive innovation in AI are not yet available, initial economic analysis suggests that stronger IP protection can incentivize innovation in high-income economies (Maskus, 2000). At the same time, technology transfer mechanisms are necessary for greater knowledge diffusion and access to frontier technologies by low-income economies (Dosi and Stiglitz, 2014). Broad awareness of the advantages of IP protection across society, and cost-effective access to the system are critical to ensure an inclusive distribution of benefits across economic sectors and actors. Well-designed IP regimes can thus help stimulate investment in knowledge creation, facilitate technology transfer and support the emergence of new firms and services (Branstetter Fisman and Foley, 2006; Papageorgiadis and Sharma, 2016). Most national IP frameworks are now being put to the test given the speed and complexity of AI's evolution.

Empirical evidence suggests a positive relationship between IP protection and AI patenting activity, though income levels remain a key explanatory factor. Cross-country data show that economies with stronger IP regimes tend to record higher rates of AI patent filings being granted. While the relationship is statistically significant, it becomes weaker when controlling for GDP per capita, indicating that IP strength may be necessary to drive innovation, but is not sufficient on its own (see Figure C.8). Nevertheless, the presence of robust IP systems tends to be associated with higher levels of AI patenting activity,

Figure C.8: Stricter IP regimes appear to favour AI patent filings



Source: WTO Secretariat calculations based on the World Economic Forum (WEF) Global Competitiveness Index and Center for Security and Emerging Technology (CSET) data.

suggesting that clear and enforceable IP rules help create an enabling environment for AI innovators. This is consistent with recent empirical evidence, which showed that stronger IP protection can enhance comparative advantage in IP-intensive industries, though the benefits taper off once stringency exceeds a certain threshold (WTO, 2018). These insights have important implications for trade in AI-related goods and services, given their high IP intensity (see also Box C.1).

Box C.1: IP policies shape the AI value chain

Different IP issues arise across the AI value chain, from infrastructure and data to software and outputs. Understanding how IP frameworks interact with trade policy at each stage can help promote innovation, access to and cross-border flow of AI-related technologies. It can help policymakers to design AI-related IP policies that reduce legal risk, support the growth of the AI sector and safeguard public policy goals (see also Section D.1).

Patent protection for physical AI infrastructure: AI development relies on hardware and cloud infrastructure, including semiconductors, data centres and edge devices, such as sensors, routers, gateways, and other smart devices. Many AI inventions also interact with or control physical systems, such as networks or sensors. These technologies can be protected by patents. Evaluating how national patent laws apply to AI technologies, including the protection of AI-related designs of integrated circuits, is useful to ensure that IP frameworks encourage investment in AI innovation, support technology transfer and help to identify where reforms may be needed.

Copyright and AI training data: Training AI models may require large amounts of copyrighted content, raising the question of whether permission from rights-holders is required for such use. Clarifying how domestic copyright law applies to text and data mining is important both for providing AI developers with a lawful avenue to use IP-protected content for training AI models, and for ensuring that, where it is due, all rights-holders receive adequate remuneration for the use of their content. The legal solutions and mechanisms deployed in this area can impact inclusiveness of AI benefits in different ways: complex or institutionally biased mechanisms for AI developers to obtain necessary authorizations may impede market entry for new developers or favour large competitors. Similarly, certain remuneration mechanisms may favour successful or well-organized rights-holders over small creators with little market power. Jurisdictions currently use very different approaches of legal rights and technical tools to opt out of unauthorized data mining, as well as transparency through training data summaries, with the aim of empowering creators to monitor and potentially negotiate remuneration for use of their work by AI developers. In this context, fostering the development of appropriate, clear and practical licensing mechanisms, including through collective licensing, can help balance creators' rights with AI developers' needs and thus maximize inclusiveness of benefits on both sides. Identifying best practices in different jurisdictions, jurisprudence and international trends can inform copyright policies for AI training data.

Software and trade secrets: AI systems are powered by algorithms, software and applications, which can be protected through patent, copyright and trade secret laws. Assessing how IP protection is applied and enforced in relation to AI algorithms and software, including open-source models, is key to ensuring that the legal framework is clear and takes both public and private interests into account. This helps reduce legal uncertainty, supports a competitive AI sector and fosters more sustainable AI-related business models.

AI-generated outputs: Generative AI can assist in creating or autonomously producing outputs resembling human-created works or inventions, raising questions about who holds the IP rights to these outputs. Clearly determining whether, and under what conditions, to extend IP protection to AI-generated and AI-assisted outputs, including considerations of liability, is important to support more widespread – and thus more inclusive – use of generative AI tools while discouraging harmful use and reducing market distortions.

The growth of generative AI has introduced new challenges for copyright law, particularly in the treatment of training data and AI-generated content. Legal approaches vary widely across jurisdictions, especially in the interpretation of fair use and the scope of permissible data use for model training (WTO, 2024; OECD, 2025). In response, some economies have proposed AI-specific licensing regimes to ensure that original content creators receive appropriate recognition and remuneration. Meanwhile, national debates over whether AI-assisted or AI-generated inventions are eligible for IP protection are ongoing, and legislative and judicial responses continue to diverge. These tensions underline the need to assess IP frameworks in the light of these new technological capabilities.

The economic significance of IP in AI trade is visible in cross-border licensing and digitally deliverable services. Payments for the use of IP, including copyright-based assets, such as software and databases, exceeded US$ 1 trillion in 2022, more than double their value in 2010 (Bonaglia and Wunsch-Vincent, 2024). A significant share of this growth stems from licensing revenues related to training data, algorithms and software – critical inputs for training generative AI systems. Economies with well-developed and effective copyright frameworks are better positioned to support high-value digital trade, including AI-related services (IMF-OECD-UN-WBG-WTO, 2023), suggesting a positive correlation between copyright enforcement and AI-related trade value.

As AI becomes increasingly embedded in traded goods and services, the role of IP policy in facilitating cross-border innovation and investment is expected to grow. Inclusive trade-led growth in the AI era will depend in part on international cooperation on matters including capacity-building in IP administration, clearer guidance on AI-generated inventions, and mechanisms for addressing cross-border disputes in digital trade involving IP. Without such steps, disparities in IP regimes – particularly on the AI-specific IP issues identified in Box C.1 – may exacerbate existing divides in AI development, limit the diffusion of frontier technologies (i.e., advanced new technologies implemented for real-world uses)[9] and reduce economic growth opportunities stemming from AI use.

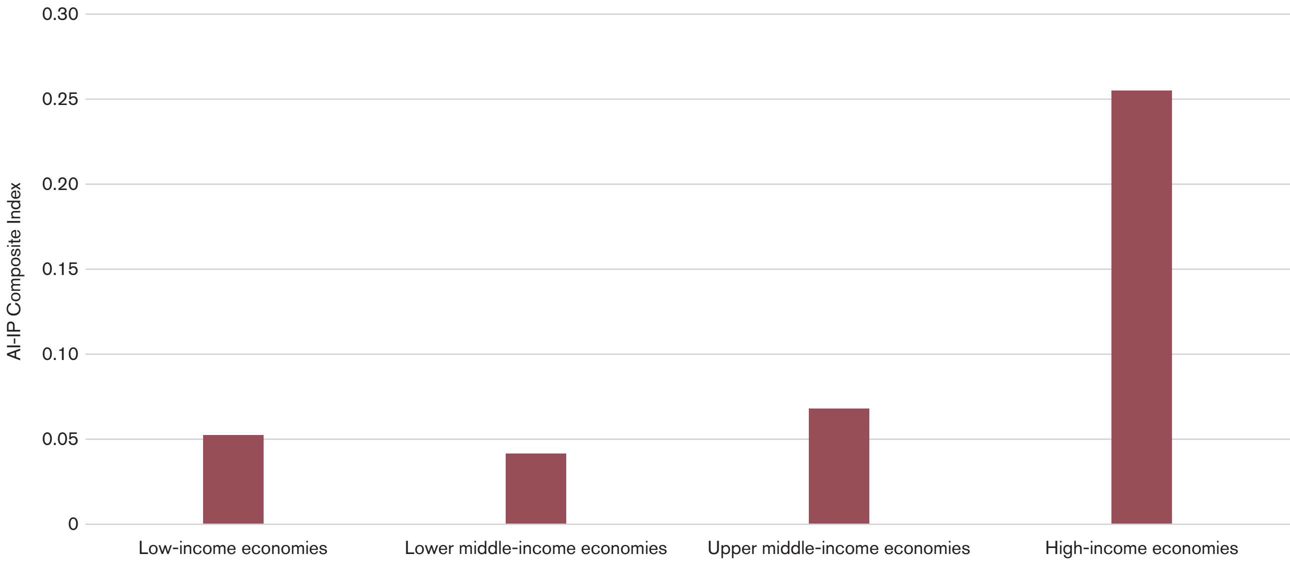
Policy frameworks are evolving to address the multiple dimensions of AI-IP interaction. The forthcoming AI-IP Composite Index,[10] developed by Cáceres (2025), provides a systematic comparison of how national regimes address five key areas: protection for AI-generated works and inventions; governance of training data use; regulation of algorithms and models; the use of AI tools within IP offices; and oversight mechanisms for AI-related IP issues. The number of economies with at least one AI-related IP policy rose from 41 in 2017 to 140 in 2024, reflecting growing global engagement with the topic.

However, significant disparities remain across income groups. High-income economies generally offer more comprehensive and detailed policy frameworks across all five dimensions, while lower-income economies often lack specific legislation or institutional capacity (see Figure C.9). This gap may hinder firms in emerging markets from protecting and commercializing AI-related innovations, limiting their ability to participate in global value chains linked to knowledge-intensive services and digital trade. This challenge reflects broader trends in digital trade regulation, where many developing economies, particularly least-developed countries (LDCs), still face considerable gaps in legislative and institutional readiness (UNCTAD, 2018).

(b) Competition policy needs to prevent excessive market concentration without foregoing economies of scale

A competitive environment and fair market entry conditions are critical for innovation in AI and for AI to support inclusive growth, but market concentration is a severe concern. The fundamental characteristics of AI, including scale economies, low marginal costs, data dependency and cross-service interoperability, favour market concentration and could reinforce the dominance of incumbent digital firms. Large companies, especially in the digital platform sector, are leveraging AI to deepen their digital ecosystems, thereby consolidating market share. Recent estimates indicate that between 2017 and 2025, the combined share of global sales in digital markets made by the top five enterprises more than doubled, from 21 per cent to 48 per cent, while their share of total assets increased from 17 per cent to 35 per cent. Moreover, eight of the world's ten most valuable companies, including the top six,[11] are part of the digital economy and dominate its value chain. This also affects the AI market, where just three companies received

Figure C.9: IP policies have a broader coverage of AI issues in high-income economies



Source: WTO Secretariat calculations based on Cáceres (2025).
Note: Values are averaged across economies by income group.

78 per cent of the traffic on the ten most visited AI websites (UNCTAD, 2025).

Concentration in digital sectors has long raised antitrust concerns, and similar dynamics are emerging in AI markets. Competition authorities are increasingly aware of the risks of excessive concentration, lock-in effects and exclusionary behaviour in the emerging AI economy (OECD, 2024b). Recent strategic partnerships, such as that between Microsoft and OpenAI,[12] or that between Amazon and Anthropic,[13] have blurred the lines between collaboration and consolidation, prompting investigations by competition authorities in the European Union, United Kingdom and United States (Federal Trade Commission, 2025). These alliances may constrain competition by absorbing key technical talent and creating dependencies that might disadvantage new entrants or smaller firms. While traditional tools of competition policy, including merger control or abuse-of-dominance investigations, remain essential, AI-specific challenges, such as data control, platform integration and network effects, might require regulatory adaptation (Autoridade da Concorrencia, 2023). Recent work highlights that digital platforms often resemble public utilities, with high fixed costs and strong network effects creating barriers to entry and enabling market power. Competition policy must therefore evolve to ensure contestability (i.e., low barriers to market entry and exit), while avoiding the pitfalls of overregulation (Tirole, 2023).

AI market concentration risks excluding smaller firms and low-income economies from participating in frontier technological innovation and value creation. MSMEs in low-income and middle-income economies face challenges in accessing cloud infrastructure, proprietary data and skilled labour, barriers that can entrench existing technological divides (OECD 2023). Even within advanced economies, the diffusion of AI capabilities is concentrated in a small group of firms, raising concerns about skewed productivity growth and wage inequality (Acemoglu and Restrepo, 2022). Trade in AI-related services may reinforce these divides if policies do not actively promote interoperability, capacity-building and knowledge transfer. To support inclusive AI-driven trade, competition policies must ensure not only market contestability but also equitable access to critical inputs.

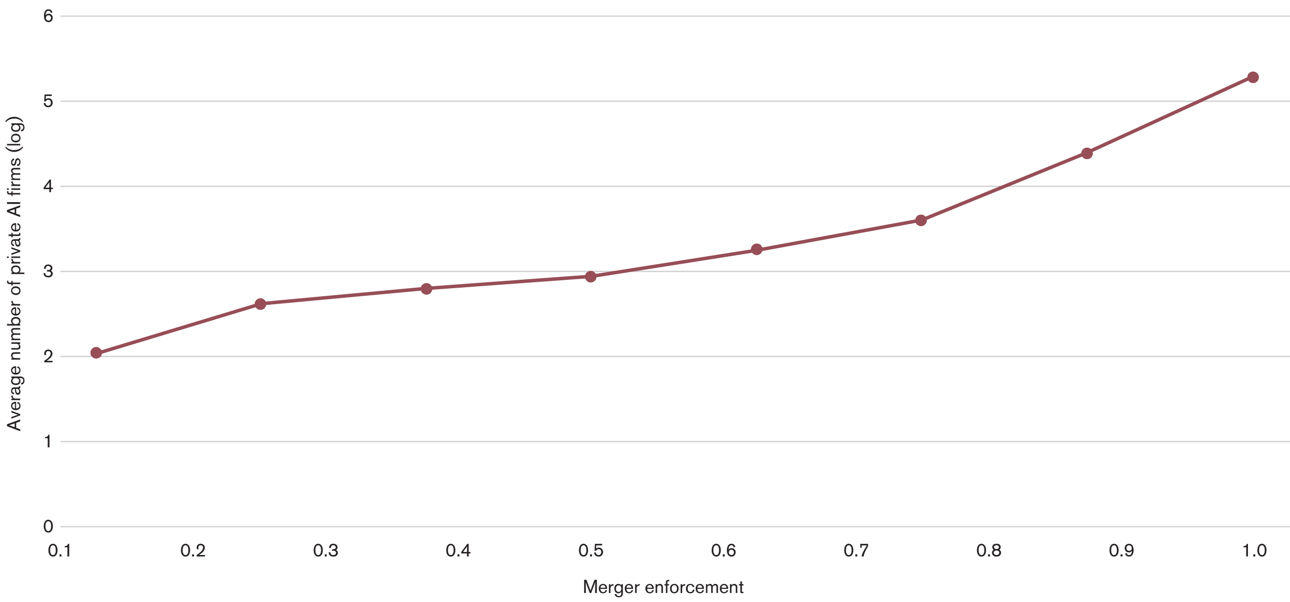
Market concentration may accelerate innovation through resource bundling and economies of scale, but it risks limiting consumer choice and long-run investment. This trade-off is particularly salient for AI, in which innovation and market structure are deeply intertwined. For instance, access to large proprietary datasets for training purposes can give significant advantages to AI development, and certain acquisitions may generate such welfare-enhancing scale effects (Petit Schrepel, and Heiden, 2024). Moreover, in highly dynamic sectors, monopoly power may be less of a concern, as leadership positions are unstable and contingent on continued innovation (Teece, 2023). Effective competition policy must therefore balance short-term innovation incentives with long-term market contestability.

Empirical evidence suggests that robust competition policy can foster more market entry in the AI sector. Figure C.10 shows that economies with stronger enforcement regulation of merger rules and abuse of dominance, based on Bradford and Chilton (2018)'s competition law index, tend to have more private companies filing patents related to AI, based on data from Georgetown University's Center for Security and Emerging Technology. This is in line with generic evidence on the impact of such competition enforcement, which has shown that strengthening competition laws enhances firm valuations by reducing agency and collusion distortions (Levine, Lin and Xie, 2021). Such evidence supports the view that predictability and legal clarity incentivize private investment and prevent unproductive mergers.

AI-specific competition regulation is increasing rapidly but in an uncoordinated manner that risks creating a fragmented and incoherent global policy landscape. According to Digital Policy Alert, the number of competition policy changes explicitly targeting "Machine learning and AI development" has increased sharply since the release of ChatGPT on 30 November 2022. In the two years prior to that date, none of the 379 recorded digital policy changes concerned AI. In the two years that followed, 44 out of 582 were AI-specific. Most of these interventions have been adopted at the national level, often without coordination across jurisdictions. More than 80 per cent were introduced by high-income and upper middle-income economies, and only two policy changes (less than 5 per cent) originated in low-income economies. This patchwork approach increases uncertainty and can raise compliance costs, particularly for smaller firms navigating multiple legal environments.

Competition policy for AI is interlinked with other areas, including industrial and taxation policies that might affect market structures through trade-distortive measures. According to recent evidence, over 89 per cent of industrial policies targeting AI-related products introduced

Figure C.10: Competition policy enforcement is positively correlated with the number of private firms filing AI-related patents



Source: WTO Secretariat calculations based on Bradford and Chilton (2018) and data by Georgetown University's Center for Security and Emerging Technology.
Note: Figure C.10 relies on Bradford and Chilton (2018)'s competition law index subcomponent for merger control and abuse of dominance enforcement. The number of private AI firms (in logs) is the average across all economies with the same merger enforcement index value. It is based on a dataset by Georgetown University's Center for Security and Emerging Technology on private firms filing AI-related patents.

in 2023 were trade-distorting (Evenett et al., 2024; see also Section C.2(e)). Such interventions may reinforce market concentration when support targets individual firms. To that effect, data from the Global Trade Alert[14] – a repository of policy changes affecting global trade and investment – show that 79 per cent of semiconductors and information and communication technology (ICT) industrial policies are firm-specific. Beyond industrial policy, digital taxation can also address concerns linked to the AI market structure. Because digital firms operate globally with limited physical presence, traditional tax systems often fail to capture their economic activity. Digital services taxes have emerged as a response, aiming to ensure fair taxation of revenues generated across jurisdictions. However, digital services taxes remain controversial and risk introducing trade obstacles. Balancing revenue collection with open digital markets remains a delicate policy challenge, especially when large digital firms have the capacity to restructure operations to minimize tax liability.

(c) Infrastructure and energy policies are necessary if trade and AI are to contribute to sustainable and inclusive growth

For AI to support inclusive trade and growth, the underlying infrastructure needs to be as widely available as possible. The diffusion of AI depends not only on access to data and intermediate goods and services, but also on physical infrastructure being available in all regions of an economy. Exploiting AI capabilities requires, for instance, a reliable electricity supply and fast digital connectivity, factors that remain highly uneven across and within economies. The energy-intensive nature of AI, which encompasses a number of significant challenges (see below), provides opportunities for energy-rich economies. For instance, by deploying policies that invest in the green comparative advantage of an economy, economies with access to solar, wind or hydro energy can participate upstream the AI value chain (WTO, 2023). To use these opportunities for inclusive growth, the significant divides in access to digital infrastructure identified in Chapter B need to be addressed.

Major economies have announced large-scale public investments in AI infrastructure, highlighting both the scale of ambition and the widening gap in national capacities. The United States government has indicated support for the private Stargate Project, launched in early 2025, which promises to invest a total of US$ 500 billion in data centres and digital talent development, through executive orders that facilitate and accelerate project planning. The European Commission unveiled its AI Continent Action Plan in April 2025, allocating EUR 200 billion to support AI development, EUR 20 billion for the establishment of up to five AI gigafactories, and funding for at least 13 AI factories to help startups, industry and researchers develop advanced AI models (European Commission, 2025). In China, a US$ 8.2 billion AI investment fund was announced in early 2025 (Chang, Arcesati and Hmaidi, 2025). In contrast, most other economies remain well behind in terms of funding and capacity, often due to fiscal constraints.

Data centres rely on stable digital infrastructure that consumes substantial quantities of electricity. These centres, the backbone of the AI ecosystem, require continuous power for computing, storage, cooling and backup systems. Large hyperscale AI data centres have power demands of 100 Megawatts (MW) or more, and consume as much electricity annually as 100,000 households. Electricity consumption from data centres reached approximately 415 terawatt-hours in 2024 – about 1.5 per cent of global electricity demand – and has grown at an average annual rate of 12 per cent over the past five years (IEA, 2025). Already today, data centres use more energy than the national energy consumption of Germany or France, and it is estimated that they will exceed India’s national energy consumption by 2030 (Bogmans et al., 2025). As AI models are increasingly widely used, energy demand continues to accelerate, although innovation may make these models substantially more efficient. This requires an alignment of energy policies with AI development to allow AI to expand without causing major environmental degradation.

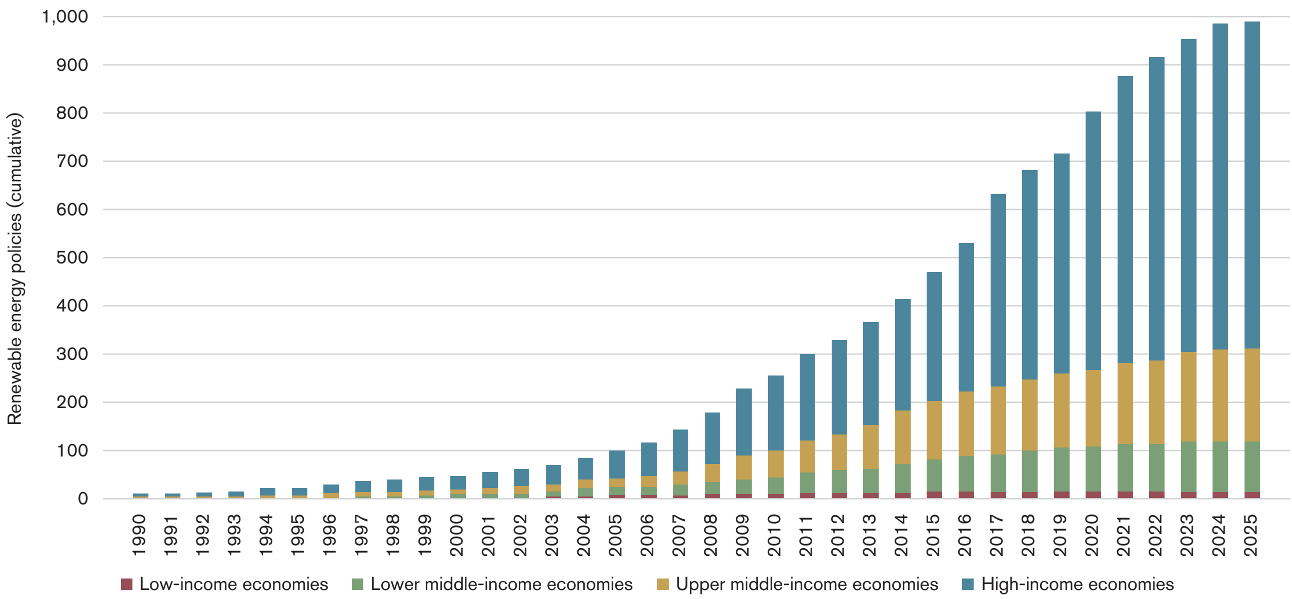
Governments are responding to this surge in energy demand by implementing energy policies to expand clean electricity supply. Many high-income economies are directing financial support, tax incentives and strategic investments toward solar, wind and durable battery technologies. For instance, the “Future Made in Australia” plan allocates AUD 1.4 billion for clean energy technology manufacturing, primarily focusing on solar energy and batteries. France’s Green Industry Law introduced a 20 per cent investment tax credit for industrial decarbonization projects across battery, heat pump, wind and solar photovoltaic value chains. Some economies have also introduced targeted energy policies aimed at promoting inclusive access to clean energy. In Indonesia, the government allocated IDR 94.4 billion in its 2023 budget to support rooftop solar panel installation in underdeveloped regions. Poland's "Energy for the countryside" programme provides direct grants and loans to farmers and energy cooperatives to develop small-scale renewable projects, including biogas plants, solar panels and energy storage systems.

Policy activity on renewable energy is concentrated in high-income economies. The number of renewable energy policies has increased exponentially since the early 1990s, but distribution of these policies is highly uneven, with high-income economies accounting for a large majority of the surge. By 2025, high-income economies accounted for approximately 69 per cent of all renewable energy policies worldwide, up from 58 per cent in 2000. In contrast, low-income economies represented just 1.5 per cent, down from 6.3 per cent in 2000 (see Figure C.11). This gap reflects significant disparities in institutional capacity, fiscal space and access to international finance, which limit many low-income economies in their ability to operationalize their renewable potential.

Many low-income economies possess strong green comparative advantages but lack the policy frameworks to leverage them. Economies in North Africa, South Asia, Latin America, and parts of Sub-Saharan Africa benefit from high solar irradiation and favourable conditions for wind power. These resource endowments could offer comparative advantages in energy-intensive sectors, particularly for hosting AI data centres. However, high-income and upper middle-income economies provide a much more favourable policy environment to support energy potential. For example, when high-income and upper middle-income economies have levels of theoretical solar potential – measured by global horizontal irradiation that captures the total direct and diffuse solar radiation received by a horizontal surface – comparable to low-income economies, the former consistently adopt more policies to support solar deployment. Among economies with high solar potential, high-income and upper middle-income economies introduced an average of 5.3 and 5 solar policies respectively, compared to just one in low-income economies. These gaps, combined with structural barriers in supply chains and infrastructure, limit the ability of resource-rich low-income economies to capture value from the green transition.

While abundant green resources create potential advantages for low-income economies, other forces risk reinforcing the dominance of high-income economies in AI-driven energy

Figure C.11: High-income economies have adopted significantly more policies to support renewable energy



Source: WTO Secretariat calculations based on IEA Energy Policy Database.

development. High-income economies are consolidating first-mover advantages not only by investing in digital infrastructure, but also by securing upstream positions in renewable energy supply chains. Economies with advanced AI capabilities are already applying these tools to optimize energy systems and reduce production costs. For example, ENEDIS, a French electricity distribution grid operator, uses machine learning to forecast power outages with high accuracy (ENEDIS, 2024). Such applications reinforce the cost advantages of technologically advanced economies by lowering costs, increasing energy system resilience and accelerating innovation. In addition, growing concerns around data sovereignty have led many economies to host data centres domestically, even at higher energy costs, further limiting the scope for international distribution of AI infrastructure (see Section C.1(d) on data localization).

(d) Education and labour market policies can build an agile workforce and render regions more resilient

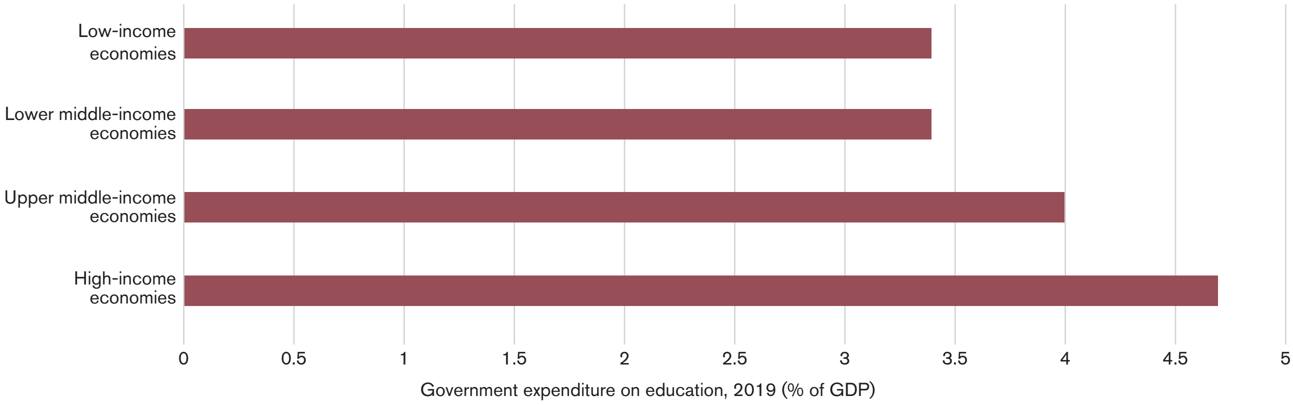
In order to benefit fully and inclusively from AI, economies need to educate a flexible workforce with appropriate skills. Human capital accumulation is potentially the most important driver of economic growth (Jones, 2014; Lucas, 2015). Educational attainment shapes comparative advantage and trade patterns, with richer economies typically exporting more complex products (Hidalgo and Hausmann, 2009; Blanchard and Willmann, 2016). Recent evidence also suggests that economies with high education levels are more successful in developing comparative advantage in new products (Felipe, Jin and Mehta, 2024). This suggests that such economies will find it easier to develop comparative advantage in AI-related products; high-income and upper middle-income economies already lead in AI-intensive services exports such as software development, R&D and financial analytics (UNCTAD, 2025).

Economies need to support their workforce continuously with labour market policies, as AI may lead to changing patterns in the labour market. AI, reinforced by changes in trade patterns, has the potential to affect the labour market severely (see Section B.1(b)). Given the uncertainty around how AI will transform jobs, policies should focus on enabling workforce adaptability. This includes both structural reforms and targeted interventions. On the one hand, public investment in digital infrastructure, education and mobility is foundational for broadening labour market participation. On the other hand, labour market policies, including place-based regional policies, are critical to support workers and regions that may be at risk of falling behind. Such labour market policies should cover both passive policies, such as unemployment benefits, to cushion the immediate effects of displacement, and active ones, like training or wage insurance to accelerate re-employment and upskilling (WTO, 2024; Hyman, Kovak, and Leive, 2024).

High-income and upper middle-income economies are investing substantially more public money in education than low-income and lower middle-income economies. According to data from the United Nations Educational, Scientific and Cultural Organization (UNESCO), high-income and upper middle-income economies spent 4.7 and 4.0 per cent of GDP, respectively, on education in 2019, compared to only 3.4 per cent in low-income and lower middle-income economies (see Figure C.12). The difference in GDP shares translates into major spending differences, given that the GDPs of richer economies are substantially larger. Larger investments in education tend to result in better educational outcomes until a certain relatively high threshold is reached (OECD, 2012). As a result, low-income and lower middle-income economies have substantial scope to increase spending on education to increase their workforce's skill levels.

High-income and upper middle-income economies are also moving ahead of lower-income economies by re-orienting their education systems towards AI. In 2023, the number of AI-themed study programmes in English offered by universities reached 744 in the United Kingdom, 667 in the United States, and over 80 each in Australia, Canada and Germany, marking year-on-year growth rates between 1 and 54 per cent (Maslej et al., 2024). Many national education strategies now emphasize digital skills development, lifelong learning and broader access to training. For instance, the United Kingdom's 2021 National AI Strategy set a goal of enabling 1,000 students to attain PhDs focused on AI by 2025, while its £187 million TechFirst programme aims to deliver AI training to 1 million secondary school students and to 7.5 million workers by 2030 (UK Government, 2025). The European Union is setting up three new digital skills academies, targeting critical talent shortages across key digital areas, funded under the recently

Figure C.12: Government expenditure on education increases with income



Source: World Development Indicators based on the UNESCO Institute for Statistics.
Note: 2019 is the latest available year with broad data coverage.

adopted Digital Europe Work Programme.[15] China designated AI talent development as a national priority under its New Generation AI Plan; over 626 institutions were offering AI-related degrees by 2024, and pilot curricula in AI had been launched in primary and secondary schools (Maslej et al., 2024). Malaysia's National AI Roadmap (2021-25) establishes a central AI Office and supporting programmes, such as Data Star, which has trained hundreds of data science professionals for deployment across key export-oriented sectors (Malaysia Digital Economy Corporation, 2021).

In low-income economies, access to AI education is limited despite growing global momentum. Fewer than one-third of developing economies had adopted AI education strategies as of 2025 (UNCTAD, 2025). Barriers to digital education include limited internet connectivity, shortages of qualified instructors and gaps in equipment and infrastructure (UN and ILO, 2024). Gender and regional disparities are pronounced, with women and learners outside urban centres facing disproportionately limited access to advanced digital training that could support export sector participation (UNCTAD, 2025). World Bank and African Development Bank initiatives have established coding bootcamps and digital hubs in several economies, including Kenya, Nigeria and Rwanda, which aim to prepare young people for eventual participation in technology-enabled export sectors (World Bank, 2024). Online platforms have proven crucial to expand access to AI, with massive open online courses like Elements of AI by MinnaLearn and the University of Helsinki reaching over 1 million participants globally, including in many low-income and lower middle-income economies (University of Helsinki, 2024).

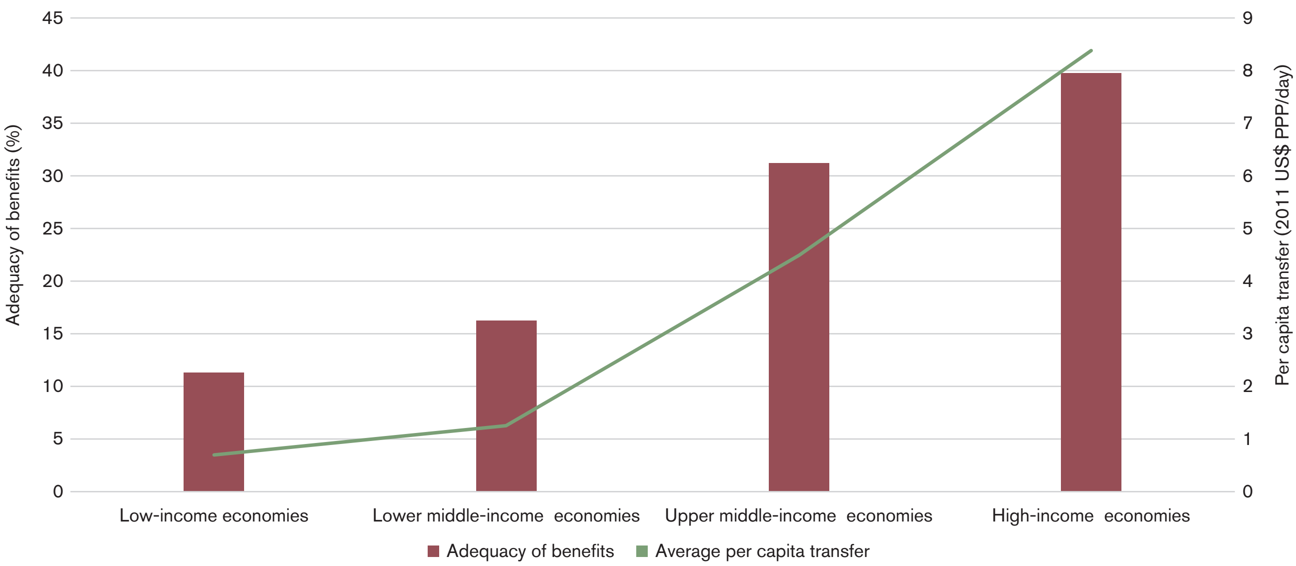
For the existing workforce, labour market policies can significantly ease adjustments to work displacement. Well-designed passive, or social, policies, such as unemployment benefits and other income support schemes, reduce the income volatility associated with labour market displacement and the negative spillovers in demand, helping to stabilize communities in transition (Bacchetta, Milet and Monteiro, 2019; Nekoei and Weber, 2017; Farooq, Kugler and Muratori, 2020). Active policies, such as training and insurance programmes, increase the efficiency of the labour market, and have been shown to improve re-employment outcomes and earnings, especially when these policies are tailored to the needs of displaced workers (Boeri and Van Ours, 2008; OECD, 2015; Van Der Klaauw and Van Ours, 2013). For example, wage insurance programmes – which provide additional temporary income to displaced workers who are re-employed at a lower wage – appear to be effective in shortening the transition into new jobs while reducing long-term income losses (Dix-Carneiro, 2014; Hyman, Kovak and Leive, 2024). Similarly, job search assistance, on-the-job training and re-employment bonuses have also proven effective in multiple settings (WTO, 2017).

At the same time, excessively rigid labour market regulations can hinder adjustments to technological developments or unexpected changes in trade patterns. While labour market regulations can protect displaced or vulnerable workers, overly stringent employment protections tend to slow job reallocation, particularly in sectors requiring labour adaptation (Haltiwanger, Scarpetta and Schweiger, 2014). While high dismissal costs may mitigate short-term unemployment effects, they also reduce worker mobility and reallocation rates, and may limit the expansion of productive firms (Kambourov, 2009; Ruggieri, 2022).

High-income and upper middle-income economies are better equipped to respond to labour market challenges, but with the risk of deepening the global divide. For example, as with education, spending on both passive and active labour market programmes remains significantly higher in high-income and upper middle-income economies. World Bank data suggest a large disparity in the scale of labour market support across economies based on income from 2010 to 2019 (see Figure C.13). In high-income economies, social and labour market programmes reach transfer adequacy rates close to 40 per cent of beneficiaries' expenditure and sustain average daily transfers approaching US$ 8 per beneficiary per day. In contrast, low-income economies often achieve adequacy rates below 15 per cent and deliver daily transfers of less than US$ 1. These disparities underscore the limitations many economies might face in providing meaningful support to displaced workers. This limits the ability of workers to respond to the effects of changing trade patterns and technological developments. Without adequate social protection and retraining, they may struggle to re-enter the labour market.

Targeted training programmes can help bridge the gaps in worker support, though their impact varies. Training-based labour market policies can support displaced workers in adapting to evolving labour demands, including those driven by AI. While evidence on their effectiveness is mixed, programmes tied to in-demand sectors have improved employment and wage outcomes, particularly for women and youth (Ernst, Merola and Reljic, 2022; Escudero et al., 2019; Katz et al., 2022). In parts of Latin America and Asia, these programmes have contributed to more inclusive labour markets. Sector-specific training, especially when integrated with job placement services, appears particularly effective in enabling low-wage workers to access higher-quality jobs (Rodrik and Stantcheva, 2021). Public–private partnerships and firm-led training models can complement public programmes. To support these efforts, several governments have introduced incentives for firms investing in workforce

Figure C.13: Spending on social and labour market policies increases with income



Source: Secretariat calculations based on data from the World Bank Atlas of Social Protection Indicators of Resilience and Equity (ASPIRE) Database,[16] 2010-19.
Note: Adequacy of social protection and labour benefits is measured by the total transfer amount received by the population participating in social insurance, social safety nets, unemployment benefits and active labour market programmes as a share of their total income or total expenditure. PPP stands for purchasing power parity.

upskilling. Public partnerships with multinational firms to offer training and certification – particularly in sectors where AI adoption could support export diversification – are especially relevant for middle-income economies facing constrained budgets, low AI enrolment and the exit of skilled talent (Sidhu et al., 2024).

Regional policies need to complement labour market policies, as the structural change that AI may trigger is likely to increase regional inequality. Exporters of services and digital technologies, innovative firms and highly skilled workers more generally tend to be located in urban areas (Gervais and Jensen, 2019; Fajgelbaum and Gaubert, 2020; Nano and Stolzenburg, 2021; see also Section B.1(b)). The uptake of AI may exacerbate pre-existing inequalities, deepen the gap between urban and rural incomes, and limit opportunities and training for workers in certain regions. Labour mobility is often proposed as a solution, but many workers are unable or unwilling to relocate due to financial, social or personal constraints. Moreover, mobility can exacerbate inequality when it is limited to workers with the highest level of employability. Well-designed regional development policies can offer an alternative by creating in-place employment opportunities. Evidence suggests that some locally targeted interventions can trigger local multiplier effects and improve regional well-being (Suedekum, 2017). More broadly, regional policy frameworks that integrate skills, infrastructure and economic diversification, such as investment in education and digital connectivity, incentives for firms to locate in lagging (i.e., low-growth or low-income) regions, and support for innovation beyond major cities, can build resilient local economies and ensure that AI-enabled trade supports inclusive development.

(e) Inclusive government support can accelerate AI development and diffusion through trade

Targeted government support through subsidies or public procurement can be an accelerator of AI development and diffusion, and boost growth in the AI sector. Recent theoretical work finds modest but meaningful gains from optimal industrial policy that range from an average across economies of 1.08 per cent to 4.06 per cent of GDP (Bartelme et al., 2025). While the empirical literature on industrial policy tends to report mixed results on its effectiveness, recent studies emphasize that industrial policy can, in some circumstances, be effective in supporting the development of targeted sectors (Juhász, Lane and Rodrik, 2023). For instance, evidence from the Republic of Korea's heavy and chemical industry drive involving a large-scale government support programme in the 1970s targeting select manufacturing sectors finds that the programme promoted the persistent expansion and comparative advantage of directly targeted and downstream industries (Lane, 2025).

A central factor for the success of government support is government capacity. To understand the mixed empirical evidence, the literature has examined different factors that may contribute to whether government support achieves its objectives. Among the factors that stand out in explaining successful industrial policies is that such programmes must be within governance capacity constraints. The literature argues that industrial policy requires extensive capacity, including financial resources, qualified staff, technology and market knowledge (Juhász and Lane, 2024). This is also reflected in arguments for mission-oriented industrial policy (Mazzucato, 2021). This approach considers government intervention as necessary to address major social challenges in a sustainable way, including with respect to AI, but only on condition that there is a competent public sector in place (Mazzucato, 2013; Schaake et al., 2022). As governance capacity tends to grow with income, this may tilt the scale against low- and lower middle-income economies, which tend to have limited institutional capabilities and resources.

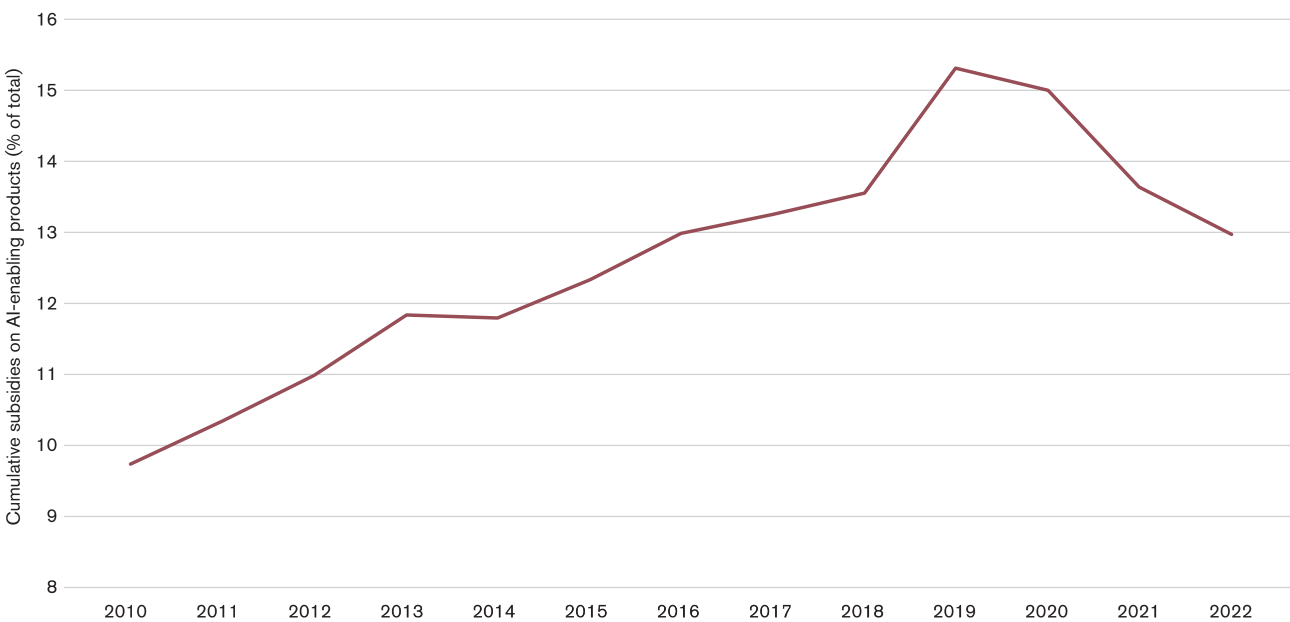
Sectoral characteristics affect the impact of government support, as they determine the extent of private under-investment. Sectors exhibit external economies of scale to different degrees. This means that the growth of firms in a sector creates social benefits beyond the firm itself, for instance due to learning-by-doing spillovers. In such cases, the private sector will underinvest relative to the optimum level and government support can efficiently complement private investment (Bartelme et al., 2025). These externalities have been found, albeit to a limited degree, in the semiconductor industry, a critical AI-enabling product that has received major government support through programmes such as the US CHIPS and Science Act (2022), the European Chips Act (2023), the Republic of Korea's K-Semiconductor Strategy (announced in 2021), Japan's Specified Semiconductor Fund (approved in 2021) and China's "Big Fund" (i.e., the National Integrated Circuit Industry Investment Fund, which was launched in 2014, and of which the third phase was launched in 2024) (Goldberg et al., 2024). Government support has also been found to be more effective when it targets upstream sectors, as support to these sectors diffuses downstream along the value chain (Liu, 2019; Lane, 2025). This also tends to be the case for many AI-enabling products, such as IT inputs or AI-enabled services.

Government support may lead to benefits beyond the subsidizing economy along the value chains of targeted products. In the context of the semiconductor industry, evidence suggests that subsidies targeting sectors dominated by multinational enterprises (MNEs) and global value chains tend to create positive spillovers abroad. Support for chip-designing MNEs benefits their supplying foundries as well as their downstream customers across the globe, and therefore subsidies can have significant positive international spillovers. However, this depends on the existence of a supportive policy framework that does not limit such diffusion (Goldberg et al., 2024). It is important to note that the opposite effect may also arise where subsidy races, combined with anti-diffusion policies, lead to negative international spillovers, with benefits accruing only to subsidizing economies (WTO, 2023).

Data suggest that policies targeting AI-related products are an important component of the recent surge of industrial policy in high-income and middle-income economies. Figure C.14, which relies on a dataset that Juhász et al. (2022) compiled on the basis of Global Trade Alert data, shows that the number of subsidies targeting AI-related products has increased noticeably since 2010. These AI-related subsidies account for a sizeable share of total subsidies. In 2019, more than 15 per cent of implemented subsidy measures targeted AI-related products. However, the COVID-19 pandemic led to a temporary decline in the share between 2020 and 2022, as the focus of industrial policy shifted to increasing resilience in goods such as personal protective equipment or vaccines.[17]

The rollout of subsidy measures targeting AI-enabling products is dominated by high-income and upper middle-income economies, and this may widen the divide in AI development and uptake. These two income groups account for more than 98 per cent of the cumulative subsidy measures implemented since 2010 (see Figure C.15). While certain lower middle-income economies have also put subsidies targeting AI-related products into place, the combined share of lower middle-income

Figure C.14: Share of subsidies on AI-enabling goods in total subsidies



Source: WTO Secretariat calculations based on data from Global Trade Alert compiled by Juhász et al. (2025).
Note: Subsidies are considered to target AI-related goods if the Harmonized System codes associated with the subsidy by Juhász et al. (2025) appear in the list of AI-enabling products defined for this report (see Annex A.1). The underlying data provide a count of subsidy measures that may hide heterogeneity in subsidy values.

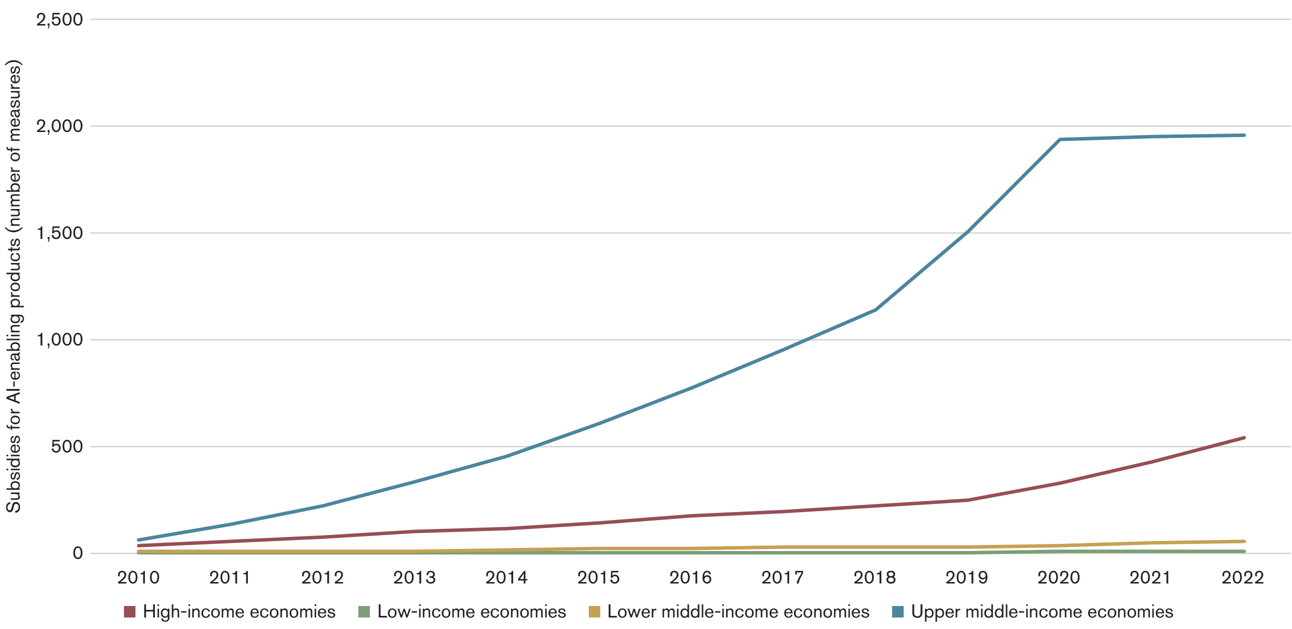
and low-income economies remains negligible. This is a common feature of industrial policy, which reflects differences in fiscal and institutional capacity (WTO, 2024b; Juhász et al., 2025). Insofar as these policies can accelerate AI development and uptake, this divide is a relevant challenge to AI's contribution to inclusive trade-led growth.

Public procurement is another major source through which governments can accelerate AI development and uptake. According to estimates, global public procurement amounts to US$ 13 trillion per year, and in some economies, public procurement accounts for over one third of GDP, making it a key tool to shape structural change (Open Contracting Partnership, 2020). AI intended for use in the public sector, such as in public education and public healthcare, will predominantly be acquired through government procurement procedures. This provides governments with a major tool not just to stimulate the sector, but also to shape AI development by stipulating conditions that promote the use of "responsible AI". This may include requirements for human supervision, mitigation of algorithmic bias and auditability of AI systems.

Most public procurement spending originates in upper middle-income and high-income economies. As with subsidies, there is a major divide along income lines when it comes to public procurement amounts. While other factors, such as the size of the welfare state or the economic system, are important, GDP is the most relevant determinant for the nominal procurement value. Estimates from the think tank Open Contracting Partnership for 2017 accordingly suggest that, among the ten largest public procurers, seven were high-income economies and two were upper middle-income economies. As a share of total public procurement globally, high-income and upper middle-income economies accounted for 92 per cent (Open Contracting Partnership, 2020).

Public procurement can stimulate AI investment globally, but several economies impose restrictions on foreign suppliers. International trade plays a pivotal role in broadening access of procuring entities to innovative and cost-effective AI solutions. This can substantially magnify the impact of public spending. However, certain regulations may prevent governments from sourcing solutions abroad. According to data from the Digital Trade Integration Project, only five out of 146 economies in the database have no explicit limitations on foreign participation in public procurement. These

Figure C.15: Cumulative AI-related subsidy measures by income group



Source: WTO Secretariat calculations based on data from Global Trade Alert compiled by Juhász et al. (2025).
Note: Subsidies are considered to target AI-related goods if the HS codes associated with the subsidy by Juhász et al. (2025) appear in the list of AI-enabling products defined for this report (see Annex A.1). The underlying data provides a count of subsidy measures that may hide heterogeneity in subsidy values.

limitations tend to be particularly restrictive among upper middle-income and high-income economies, which, as demonstrated above, have the largest procurement markets (Ferracane, Gonzalez Ugarte and Rogaler, 2025).

Overall, evidence from both data and the literature suggests that government support may skew the benefits of AI towards high-income and upper middle-income economies. These economies are far more active in providing support. Moreover, the factors identified by the literature as critical for successful industrial policy tend to develop with income. Nevertheless, an important caveat is that even in high-income economies, government support has often failed to achieve its objectives. For instance, a recent report on EU R&D support finds that, despite considerable support over the past two decades, the share of EU firms in high-tech sectors has dropped from 22 per cent to 11 per cent (Fuest et al., 2025). In addition, restrictive public procurement rules may hamper the impact of public investment. Hence, in the absence of concrete evidence, it remains an open question how government support will shape AI's role for inclusive trade-led growth.

3. Conclusions

Trade and trade-related policies are critical for AI to contribute to inclusive growth. The development and deployment of AI depend not only on domestic capabilities, but also on access to global markets, data and technologies. Whether through tariffs, export restrictions, standards on AI-enabling inputs, rules governing cross-border data flows, or IP and competition policies, trade-related measures shape how AI is produced, diffused and used. As such, policy choices can either unlock opportunities for inclusive trade-led growth or entrench and reinforce existing divides.

There is a clear and widening divide in the adoption of AI-related trade policies across income groups. High-income and upper middle-income economies move faster and more comprehensively across several policy areas central to AI, from data regulation to digital infrastructure, education, competition and government support. With the help of their superior fiscal and institutional capacities, they are not only first movers in AI development, but also in shaping the global rules and standards that govern its use. In contrast, many lower-income economies are still at an early stage of policy development, often constrained by difficult trade-offs stemming from limited resources.

Without deliberate efforts to address this divide, trade and trade-related measures may exacerbate the divide in AI-driven innovation and growth. As structural divides are reinforced by policy divides, the benefits of AI will disperse unequally. Policies enacted by advanced economies, such as export restrictions or divergent data standards, can inadvertently limit opportunities for other economies and reduce positive global spillovers and innovation synergies. They raise obstacles to trade, hinder technology diffusion, and reduce the potential for AI to support inclusive growth. The risks inherent in an uneven patchwork landscape of policies are particularly high for smaller firms and low-income economies, which face high compliance costs and limited access to key technologies and markets.

International cooperation is required to limit the harm of fragmented approaches to AI policies and to foster a global policy environment that supports inclusive and sustainable AI-driven growth through trade. Uncertainty around the effects of different policies on AI development and diffusion remains considerable. At the same time, the geopolitical environment is continuing to evolve, leading to an increase in strategic rivalries. Hence, policymakers are likely to continue to experiment with different domestic policy levers to regulate AI, even if this comes at the expense of AI diffusion. In this context, international cooperation becomes essential to ensure interoperability and trust, and to foster more inclusive participation in AI-enabled trade. The next chapter explores how multilateral dialogue and coordinated approaches can help to overcome fragmentation and promote more equitable outcomes.

Endnotes

1 See Annex A for the list of AI-enabling products considered in the analysis.

2 See https://www.wto.org/english/tratop_e/inftec_e/inftec_e.htm.

3 The Digital Trade Integration (DTI) index is still under development; therefore, some values might change in the final version of the index, which will soon be released on the DTI website: https://dti.eui.eu/. It is a partnership of the European Center for International Political Economy (ECIPE), the United Nations Economic and Social Commission for Asia and the Pacific (UN-ESCAP), the United Nations Economic Commission for Africa (UN-ECA), the Trade and Investment in Services Associates (TIISA), the Digital Cooperation Organization (DCO), the School of Computing, Engineering & Digital Technologies at Teesside University (SCEDT) and the Asian Development Bank (ADB).

4 See https://eping.wto.org/.

5 See https://www.wto.org/english/tratop_e/serv_e/gatsqa_e.htm.

6 Amini is a data infrastructure company headquartered In Nairobi, Kenya: https://www.amini.ai/.

7 See endnote 3.

8 See https://artificialintelligenceact.eu/.

9 For more explanation, see https://www.wipo.int/en/web/frontier-technologies.

10 The AI-IP Composite Index is based on 1,654 AI-related IP policy measures from 191 economies. The index ranges from 0 to 1, where values closer to 1 indicate a broader IP response to AI, while a value of 0 indicates no AI-IP response.

11 In order of market capitalization on 26 June 2025: NVIDIA, Microsoft, Apple, Amazon, Alphabet, Meta Platforms, Broadcom and TSMC.

12 See, for example, https://blogs.microsoft.com/blog/2025/01/21/microsoft-and-openai-evolve-partnership-to-drive-the-next-phase-of-ai/.

13 See, for example, https://www.anthropic.com/news/anthropic-amazon-trainium and https://www.aboutamazon.com/news/aws/amazon-invests-additional-4-billion-anthropic-ai.

14 https://globaltradealert.org/.

15 See https://digital-strategy.ec.europa.eu/en/news/new-digital-skills-academies-support-eus-technological-sovereignty-competitiveness-and-preparedness.

16 See https://www.worldbank.org/en/data/datatopics/aspire.

17 2022 is the last year with available data.

D International cooperation to make trade and AI work for all

As trade shapes the development and deployment of AI, and AI could, in turn, reshape global trade, stronger international trade cooperation, both at the WTO and with other international organizations, is important to ensure that AI is beneficial and that the benefits of AI are more widely shared. This chapter explores how the WTO can better address emerging trade-related challenges posed by AI. While existing WTO rules already promote more open, predictable trade in AI-related goods and services, it could be rendered more inclusive by improving AI-related market access, regulatory coherence and support for developing economies. The WTO can help advance a more inclusive AI future that requires open, predictable, forward-looking, flexible trade policies and enhanced international cooperation. It can help to foster dialogue on trade-related aspects of AI and collaborate with other international organizations to address digital divides, manage environmental and labour impacts of AI, and respond to market concentration in the AI sector.

Contents

KEY POINTS

- WTO agreements already help to support AI development and deployment by promoting open markets in AI-related goods and services, supporting AI innovation and diffusion through intellectual property rights and knowledge-sharing, and encouraging greater regulatory coherence on trade-related aspects of AI.

- An increasing number of trade-related policies relevant to AI have been discussed in various WTO bodies, although these have so far focused more on goods than on services.

- Improving the predictability of trade in AI-related goods and services – by lowering bound tariffs, reducing or eliminating applied tariffs on key raw materials and equipment, and improving market access commitments in AI-related services – could encourage AI investment, especially in developing economies, and help to make it more affordable and inclusive.

- Addressing regulatory fragmentation in AI-related policies would benefit both developers and users by fostering innovation through better access to inputs, markets and opportunities across borders – an objective the WTO can support through more informed discussion on trade-related aspects of digital policy, including data governance.

- Leveraging AI to implement WTO agreements presents both opportunities and challenges: it can help streamline trade procedures, particularly benefiting small enterprises and developing economies, but concerns about confidentiality, potential bias and a lack of transparency and fairness must be addressed to uphold WTO principles.

- Cross-institutional collaboration is important, as many trade-related AI challenges extend beyond the WTO's scope and require more coordinated efforts with other international organizations and initiatives to ensure that trade, competition, labour and environmental policies support more inclusive AI.

1. Inclusive AI would benefit from more cooperation at the WTO

International cooperation can help to address negative cross-border spillovers, improve the credibility of domestic policies and encourage better policy coordination. These considerations are just as relevant – if not more so – in the context of AI, given its far-reaching implications across borders, sectors and policy areas. As AI becomes more integrated in the global economy, trade-related challenges are becoming more prominent. An open and predictable trade environment is important to support AI development and deployment, by facilitating access to data, computational resources, talent and global markets. The ability of AI creators to operate across borders supports innovation and helps broaden the diffusion of AI benefits. However, while differences in national approaches to data governance, AI regulation, IP and competition policy reflect domestic priorities, they can also contribute to regulatory fragmentation, with potential implications for international trade. In the absence of cooperation, governments may resort to beggar-thy-neighbour measures, such as export restrictions on critical inputs or laxer regulations, which can have unintended effects on other economies and on the inclusiveness of AI development and deployment. Similarly, trade uncertainty and a lack of credible domestic policies may affect trust in digital markets and reduce incentives for AI-related investment, innovation and trade.

This chapter examines the role of international cooperation in addressing these challenges and ensuring that the gains from AI are more equitably distributed. It explores how the WTO can contribute to making AI more inclusive by fostering open, predictable and transparent trade in AI-related goods and services, and by providing a platform for dialogue and rulemaking. It highlights the information-sharing function of WTO commitments, and the potential for clarifying disciplines to meet emerging needs. The chapter then looks beyond the WTO, to examine how greater coherence is needed in trade policy and other relevant policy areas, such as digital infrastructure development, competition law, environmental policy and investment policy, to bridge the digital divide and prevent the fragmentation of AI governance. By promoting synergies across these domains, international cooperation can help to reduce wasteful obstacles to trade and to anchor regulatory commitments. Together, these efforts can foster a global policy environment that supports inclusive and sustainable AI-driven growth.

(a) The WTO covers many aspects of AI trade, making its benefits more accessible for all

WTO agreements cover important AI-related trade issues that enable and support the development and deployment of AI. This includes promoting predictable and non-discriminatory market access for essential hardware, information and communication technology (ICT), and digital goods and services; promoting IP rights related to AI algorithms, training data and outputs; and preventing trade distortions and unfair competitive advantages stemming from AI subsidies. It also involves fostering transparent, least-trade-restrictive and less fragmented standards, technical regulations and conformity assessments for AI goods (WTO, 2024a).

(i) WTO agreements help to make AI-related goods and services more widely available and affordable

The General Agreement on Tariffs and Trade (GATT) promotes non-discriminatory trade in AI-related goods, including the raw materials used to produce them. The GATT's non-discrimination principles – most-favoured-nation (MFN) and national treatment – help to make access to AI-related goods more inclusive by promoting equal treatment of imports from all WTO members. The GATT further commits WTO members to reduce their tariffs on AI-related goods, including by binding them at agreed maximum levels. Predictable tariffs reduce uncertainty and lower risks and costs for firms of all sizes, including micro, small and medium-sized enterprises (MSMEs), making it easier for them to trade and invest in AI. This helps to broaden access to AI-related goods in all economies, including developing economies.

The WTO's Information Technology Agreement (ITA) further supports AI by making ICT that is key for the development and application of AI more affordable. This plurilateral agreement builds on the GATT by binding and eliminating customs duties on a wide range of IT goods, including many that are essential for AI, such as semiconductors and computer equipment (WTO, 2018). As of 2025, 82 WTO members, representing about 97 per cent of world trade in IT goods, are parties to the ITA. Furthermore, in 2015, 54 of these members agreed to eliminate tariffs on 201 additional IT-related goods under the ITA Expansion (ITA 2) Agreement. Discussions continue on the possibility of further expanding its scope. The tariff elimination under both ITA and ITA 2 is applied on an MFN basis, thereby benefitting all WTO members. This provides firms producing AI-enabling goods, including those in economies that are not part of the ITA, with the opportunity to engage in AI-related international markets under more open and predictable conditions.

The WTO's General Agreement on Trade in Services (GATS) supports more open and predictable trade in services involved in developing and deploying AI. As discussed in Chapter B, computer and telecommunications services supply the technical infrastructure, specialized software, data processing and expertise needed for AI systems. AI is also reshaping trade in services by enhancing productivity, lowering costs and creating new kinds of services. AI-related services can be traded internationally through various channels, including the cross-border digital supply of AI-related services (such as software development, data analysis or remote consulting), the establishment of a commercial presence abroad to deploy or maintain AI systems, and the temporary movement of specialists who travel to deliver or customize AI solutions. The cost of trading AI-related services internationally depends on several factors, including the trade policies that economies apply to services. Under the GATS, WTO members make commitments that set the level of market access openness and guarantee non-discriminatory treatment for foreign suppliers of AI-related services. A total of 116 WTO members has made commitments with regard to telecommunications services, and about 60 per cent have also made specific commitments with regard to computer services (WTO, 2019). GATS commitments help make the trade environment for AI-related services more predictable, supporting the monetization of AI technologies, attracting investment, and enabling international scaling of operations, thus fostering the development and deployment of AI across borders. However, gaps may exist between these commitments and the policies actually applied. For example, a country's GATS schedule might list restrictions on foreign AI firms offering data-processing services, but in practice those restrictions are not applied. Such discrepancies reduce predictability of AI-related GATS commitments.

The WTO's moratorium on customs duties for electronic transmissions can support AI-related digital trade, though members have differing views on its renewal. In place since 1998 and periodically renewed, the WTO moratorium prevents the imposition of customs tariffs on electronic transmissions, keeping costs lower and facilitating digital trade, including in AI-related trade. Its most recent extension, agreed at the 13th WTO Ministerial Conference in 2024, keeps the moratorium in place until the 14th Ministerial Conference (due to be held in March 2026) or 31 March 2026, whichever comes first. The Ministerial Decision on the Work Programme on Electronic Commerce[1] further notes that the moratorium will expire on that date. There is, however, no consensus among WTO members on the renewal of the moratorium on customs duties. Supporters of the moratorium argue that it has fostered a stable environment for digital trade, while others voice concerns about unclear scope, potential revenue losses and constraints on their ability to respond to evolving technological developments and industrial needs (IMF et al., 2023). WTO members have long debated whether certain digital products fall under the rules for goods or services, an issue that may become more relevant in the context of AI systems, though it is not yet discussed in the WTO context.

(ii) The WTO can help promote AI innovation and adoption while safeguarding against unfair trade practices

The WTO's Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) can support AI development and deployment by encouraging innovation. Although it does not include any explicit provisions on AI, its rules apply equally to AI-related products, such as AI training data, chips and computer programmes, including algorithms, reflecting its technological neutrality. The TRIPS Agreement sets minimum standards for the protection and enforcement of IP rights related to AI technologies and AI-generated creations, including copyrights, patents, trademarks, industrial designs and trade secrets. As discussed in Chapter C, IP rights provide the legal certainty and exclusive, time-limited control over the innovation that can incentivize investment in AI research and development (R&D).[2] This, in turn, encourages innovators to take risks that advance AI-related technologies (WTO, 2020). Effective IP frameworks can also facilitate cross-border AI technology pooling, which can strengthen complex global supply chains and support the creation of AI-driven intangible assets, as well as facilitating international trade in IP-protected AI systems, algorithms and related licences. Moreover, well-functioning IP ecosystems can foster collaboration between public research institutions and private firms, allowing commercially viable AI-related innovations to benefit from broader diffusion prospects. Trade openness, supported by other WTO agreements, further helps to create the enabling environment that AI developers need to access markets, inputs and opportunities across borders.

While the use of copyrighted material to train AI models and the determination of ownership of AI-generated content raise legal challenges, the TRIPS Agreement provides a framework for protecting the rights of creators. As discussed in Chapter B, AI – and in particular generative AI models, such as large language models and image generators – relies on vast datasets for training. These data are often compiled by scraping internet content, which includes material protected by copyright and made available for sale, such as articles, books, images and videos. This practice has sparked significant legal and ethical debates (Samuelson, 2023). For instance, recent lawsuits have involved Google and OpenAI facing allegations of large-scale data scraping without publishers' consent. Whether exceptions and limitations to copyrights apply to training data, the TRIPS Agreement covers the conditions under which such exceptions, including for text- and data-mining in AI development, may be granted. Similarly, although it is unclear whether IP rights protect works created solely by AI, their possible application to human-led innovations and creations assisted by AI may give inventors and creators a way to safeguard their economic interests and promote further innovation (WTO, 2024a).

The TRIPS Agreement seeks to incentivize AI innovation and mechanisms that promote the diffusion and licensing of AI-related technology. It gives owners of IP rights related to AI technologies the flexibility to decide how openly or restrictively they exercise those rights, shaping how AI innovations spread and evolve. For instance, AI creators applying for patents must disclose their inventions in sufficient detail to enable replication, granting early public access to emerging technological knowledge that can spur further innovation and technology transfer. Similarly, AI developers who rely on copyright protection for their software can publish their algorithms, promoting transparency instead of keeping these algorithms hidden as trade secrets. Domestic IP systems based on TRIPS standards provide the basis for AI innovators to also license their inventions, often subject to a fee, which can attract investment and accelerate the commercialization of new AI-related products. Other AI developers may adopt open source licences that let others freely use, modify and share AI innovations, potentially fostering broader collaboration.

The WTO's plurilateral Government Procurement Agreement 2012 (GPA 2012) can help promote open, transparent and competitive innovation procurement in AI technology. Governments, especially in developed and emerging economies, increasingly use public procurement not only to meet routine needs, but also to help create or reshape markets in ways that drive innovation, including in the context of AI. This so-called "innovation procurement" leverages a government's purchasing power to buy either the process of innovation itself, such as R&D activities, or its innovative products (WTO, 2020). As of 2025, 49 WTO members are covered by the GPA 2012, which requires them to procure covered AI-related goods and services in accordance with GPA 2012 rules, including the obligation not to discriminate against suppliers from other GPA Parties. The GPA 2012 also allows governments to award public contracts based on criteria not related to price alone, encourages performance-based technical specifications and provides flexibilities for purchasing prototypes, all of which can help to drive early-stage AI development. This can allow governments to tap into innovative global suppliers' AI capabilities and promote inclusive access for start-ups and MSMEs to additional government procurement markets. MSMEs are often at the forefront of AI innovation. Mindful of what MSMEs can contribute, the WTO Committee on Government Procurement has adopted a list of best practices aiming at promoting participation by MSMEs in government procurement.

Several WTO agreements also seek to promote technology transfer, which can support the development and deployment of AI. The TRIPS Agreement requires developed members to provide incentives to their enterprises and institutions to promote and encourage technology transfer, which may include AI-related technologies, to least-developed countries (LDCs) (Fernández, 2025). A few developed economies, including the European Union, Canada, Switzerland and the United States, have adopted programmes to support the transfer of AI-related technologies to some LDCs.[3] Furthermore, the GATS encourages developed members to make commitments that help developing economies to gain commercial access to technology, including potentially AI-related technologies. As discussed below, WTO technical assistance initiatives can help LDCs develop their approach in the trade–technology transfer space, including considering the enabling environment they wish to create and clarifying what they want to achieve, which in the early stages may focus more on AI adoption and in the medium term on AI development.

The WTO's Agreement on Subsidies and Countervailing Measures (SCM) can help to support more inclusive AI development by limiting the risks of subsidy competition. As discussed in chapters B and C, governments that wish to attract AI-related companies within their borders may try to outbid each other by offering generous subsidies. This can lead to an inefficient use of public money and distort competition, disadvantaging companies in economies that cannot afford such incentives. In that context, the SCM Agreement sets rules to ensure that public financial support measures for AI-related goods benefiting certain companies or industries do not distort trade or trigger retaliatory actions between economies. It separates automatically challengeable prohibited subsidies, which are presumed to distort trade by being tied to export performance or local content requirement, from actionable subsidies, which require evidence of adverse trade effects before any remedies can be applied. Remedies for both prohibited and actionable subsidies can be pursued through multilateral dispute settlement or by imposing countervailing duties.

The WTO's Agreement on Safeguards allows the temporary restriction of imports of AI-related goods to shield domestic industries from damaging import spikes. As discussed in Chapter B, a major challenge is the uncertain impact of AI on global labour markets. AI could boost trade opportunities for developing economies, potentially disrupting the job market in developed economies, while also enabling developed economies to bring back outsourced production, potentially harming employment in developing economies. These dynamics could lead to social tensions and protectionist pressures. The Agreement on Safeguards allows members to restrict imports temporarily when a surge in imports of AI-related goods under certain conditions causes or threatens serious harm to domestic AI industries. Members using safeguards may have to offer compensation (or accept retaliation) to affected exporting economies to preserve the balance of concessions under the WTO (WTO, 2017b).

More informed discussions may be warranted to ensure that WTO disciplines remain effective in supporting inclusive AI. AI is likely to disrupt existing trade patterns, with the services sector, particularly digitally delivered services, likely to be most affected. In addition, AI presents new IP challenges related to authorship, ownership and enforcement. While WTO agreements provide a foundation for global trade, some may not yet fully capture the trade-related implications of AI, particularly in ways that support the promotion of more inclusive AI development and deployment. As discussed below, these issues, including those related to IP, safeguards and support measures, may benefit from closer consideration.

(iii) The WTO helps to minimize trade restrictions while balancing legitimate interests

General exceptions under WTO agreements may offer, under certain conditions, flexibility to adopt trade-restrictive AI measures aimed at public interest objectives. As AI technologies raise complex ethical, safety and societal concerns, governments may invoke general exceptions, such as those under the GATT and GATS, to justify regulations aimed at legitimate public policy objectives, such as protecting public morals and human life. However, any such measures must comply with WTO conditions, including non-discrimination and proportionality, and should not serve as disguised restrictions on trade. While no WTO disputes to date have directly addressed AI-specific regulations, past cases suggest that measures justified under general exceptions must show a clear link to the policy objective and that no less trade-restrictive alternative is reasonably available.

The WTO's Agreement on Technical Barriers to Trade (TBT) promotes regulatory convergence and mutual recognition to facilitate trade in AI-related goods. It requires members to ensure that their standards and regulations, including those on AI-related products, are non-discriminatory and no more trade-restrictive than necessary to achieve their legitimate objectives, such as product safety or consumer protection (WTO, 2024a). The TBT Agreement further requires members to use relevant international standards when developing domestic regulations on AI-related goods, on the premise that this avoids duplicative testing of AI models and devices, lowers compliance costs and shortens regulatory cycles. In cases where harmonization is not feasible, it encourages governments to accept each other's testing and certification results (mutual recognition) and to treat different rules as equal if they achieve the same goals (equivalence). This helps to avoid duplicate checks and keeps certification procedures from becoming a barrier to trade in AI-related goods (Meltzer, 2023).

The TBT Agreement promotes inclusive participation in international standard-setting for AI-related goods, yet developing economies remain underrepresented in AI standard-setting. International standards set best practices, support interoperability and reduce trade barriers for AI goods and services, particularly benefiting MSMEs engaged in international markets. The TBT Agreement encourages members to participate actively in the development of international standards, including those for AI-related goods. According to the TBT Committee's Six Principles for the Development of International Standards, Guides and Recommendations,[4] international standards should be developed transparently, through open and consensus-based processes, should remain relevant and coherent, and should take into account the needs of developing economies. As discussed in Section D.2, international efforts are underway to develop AI standards through various organizations. Although the participation of developing economies in standard-setting processes has improved, it remains limited due to resource, expertise and language constraints. For example, although over 70 per cent of WTO members are low-income or middle-income economies, only 38 per cent of participants in the AI standard-setting work of the International Organization for Standardization (ISO) and International Electrotechnical Commission (IEC) are from developing economies.[5]

(iv) The WTO offers a forum to build shared understanding on trade-related AI issues

Transparency provisions in WTO agreements help members to monitor AI regulatory developments affecting trade. All WTO agreements include transparency provisions requiring members to notify to the WTO and publish new or amended laws and regulations that impact trade, including those related to AI, and to set up enquiry points for stakeholders.[6] In the case of the TRIPS Agreement, laws and regulations need to be notified, however publication requirements also apply to final judicial decisions and administrative rulings of general application, which are important in monitoring developments related to AI. The TBT Agreement requires members to notify AI-related technical regulations at the draft stage, allowing other members to comment, adapt and prepare, and thereby helping to level the playing field. The ePing SPS and TBT platform sends alerts on members' notifications, including AI-related ones, enabling stakeholders to track developments and engage early.[7] Although TBT notifications that explicitly address AI are still limited,[8] an increasing number of measures covering AI-relevant products, such as cybersecurity certification, have been notified in the last four years. Similarly, AI has been explicitly discussed in the trade policy reviews reports – the WTO's mechanism for periodically examining members' trade policies – of several WTO members in the last three years.[9] Other relevant transparency provisions include the obligation under the SCM Agreement to notify subsidy programmes regularly, reducing the risk of hidden subsidy escalation and helping firms to compete on more equal terms.

The WTO serves as a forum for dialogue on AI-related trade issues. Different WTO institutional bodies give members a space to discuss AI-related trade measures. If a member believes a proposed AI regulation might unfairly restrict its exports or create unnecessary trade barriers, it can raise its concern early in the relevant committee, and thereby possibly avoid costly disputes later on. Through regular discussions, members can learn from each other's experiences with AI, understand different regulatory approaches, and explore areas of common interest. For instance, the WTO's TBT Committee organized a thematic session on regulatory cooperation for emerging technologies in November 2023, with contributions from international standard-setting bodies and member-led experience-sharing.[10] Other WTO bodies, such as the TRIPS

Council, have also held AI-related discussions. WTO bodies also issue voluntary guidance ("soft law") that can support members in their AI-related trade policies. For instance, the 2024 TBT Committee Guidelines on designing and applying certification procedures call for conformity assessment procedures to be adaptive and responsive and to remain relevant in the face of uncertainty due to rapidly changing technological trends.

AI and inclusive trade considerations have been raised in several WTO settings. Recently, members held dedicated discussions on the implications of AI for trade under the Work Programme on Electronic Commerce with a particular focus on bridging the digital divide, addressing the specific needs of MSMEs in an AI-driven economy, and ensuring that technological progress supports inclusive trade. The Work Programme allows members to explore both the trade opportunities and challenges posed by emerging digital technologies, such as AI, in a multilateral setting. Digitalization, including AI, has also been a key focus of the Informal Working Group on MSMEs. Thematic discussions and practical tools like the Trade4MSMEs platform provide businesses with insights on AI tools for trade. Box D.1 provides some examples of how helping MSMEs to adopt AI technologies can enable them to succeed in the global marketplace.

Despite some progress, transparency and information-sharing on some AI-related trade issues remain challenging. While services trade stands to benefit the most from AI, information-sharing on services trade measures remains limited. Notifications of services measures under the GATS are relatively scarce compared to other WTO agreements dealing with regulatory measures. The paucity of services notifications may reflect the self-judging and narrower scope of transparency-related GATS obligations, the complexity and breadth of the services economy, the extensive role of domestic regulation,

Box D.1: Selected examples of how AI technologies can help MSMEs to grow internationally

AI tools help MSMES by reducing market research and targeted advertising costs. Unplug Studio is a technology-focused website development company based in El Salvador that incorporates AI across multiple business functions. Aside from driving efficiency and improving client satisfaction, AI has been instrumental in Unplug Studio's expansion into EU markets, particularly into the Netherlands. By leveraging AI-driven market research tools, the company has been able to gain insights into consumer behaviour and industry trends, which has allowed it to tailor its offerings for new overseas markets. The company also uses AI to plan its marketing campaigns to enable more targeted advertising. Unplug Studio is aligned with EU web accessibility standards and data privacy regulations, and actively monitors developments to ensure compliance.

AI-powered agronomic advice can help small businesses to improve agricultural productivity. Farmerline, a Ghana-based agritech company, offers a marketplace platform that helps over 2.3 million smallholder farmers to gain access to technology, finance and information. Their conversational AI tool, Darli AI, delivers personalized, voice-based and text-based agronomic advice in 27 languages, and is accessible on even basic mobile phones. The tool can adjust advice based on location, weather data, crop stage and farmer feedback. Farmers that have adopted the tool in pilot areas have seen improvements in crop yield of up to 35 per cent. Farmerline is now able to serve farmers globally and meet the communication needs of farmers in more than 50 countries globally.

AI can help businesses in regions where regional languages and dialects are prevalent. LAfricaMobile is a pan-African B2B mobile communications and marketing company based in Dakar, Senegal. It introduced AI into its services in 2023. The company employs an innovative text-to-speech tool that converts written content into regional languages, such as Wolof and Diola. Although major companies like Google offer multilingual AI tools, they lack support for many African languages and dialects. LAfricaMobile's service allows their business, non-governmental organization and government institution clients to engage regional communities better and enable inclusive communications. However, regulatory considerations, particularly in areas such as data privacy and ethical AI usage, may impact the company's ability to train AI models effectively.

Source: International Trade Centre (ITC).

and the challenges of coordinating across multiple agencies to identify relevant measures. Similarly, the use of the WTO's Council for Trade in Services to discuss specific trade concerns is a relatively recent development. While several trade concerns relevant to AI have been raised in the Council, they often involve politically sensitive matters tied to national security, making them harder to resolve. As discussed below, members could make greater use of the WTO to address trade-related AI issues.

(b) Greater cooperation among WTO members could help make AI work for all

While it already contributes to AI development and deployment, the WTO could do more to foster an environment that is supportive of more inclusive AI. The WTO can help not only to keep markets open, but also to make them more open and predictable specifically for trade in AI-related goods and services. It can advance potential rulemaking in key areas, including data policy coordination, the investment environment and strategic trade policies, and it can enhance trust by promoting transparency, dialogue and experience-sharing with regard to trade-related AI measures. In addition, as discussed in Section D.2, coordination between the WTO and other international organizations can help to make trade and other AI-related policies more coherent and mutually supportive. In parallel, AI technologies may help with the easier implementation of certain WTO functions (see Box D.2), although this might also pose some risks if AI technologies are not sufficiently overseen.

(i) AI markets could be made more inclusive by ensuring WTO remains relevant for AI trade

The matter of ensuring that the WTO remains relevant for AI trade touches on different areas, including market access, safeguards and subsidies. As discussed above, the WTO can help to foster the development and deployment of AI by keeping markets open, which can ease access both to key AI-enabling products and to exports of AI-enabled products. This section discusses how strengthening WTO members' existing market access commitments could help to create a more supportive environment for AI. At the same time, WTO agreements can help to safeguard market access against unfair practices and to address domestic disruptions. However, existing WTO agreements may not fully account for the evolving challenges and opportunities associated with AI-related trade, and this may warrant further consideration.

Members can improve their market access to IT goods by joining the ITA and ITA 2, and this, in turn, could foster more inclusive AI development and deployment. As discussed above, the ITA and ITA 2 play a key enabling role for AI by making the hardware and tools needed for AI more affordable and widely available. Yet, as a plurilateral agreement, the ITA still holds significant potential for broader membership expansion. While the Agreement enjoys strong uptake among high-income economies, where approximately 86 per cent are parties to the ITA, its membership among lower-income economies remains limited:[11] only 5 per cent of low-income and 27 per cent of lower middle-income WTO members are parties to it. While ITA members have bound their tariff rates to zero, non-ITA members maintain significantly higher final bound and MFN applied rates, up to 87 per cent on goods not covered by the ITA expansion. Making binding tariff-cutting commitments under the ITA could help to create a more predictable trading environment conducive to investment and competitiveness in AI-related activities (WTO, 2017a).

Lowering bound tariffs on AI-related raw materials would provide more predictability for investors. As noted in Chapter B, many essential raw materials, including rare earths metals, are geographically concentrated, so that most economies engaged in the production of AI-enabling goods are obliged to import them. Although MFN applied tariffs on these AI-enabling intermediate goods are generally low, ranging between 3 per cent and 7 per cent, bound tariffs remain relatively high, between 20 per cent and 45 per cent. Although both tariff rates decrease with income level, the gap between bound and applied MFN rates, known as "water", is still sizeable, especially for low-income economies (see Figure D.1). However, while these tariff flexibilities can help to address specific development concerns, they come at the cost of predictability (WTO, 2024b). In that context, lowering bound tariffs on these goods could help reduce trade policy uncertainty, support investment and strengthen firms' positions in highly competitive AI-related global value chains.

Advancing cooperation among WTO members with regard to export restrictions could also help to support a more predictable trade environment, including for key AI inputs. The raw materials used to produce AI-related inputs, such as microchips and batteries, may be subject to strategic trade policies, such as export measures. While quantitative export restrictions are subject to

Box D.2: AI can support certain WTO functions, but its use can also present some risks

The WTO's main objective is to help international trade to flow as freely and predictably as possible. It pursues this goal by facilitating trade negotiations, trade policy monitoring, dispute settlement, technical assistance and cooperation with other international organizations. Some of these WTO functions could potentially benefit from the integration of AI technologies, although significant risks, including with respect to the trustworthiness of AI, limit its potential applications in some areas.

The WTO's trade policy monitoring and review exercises could be enhanced by means of AI. The WTO monitors and reviews members' trade policies and practices and promotes transparency. AI-driven systems could help members in this process by scraping the web for relevant trade policy information and automatically organizing and translating it. AI could also analyse large volumes of trade policy data, potentially in real time, to detect broader patterns and trends in tariff and non-tariff measures over time. AI chatbots could offer users personalized guidance for certain tools, such as for the ePing SPS and TBT platform (i.e., a platform which facilitates the tracking of information on sanitary and phytosanitary (SPS) measures and technical barriers to trade (TBT)), to improve the accuracy and relevance of WTO members' notifications.

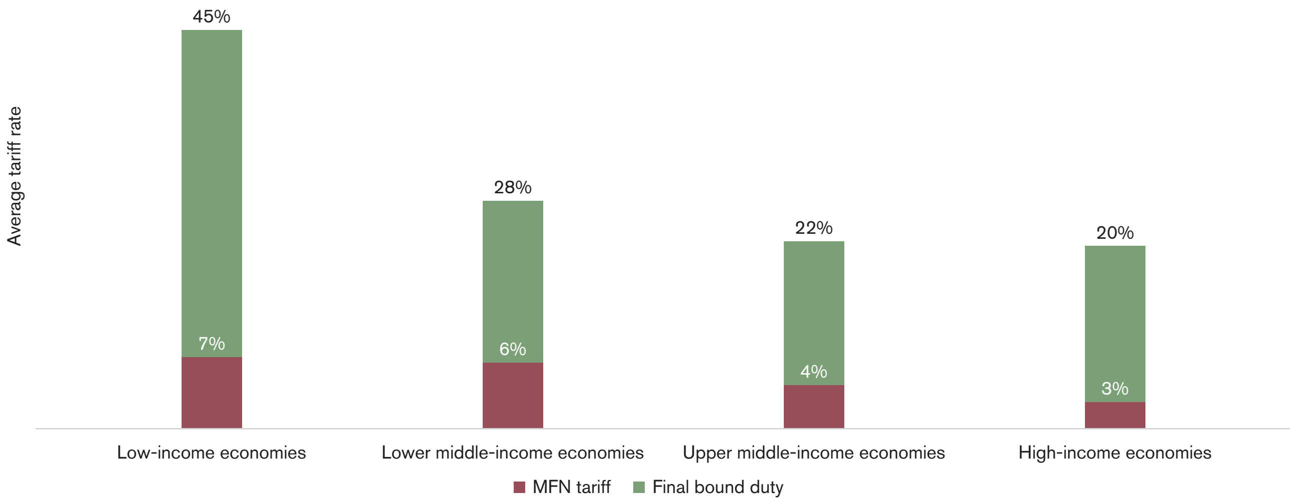
AI could help, to a certain extent, with WTO trade negotiations. The WTO serves as a forum for its members to negotiate new trade agreements and update existing rules. AI-driven algorithms could help negotiators to locate and manage pertinent information more systematically and efficiently, as well as to identify potential trading opportunities and evaluate the best alternatives for a negotiated agreement (Eidenmueller, 2024). AI models, in particular large language models that address confidentiality issues, could also assist in drafting the legal text of agreements.

AI could assist members in the resolution of WTO disputes. The WTO provides a structured process for resolving trade disputes between members under its Dispute Settlement Understanding (DSU). By automating the analysis of large datasets, such as trade regulations, past rulings and expert commentary, AI could assist members contemplating litigation with issue-spotting and drafting, potentially shortening timelines and lowering costs. This capability could be especially valuable for developing economies that face resource constraints in complex litigations (Abad, 2024). Assuming appropriate confidentiality safeguards are in place, adjudicators and parties could also benefit from using AI to process communications and organize materials in a secure framework, without substituting human judgement or departing from the record. AI-powered machine translation can also complement existing tools by helping to reduce language-related barriers and promoting equal access to information.

However, while AI technologies offer promising support for certain WTO functions, their use must be carefully governed. AI systems often struggle to process unstructured data and cannot capture emotional or non-verbal cues, elements that can be critical for building trust in negotiations. Current AI systems may produce inaccurate or unverifiable content, or omit context (Ma et al., 2024), and external tools may not guarantee confidentiality or prevent retention or secondary use of data. AI models may encode biases where training data are unrepresentative, risking the loss of cultural and linguistic nuance (Abad, 2024). In addition, there is a risk that certain developments in generative AI, such as synthetic audio or video ("deepfakes"), could, if misused, undermine trust or disrupt negotiation dynamics and dispute resolution. Mitigation may require human oversight at all stages, restricted and auditable environments, documented data handling and retention limits, and the ability to trace and challenge outputs.

GATT disciplines,[12] WTO members can, in principle, apply export taxes, as only a few have made binding commitments regarding their use. However, beyond contributing to trade uncertainty, strategic trade policies can impose significant negative spillovers, either directly or indirectly along AI global value chains, potentially affecting AI producers in other economies. There may be scope for mutually beneficial commitments on export taxes, although individual governments' willingness to commit may depend on their specific policy objectives for using such measures. Trade-offs to exchange concessions could be found, for example, between export taxes on natural resources and import tariffs on higher

Figure D.1: Lower-income economies tend to impose higher bound tariffs on AI-related raw materials



Source: WTO Secretariat.
Note: Simple average, based on 2024 or the latest available year.

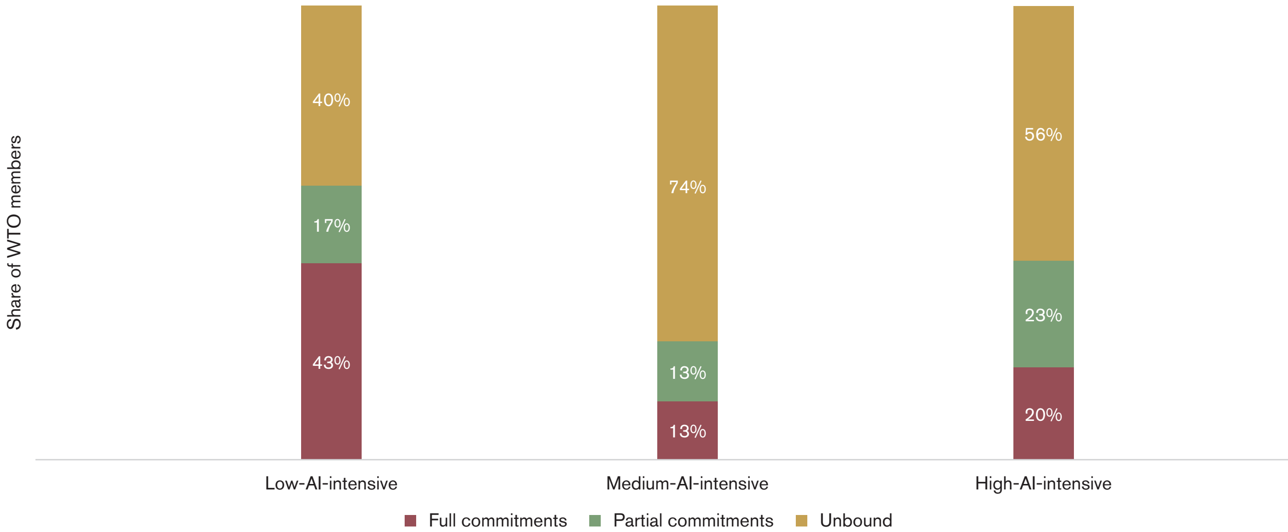
value-added products (WTO, 2010). Although not specific to AI, a limited but growing number of cooperation agreements on inputs that are critical to AI – focusing on the extraction, processing and governance of critical minerals, such as rare earths elements and advanced semiconductors – have been negotiated at the bilateral level (Dufour et al., 2025).

Market access to services particularly relevant to AI remains limited, and trade costs remain high. As discussed in Chapter C, restrictions on trade in AI-intensive services remain pervasive, but differ across income groups and modes of service supply. For instance, they tend to be higher for commercial presence abroad (mode 3 of the four GATS modes of supply)[13] in lower-income economies, and for cross-border service trade (mode 1 of the GATS) in upper middle-economies. At the same time, few WTO members have made commitments under the GATS to open their high AI-intensity service sectors to foreign competition compared to other sectors – only 20 per cent of members have made full commitments, and only 23 per cent have made partial commitments (see Figure D.2). In other words, predictability for foreign suppliers and investors tends to be lower in AI-intensive service sectors than in other parts of the services economy in a majority of WTO members.

Commitments in high AI-intensity services sectors are particularly limited in low-income economies. While WTO members' GATS commitments to opening high-AI-intensity service sectors, such as cloud services, increase with income level, they remain particularly limited in low-income economies, with almost 80 per cent of these members having made no commitments in high-AI-intensity service sectors, compared to 32 per cent in low-AI-intensity sectors, such as travel. Although members tend to be more open to allowing a commercial presence (GATS mode 3) in their markets than cross-border remote digital delivery (GATS mode 1) in AI-intensive sectors, both modes show very low shares for low-income economies, suggesting a relatively less predictable and open environment for AI-related service trade in low-income economies compared to middle-income and high-income members (see Figure D.3).

Binding members' current trade regime on AI-related services through GATS commitments would enhance predictability, while further market-opening, calibrated to implementation capacity, would create new opportunities for AI trade. As discussed in Chapter B, AI adoption could improve productivity and reduce trade costs, with digitally delivered services potentially experiencing the largest trade growth (WTO, 2024a). Improving GATS commitments for AI-related services could amplify these benefits. For example, GATS mode 1 commitments could ensure that the cross-border supply of AI-related services is not hindered by undue restrictions, such as licensing

Figure D.2: The share of full and partial commitments tends to be relatively low for high-AI-intensive and medium-AI-intensive services



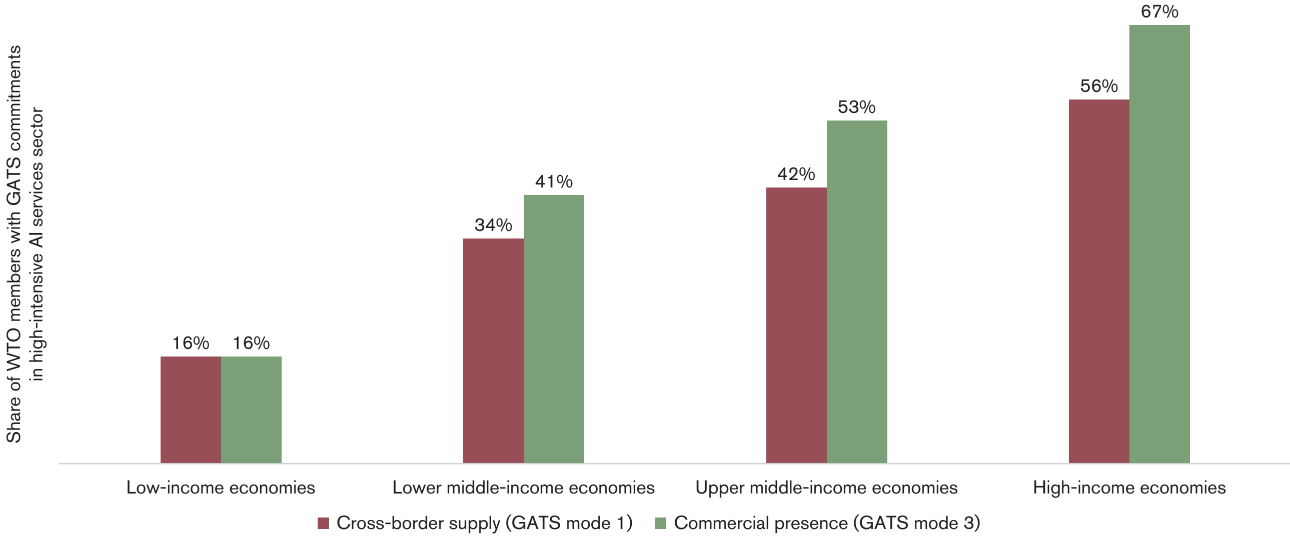
Source: WTO Secretariat, based on Calvino et al. (2024) AI-intensity classification.
Note: Most services sectors are classified as high-AI-intensive. Retailing, education and health-related and social services fall into the medium-AI-intensive category, while travel services are considered low-AI-intensive.

requirements or internet bandwidth limits, thereby improving predictability and lowering the risk of future trade barriers on AI-related services. Some scholars argue that AI's autonomous capabilities could raise questions under the GATS about service qualifications, the classification of AI-generated services, and the determination of their origin, such as automated legal advice (WTO, 2024a). Binding GATS mode 3 commitments could encourage more diverse international investment in local AI-related services markets and foster technology transfer, skills development and infrastructure-building (WTO, 2019). Deeper commitments could benefit from special and differential treatment (S&DT) provisions (i.e., special treatment given to developing economies, including LDCs, in WTO agreements) that provide relevant policy space for these economies without undermining the predictability and stability of trade policies achieved through credible commitments (WTO, 2024b).

WTO technical assistance could help developing members, particularly LDCs, in applying AI solutions to the implementation of WTO agreements. By leveraging advanced algorithms and machine learning, AI can assist governments in meeting their WTO obligations, improving the coherence, predictability and transparency of trade policies, and, by extension, lowering compliance costs (see Box D.3). This could be particularly beneficial for MSMEs and developing economies, which often have to comply with complex trade regulations (WTO, 2024b). As discussed below, capacity-building and technical assistance initiatives, such as the WTO-led Aid for Trade,[14] could help to bridge the digital divide and strengthen the capacity of developing economies to adopt trade-related AI solutions. At the same time, attention must be paid to the fact that using AI to implement WTO agreements could incur risks such as bias and inaccuracy.

The limited scope of the SCM Agreement raises questions as to its ability to address wider disparities in AI development and deployment. The Agreement[15] applies only to subsidies on AI-related goods (e.g., hardware) and excludes services and IP essential to AI technologies. Its applicability, as discussed above, is also limited to so-called specific subsidies, excluding general, or economy-wide, support available to all firms for AI development and deployment. As a result, many subsidies related to AI may not be covered by WTO disciplines, potentially making it harder for new or smaller players to compete, and thereby widening technological and economic gaps. This could be further affected by certain R&D subsidies that can be challenged following the expiration of the "non-actionable subsidies" category (which once covered certain R&D, environmental and regional development subsidies), potentially discouraging government

Figure D.3: Market access commitments for high-AI-intensive services sectors under the GATS rise with income level



Source: WTO Secretariat, based on Calvino et al. (2024) AI-intensity classification.
Note: Most services sectors are classified as high-AI-intensive. Retailing, education and health-related and social services fall into the medium-AI-intensive category, while travel services are considered low-AI-intensive.

support for AI research and innovation that could generate widespread benefits. More discussion on these issues at the WTO could contribute to more inclusive gains from AI.

The limited applicability of the WTO's Agreement on Safeguards calls into question its ability to address potentially broader AI-related disruptions. The Agreement[16] only applies to safeguards on AI-related goods. Yet, as discussed in Chapter B, the impact of AI could be particularly disruptive for services trade compared to merchandise trade, as it could reduce demand for traditional services by automating tasks, while boosting digitally delivered services. Although the Agreement on Safeguards does not provide safeguard mechanisms to prevent or remedy injury to domestic suppliers due to sudden surges in service imports, members can shape the scope and pace of their commitments, including through phased trade-opening, to allow time for market and regulatory adjustment. This flexibility may help to address concerns that could otherwise discourage market-opening, potentially limiting the global diffusion of AI-related services and undermining efforts to ensure broader access to AI's benefits. This remains an area that would benefit from further WTO discussion.

(ii) Dialogue among WTO members on key new AI-related issues could help to make AI more inclusive

Fragmented data rules may hinder inclusive AI, underscoring the need for deeper discussions. As discussed in Chapter C, AI's requirement of large datasets to enable it to learn and improve its performance is reshaping data usage (WTO, 2024a). While there are legitimate reasons for diversity in data regulation, the current regulatory landscape is becoming increasingly complex and fragmented, and this could potentially undermine opportunities for innovation and efficiency (IMF et al., 2023). Less trade-restrictive data regulations could help to promote more inclusive AI development and deployment by enabling governments to achieve their public policy objectives while allowing data flows and AI services to operate across borders (Jones, 2023). An increasing number of regional trade agreements (RTAs) and a few digital economy agreements include specific provisions requiring cross-border data flows for digital trade, with exceptions for privacy, security or public policy objectives, and exemptions, most notably for government procurement (see Box D.4). Although there are no explicit WTO provisions on cross-border data flows, existing WTO rules, including the GATS, remain relevant to measures that affect such flows. Meanwhile, 91 WTO members negotiated specific rules on digital trade issues, including personal data protection, under the Joint Statement Initiative on E-commerce. Cross-border data flows and data localization provisions were initially discussed but are not currently part of the agreement. A so-called "stabilized" text of the e-commerce agreement was published in July 2024.[17] Further WTO discussions could help to build a shared understanding of AI-related data challenges, which are particularly important for smaller economies and MSMEs.

Strengthened discussions on IP approaches to AI training data may be warranted, given their implications for inclusive AI. As discussed above, training AI requires data, some of which may be copyrighted. The TRIPS Agreement sets forth obligations for protecting copyrighted works but does not provide specific guidance on how IP rules apply to copyrighted works for AI training. Members may, consistent with these obligations, adopt the solutions best suited to their laws and economic interests.

Box D.3: AI can support more inclusive implementation of WTO agreements, provided that potential risks are managed

AI could support the implementation of the WTO's Trade Facilitation Agreement (TFA). The Agreement promotes the use of ICT, including in electronic customs processes, to simplify and expedite the flow of goods across borders. As discussed in Chapter B, AI could make customs systems more agile and resilient by improving efficiency, enhancing security, and providing deeper insights into trade flows (PWC, 2024). For example, Brazil's customs have adopted AI applications to enhance import processing and responsiveness, and to assist traders in classifying goods based on product descriptions (Segalla Reis, 2025). Similarly, Germany's customs have implemented AI voice chatbots to improve efficiency, reduce employee workloads and enhance 24/7 customer service (WCO, 2025).

The implementation of the TRIPS Agreement, in particular the registration, management and enforcement of IP rights, could be facilitated with AI. AI can help IP offices process applications more efficiently, detect IP infringements, such as trademark counterfeiting and copyright piracy, for instance through content recognition software, and monitor trade to identify violations of TRIPS-covered rights.

AI could facilitate implementation of the GPA 2012, particularly relating to transparency, timesaving and accountability. The GPA 2012 encourages the use of electronic means for procurement processes. AI can improve transparency and efficiency at every stage of the government procurement process (Deloitte, 2025; Coglianese, 2024). During the preparatory phase, it can help with the analysis of expenditure data to find savings, improve planning and forecast demand. During the tendering phase, it can automate document generation, bid evaluation and administrative tasks, particularly for standard purchases. AI can also enhance data quality, detect errors and duplicates, and flag potential misconduct by identifying anomalies such as irregular tenders or price changes.

Implementation of the WTO's Agreement on the Application of Sanitary and Phytosanitary Measures (SPS Agreement) and of the TBT Agreement could be facilitated by AI. AI-supported technology could enable the early detection of pests and diseases, improve risk assessments and strengthen biosecurity monitoring. It could also be applied to automate compliance checks, translate and help clarify technical regulations, and help members to navigate diverse regulatory environments more efficiently.

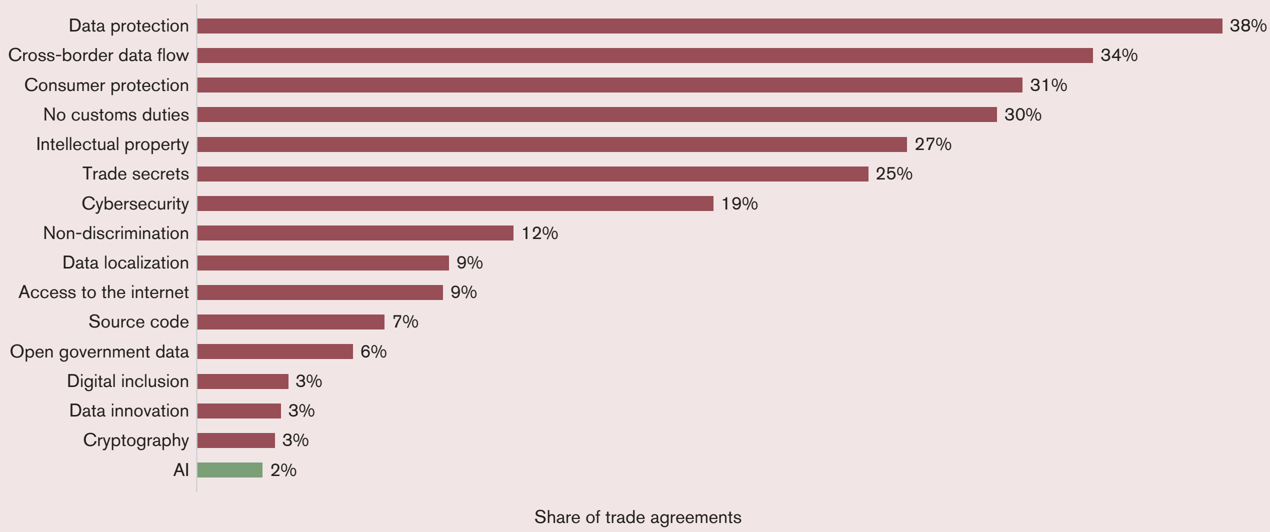
However, despite the potential of AI to improve the implementation of WTO agreements, its use must be approached with caution. Risks inherent in AI arise from its complexity, opacity and potential for bias and inaccuracy, whether these are due to the data sources or embedded in flawed design. Such risks could, for instance, lead to the misclassification of businesses or regions as high-risk, effectively restricting market access and potentially undermining WTO principles such as MFN treatment or commitments under preferential schemes like the Generalized System of Preferences (GSP).[18] Human supervision remains crucial, and addressing the risk of AI-induced discrimination is essential to ensure fair and inclusive trade practices.

Box D.4: Trade agreements increasingly address different aspects of AI

Although an increasing number of RTAs include provisions on AI-related issues, explicit provisions on AI are still limited. As shown in Figure D.4, only 2 per cent of RTAs and digital economy agreements (as of September 2025) currently incorporate explicit AI-related provisions. These provisions generally recognize AI's potential to deliver social and economic benefits, and, in some agreements, its role in facilitating international trade. Other provisions call for cooperation in developing policy frameworks aligned with international standards, and encourage the exchange of information and experiences. Only a few agreements commit the parties to collaborate in AI-related research, development and investment.

Some AI-related issues appear more widely in RTAs and digital economy agreements, such as cross-border data flows, data localization and source code. While some AI-related provisions clarify specific provisions in WTO agreements, other provisions expand commitments found in the WTO framework or establish new ones (Monteiro and Teh, 2017; Burri, Callo-Müller and Mesmer, 2025). Some agreements include commitments to avoid unnecessary barriers to cross-border electronic data flows. A few newer agreements go further, requiring parties to permit such transfers, including personal data, for business purposes, while acknowledging each party's right to maintain its own regulatory requirements. Some RTAs prohibit data localization requirements except when necessary to achieve legitimate public policy objectives. More recent RTAs explicitly prohibit requirements to transfer or access mass-market software source code as a condition for importing, selling or using software or products that contain it. These AI-related provisions complement other provisions relevant to AI, including those on market access commitments in digital services and domestic telecommunications regulatory frameworks (WTO, 2024a; 2018).

Figure D.4: Explicit provisions on AI in trade agreements remain limited



Source: WTO Secretariat, based on Burri et al. (2023) "Trade Agreement Provisions on Electronic-commerce and Data" (TAPED) database.[19]

Different approaches have been adopted to determine whether copyrighted materials can be used for AI training. In some cases, this depends on the purpose of the training (e.g., research), on specific text- and data-mining exceptions (which sometimes allow rights-holders to opt out), or on broader principles, such as fair use (which allows limited use of copyrighted material without permission if certain criteria are meet). Regulatory approaches that require AI models to comply with domestic regulations on training data, even when that training occurs abroad, may drive up AI development costs or limit the availability of AI solutions. Fragmented IP approaches to training data could therefore raise barriers for smaller firms and undermine efforts to make AI more inclusive. Informed discussions at the WTO and the World Intellectual Property Organization (WIPO) can help to identify balanced solutions to incentivize and facilitate AI development and its creative and innovative use by humans, while also protecting the interests of creators. Advancing discussions on IP approaches related to AI-generated innovations and algorithms could also help to ensure AI becomes more inclusive (WTO, 2024a).

To further foster inclusiveness, the WTO Working Group on Trade and Transfer of Technology could be used to continue addressing AI technology gaps. This working group[20] is tasked with examining how trade relates to technology transfer and ways to boost technology flows to developing economies. The effectiveness of certain WTO provisions on technology transfer – while not specifically related to AI – has been questioned by some members.[21] Revitalizing discussions in the working group could help to encourage members to propose practical ways to address AI-related technology gaps through trade.

More transparent and streamlined investment rules and processes could facilitate investments, including in AI. The fragmentation of investment rules can make it harder for investors to navigate different legal and regulatory environments, potentially reducing opportunities, especially in fields like AI that require global coordination. The Investment Facilitation for Development (IFD) Agreement, negotiated by 127 WTO members, including 90 developing economies, 27 of which are LDCs, seeks to make investment rules clearer, simplify procedures for investment, promote regulatory coherence and cooperation, and support sustainable development goals, including poverty reduction and job creation. Implementing the IFD Agreement could help members, in particular developing economies, to harness trade-led growth potential from comparative advantage in key AI-related inputs by fostering investments.[22]

The growing intersection between technical regulations for AI-enabled goods and those for AI-related services would benefit from deeper consideration to promote greater regulatory predictability. As AI-related services are increasingly embedded in AI-enabled goods, and are also traded as standalone services, the standards, compatibility and certification related to these services are likely to become relatively more important in AI trade. For instance, autonomous vehicles are AI-enabled goods that rely heavily on embedded services, such as real-time data processing, connectivity and continuous algorithmic decision-making (WTO, 2024a). This dual coverage of AI-related products may challenge standardization and conformity assessment, potentially making it harder to determine how compliance to standards should be assessed. Better coordination between the regulatory spheres for AI-related goods and services would help reduce regulatory fragmentation. Existing regulatory disciplines in the GATS, including those related to transparency that apply to AI-related services, are more limited than comparable provisions in other WTO agreements, particularly the TBT Agreement. Fewer services trade measures, whether AI-related or otherwise, have been notified to the Council for Trade in Services. As of July 2025, the Council had received a total of 811 notifications from WTO members on transparency,[23] of which 90 notifications relate to digital regulation.[24] The paucity of notifications of services regulations could create information gaps that may hinder more inclusive participation in AI-related trade. In that context, discussions at the WTO could help foster a better understanding of the issues at stake.

Greater discussion of specific trade concerns in the Council for Trade in Services could also help address regulatory fragmentation. While regulatory differences may reflect legitimate policy choices, different regulations on AI-related services, such as those related to data flows, can hinder cross-border trade in these services (see Box D.5 on financial services). Discussion of specific trade concerns in the Council for Trade in Services is a relatively recent phenomenon, beginning in 2014. In recent years, a majority of these concerns have related to the digital economy, in particular cybersecurity and cross-border data flows – issues also relevant for AI. Most of these specific trade concerns have involved high-profile and politically sensitive issues, with national security frequently cited by members as the justification. As a result, these discussions have been less conducive to resolution through dialogue, despite the fact that some of the measures in question were still in draft form and were, therefore, potentially more open to adjustment. As of 2025, only six specific trade concerns broadly related to the digital economy have been raised in the Council for Trade in Services, compared to more than 71 trade concerns on AI-related goods, such as chips, microchips, semiconductors, integrated circuits, wafers, gallium and germanium, raised in other bodies. Of these, 38 were raised in the TBT Committee, 18 in the Council for Trade in Goods and 14 in the Committee on Market Access, while one trade concern was raised in the Committee on Import Licensing. While there may be various reasons why WTO members are hesitant to raise services-related specific trade concerns, this contrast highlights the untapped potential of the Council for Trade in Services as a forum for addressing regulatory issues related to services.

Striking the right balance between WTO commitments and effective flexibilities is essential to leveraging AI in support of greater inclusiveness across economies. WTO agreements include over 155 special and differential treatment (S&DT) provisions designed to support developing members. These include measures to expand trade opportunities, safeguard trade interests, allow flexibility in commitments, extend transition periods for the implementation of agreements, provide technical assistance and offer LDC-specific support.

Box D.5: International regulatory cooperation can help advance AI opportunities in finance

AI is rapidly reshaping the financial sector by enhancing efficiency, accuracy and personalization of financial products and services. A 2024 survey of 56 diverse financial institutions found that 88 per cent are using AI, with most others planning adoption soon. All surveyed firms reported that they had increased AI investment in 2024, with half boosting AI investment by more than 25 per cent compared to 2023 (IIF and EY, 2025). AI helps to streamline loan and insurance processes, improve fraud detection, enable personalized financial advice, and automate forecasting and trading in asset management and securities markets. The financial industry is also gradually adopting generative AI for internal processes, such as summarizing and translating documents and information retrieval (OECD and FSB, 2024).

As financial institutions embrace AI, they will also have to navigate an evolving and complex landscape of technical standards and regulations. Financial service suppliers integrating AI into their operations must comply with both conduct and licensing obligations under financial regulation, as well as AI-specific laws and guidelines. These overlapping requirements may become more pronounced and burdensome as regulators respond to AI's growing impact on financial services.

Jurisdictions are taking two main approaches to AI regulation: a principles-based approach or a rules-based approach. Jurisdictions taking a principles-based approach rely on non-binding principles, often supported by technical standards and cross-sectoral regulations; examples are Singapore, the United Kingdom and the United States (Crisanto et al., 2024). While recognising AI-related risks, they view strict regulation as premature given AI's ongoing evolution. Jurisdictions following a rules-based approach (e.g., Brazil, China, the European Union and Qatar) are introducing AI legislation to ensure regulatory clarity, enable enforcement against unlawful AI deployment, and protect consumers' rights from potential harms.

The lack of harmonized AI standards poses challenges for cross-border financial firms. As economies and regions develop their own approaches, financial firms operating across borders may encounter conflicting requirements. Regulatory fragmentation may lead financial suppliers to tailor their AI governance practices, product development, third-party due diligence and risk management separately for each jurisdiction, making it difficult to manage risks consistently across the enterprise (USDT, 2024). Similarly, data localization laws in various jurisdictions may restrict cross-border data flows, impacting financial institutions' ability to outsource AI functions abroad.

AI interoperability across different regulatory regimes is crucial to minimize cross-border frictions and facilitate compliance for firms operating in foreign markets. International cooperation aimed at promoting interoperability and alignment of regulatory approaches to AI is underway in different forums, including the Financial Stability Board (FSB), the G7 and the G20. Since establishing its AI subcommittee, the International Organization for Standardization (ISO) has expanded its focus to AI in financial services. Earlier this year, the ISO technical committee on financial services and the ISO subcommittee dedicated to AI formed a joint working group to develop a technical report outlining requirements for managing AI in the sector (ISO, 2025).

Preferential schemes and technical assistance programmes have enhanced export opportunities from developing economies and LDCs (WTO, 2024b). If AI can help with the administrative costs associated with preferential schemes, and provided that it is not biased against small business, it could further help developing economies and LDCs to take advantage of these S&DT-related export opportunities. Members hold different views on proposals to modify S&DT provisions. A key point of discussion is whether such provisions should be applied uniformly to all developing economies, or whether they should be tailored to address specific needs. Notwithstanding these different views, international cooperation can support low-income economies in implementing their commitments. New commitments in services and goods would need to be accompanied by increased investment in physical and digital infrastructure (see Section D.2), enhanced technical assistance and capacity-building for technical regulations and standards, and innovative Aid for Trade financing.

2. Greater coordination between the WTO and other international organizations is needed for more inclusive AI

A growing number of international initiatives specifically focused on AI have emerged in recent years, covering diverse aspects of its ecosystem. These initiatives, covering different areas such as ethics and safety, involve a wide range of stakeholders, including governments, intergovernmental organizations, standard-setting bodies and private companies. Most take the form of high-level AI principles, voluntary guidelines, codes of conduct or policy toolkits, while some contribute to the development of AI standards. Despite these differences, most aim to promote safe, trustworthy, ethical, transparent and interoperable AI, and to encourage coordinated action to identify and manage AI-related risks and challenges (see Box D.6). These AI-related international initiatives complement other initiatives related to ICT and the digital economy. These AI-focused initiatives also complement broader international efforts and the ongoing work of international organizations related to digital technologies and governance.

Several challenges affecting the inclusiveness of AI-driven trade growth lie partly outside the scope of the WTO, highlighting the need for greater policy coherence and cross-institutional collaboration. Inclusive AI-driven trade growth requires a “trade and” strategy, one that combines open and predictable trade in AI-related goods and services with complementary policies that address broader development challenges. As discussed in Chapter B, these include bridging the digital divide, addressing AI-related labour market disruptions, fostering fairer competition and mitigating environmental effects – however, these are areas led by international organizations other than the WTO. While most AI-specific initiatives do not explicitly reference international trade, many reflect these concerns (see Figure D.5). Greater coordinated international efforts to address these challenges could help to ensure that the gains from AI and trade are more broadly shared within and across economies.

(a) Inclusive AI requires international cooperation to bridge digital infrastructural and regulatory gaps

A more inclusive and equitable access to the benefits of AI requires coordinated global action to close digital infrastructure, skills and regulatory gaps, particularly in developing economies. With 2.6 billion people still offline, mostly in developing economies (ITU, 2024), and key digital resources, including skills, mostly concentrated in developed economies, significant public and private investment, estimated at US$ 418 billion, is necessary to provide reliable, affordable access to the internet and digital networks (Oughton, Amaglobeli and Moszoro, 2023). In particular, 58 per cent of LDCs lack the basic regulatory and technical capacity needed to support cross-border digital work, including AI-related activities (UNDP, 2024). While investment in digital infrastructure and skills development, as well as the development of regulatory frameworks, were often treated as separate tracks in the past, there is now a growing recognition that aligning them could help to create synergies, especially in developing economies. The positive effects of digitalization depend not just on access to technology, but on supportive governance structures. For example, WTO estimates suggest that the reduction in trade costs generated by improved digital connectivity more than doubles in middle-income and low-income economies with an enabling regulatory environment for digitally delivered services (Bellucci, Rubínová and Piermartini, 2023). While a robust regulatory framework can

Box D.6: AI safety institutes can help to shape inclusive approaches to managing AI risks

Growing concerns about AI safety have led some advanced and emerging economies to establish dedicated institutes that aim to build the expertise needed to understand and manage AI risks. As discussed in Section B.1(b), the rapid evolution of AI poses safety risks ranging from malicious uses and technical malfunctions to wider systemic threats. As these risks can arise throughout the AI value chain, from development to deployment, technical expertise is needed to understand both the process and the evolving trajectory of AI capabilities. In response to growing concerns about AI safety, some governments, mainly in advanced economies such as Australia, Canada, France, Germany, Italy, Japan, the Republic of Korea, Singapore and the United States, have established AI safety institutes. Similar efforts are also emerging in a few developing economies, including Brazil. These institutes tend to be national government entities that conduct research, develop safety benchmarks and testing protocols, and facilitate information exchanges and collaborations.

As AI systems operate across borders, international collaboration is increasingly important to promote AI safety and to keep risk management approaches interoperable and current. Sharing information on technological developments and emerging risks can help governments to remain informed. Working toward alignment on evaluation methods can help to strengthen their robustness and applicability across diverse cultural, linguistic and societal contexts. Such coordination also helps promote greater interoperability and consistency in testing approaches. In addition, collaboration offers opportunities to pool expertise, particularly given the current global shortage of AI safety experts. Recent collaborations include the International Network of AI Safety Institutes, established in 2024 by 10 governments to support alignment on evaluation methods, and multistakeholder initiatives launched in 2025, such as the International AI Safety Report and the Singapore Consensus on Global AI Safety Research Priorities, which outline shared research goals and priorities to AI risk assessment.

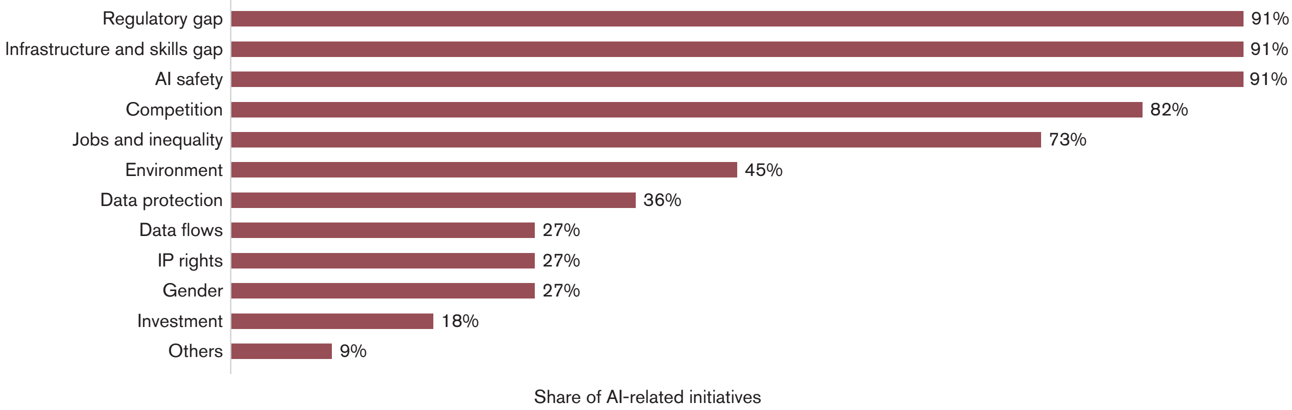
Broadening the participation of lower-income economies is critical to make global AI safety standards more inclusive and to help AI systems to perform reliably across diverse contexts. As AI safety institutes help to shape domestic and potentially international technical and industry standards, the limited participation from lower-income economies means that there is a risk of overlooking their specific contexts and vulnerabilities. Resource constraints and a global shortage of AI safety expertise may pose challenges to establishing dedicated institutes in some settings; nevertheless, the participation of lower-income economies can be supported through collaborative approaches, such as joint testing and regional initiatives. One such example is the Asia-Pacific AI Safety Red Teaming Challenge, which seeks to assess how AI models perform in regional cultures and languages.

help to foster trust in digital markets, strong institutional capacity is also essential to develop digital infrastructure and skills, and to enforce the regulatory framework (Nordås and Xu, 2025).

(i) Bridging the global AI divide requires substantial investment in infrastructure and skills

International cooperation and pooled funding are key to bridging AI-related infrastructure and skills gaps. Meeting the growing need for IT infrastructure and specialized digital skills to develop and deploy AI demands major investments, as AI technologies rely on advanced computing power, reliable connectivity and a highly trained workforce – all of which require substantial financial resources to build, scale and sustain AI-related capacity, particularly in regions with underdeveloped digital foundations (OECD, 2025). Inclusive capacity-building is emerging as a central pillar of international AI governance, with global initiatives, such as the UN AI Advisory Body, the UN Global Digital Compact, the OECD's Recommendation of the Council on Artificial Intelligence, the AI Action Summit and the Global AI Governance Action Plan, calling for investment, cooperation and shared infrastructure to help all economies access and benefit from AI technologies. Several international initiatives, including UNESCO's Recommendation on the Ethics of AI (2021) and the African Declaration on Artificial Intelligence

Figure D.5: The key international policy initiatives on AI tend to focus on the same areas of discussion



Source: WTO Secretariat.
Note: The chart shows how often each topic appears across the following 11 international AI-related policy initiatives: OECD AI principles (2023); G20 AI Principles (2019); UNESCO Recommendation on the Ethics of AI (2021); G7 Hiroshima Process on Generative AI, AI Guiding Principles, and AI Code of Conduct (2023); AI Safety Summit "Bletchley Declaration" on AI Safety (2023); UN General Assembly AI Resolution (2024); Council of Europe Framework Convention on AI, Human Rights, Democracy and the Rule of Law (2023); Seoul Summit agreement to launch an international network of AI Safety Institutes;[25] Final Report of the UN AI Advisory Body (2024); Adoption of the UN Global Digital Compact (2024); and International Scientific Report on the Safety of Advanced AI (2024). The "others" category includes culture, education and health.

(signed by the African Union, Smart Africa and 49 African economies in April 2025), also underscore the critical role of investing in open public data to promote inclusive and responsible AI development (OECD, 2024a). While some WTO agreements, such as the GATS and ITA, can help attract private AI-related investment by promoting openness and reducing barriers to trade, collaborative financial efforts between international organizations, development banks and direct donor funding can further contribute to bridging the AI divide (WTO, 2024a). Although not specific to AI, multilateral and regional development banks are increasingly supporting digital transformation through targeted investments in broadband infrastructure, digital public services and skills development in developing economies, laying critical groundwork for future AI-related opportunities.[26] Meanwhile, several international organizations already propose AI-specific initiatives supporting developing economies through targeted efforts in skills development, capacity-building and AI-related policymaking.[27]

While still limited, trade-related initiatives are beginning to incorporate provisions on AI cooperation. Explicit provisions related to digital inclusion and skills appear in 13 RTAs and digital economy agreements. These provisions, predominantly found in agreements between more digitally advanced economies, remain limited in scope and highlight the need for greater cooperation. Some of these provisions complement some explicit AI-related provisions promoting cooperation on AI research and regulation (see Box D.3). In parallel, a few cooperation agreements related to inputs particularly relevant for AI development have been negotiated, focusing on strengthening supply chain resilience and governance around critical materials such as rare earths elements and advanced semiconductors. Although not always specific to AI, several multilateral trade initiatives also contribute to narrowing digital infrastructure and skills gaps by leveraging trade for inclusive digital development, such as the WTO-led Aid for Trade initiative,[28] which supports developing economies in building trade capacity, and the Enhanced Integrated Framework,[29] which assists LDCs in integrating into the global trading system (WTO and OECD, 2024). Building on this foundation, these and similar programmes could be further leveraged to support more inclusive participation in AI-led trade.

(ii) International cooperation can help to reduce regulatory gaps in more inclusive ways

Strengthening international cooperation to address regulatory gaps is key to advancing inclusive AI. An effective domestic regulatory framework for AI – covering areas such as data governance, product safety and consumer protection

– is critical for fostering trust and confidence among firms and consumers, thereby supporting AI-enabled trade. Yet, in many developing economies, regulatory frameworks for AI remain limited, incomplete or not yet fully effective. As discussed above, efforts to bridge the digital divide depend in part on closing the digital regulatory gap. In that context, the WTO and the World Bank are working together on a project titled "Digital Trade for Africa", which is helping certain African economies to develop the regulatory framework and infrastructure they need to seize digital trade opportunities (IMF et al., 2023).[30] A similar initiative is being developed for Latin America and the Caribbean, involving the WTO, the World Bank and the Inter-American Development Bank. Another relevant initiative is the Women Exporters in the Digital Economy (WEIDE) Fund, launched by the WTO Secretariat and the International Trade Centre (ITC) in February 2024. This fund aims to help women entrepreneurs to leverage international trade and digitalization to grow their business. When the expertise of each international organization is leveraged through partnerships, this can amplify their respective efforts, so that a greater impact may be achieved than when each international organization works in isolation This model of cooperation could be extended to support more inclusive access to AI opportunities through trade.

Greater international cooperation can help address AI regulatory fragmentation, thereby creating the conditions required for more inclusive AI. As discussed in Chapter C, national approaches to AI regulation vary in priorities, scope and implementation, resulting in increasing regulatory fragmentation (Fritz and Giardini, 2024). This AI-related regulatory fragmentation can generate unnecessary costs and confer an unfair advantage on some economies. AI policy coordination can help to prevent such fragmentation and ensure that domestic AI standards are more interoperable and inclusive, and that they align with international norms (WTO, 2024a). Several international bodies are already working on AI-related standards and guidelines that could help to address AI regulatory fragmentation. For instance, the International Organization for Standardization (ISO) and the International Electrotechnical Commission (IEC) are developing technical documents on AI, including regarding terminology, risk management and governance. The Institute of Electrical and Electronics Engineers (IEEE) is focusing on guidelines and specifications related to the ethical and societal aspects of AI. The International Telecommunication Union (ITU) is addressing AI in the context of telecommunications and digital technologies, particularly with regard to interoperability.[31] Nonetheless, further international cooperation on AI is needed, as underscored by the UN's final report on "Governing AI for Humanity" (2024),[32] which identifies three global AI governance gaps: representation, coordination and implementation.[33] Taking these gaps into account is particularly important to ensure that developing economies, especially LDCs, can access shared best practices, technical assistance and capacity-building support.

Strengthening coordination and coherence on trade-related aspects of AI is key to promoting a more inclusive participation in AI-driven trade opportunities. While most AI-specific initiatives do not explicitly reference the WTO, many address issues with clear trade and WTO relevance, such as the role of regulations and standards in governing AI, the importance of interoperability, the need to avoid regulatory fragmentation, and the importance of IP protection and enforcement. One exception is the final report of the UN AI Advisory Body on "Governing AI for Humanity",[34] which explicitly references the WTO and highlights the relevance for AI of several WTO agreements, including the GATT, the GATS, the ITA, the TBT Agreement, the TFA and the TRIPS Agreement, and emphasizes the need for coordination across international organizations (WTO, 2024a).[35]

(b) Strengthening competition can help make AI more accessible and inclusive

AI's potential to foster inclusive growth depends in part on market competition, including whether markets are open and accessible or dominated by a few players. As discussed in Chapter B, the AI ecosystem, which includes data, computing power, cloud infrastructure and foundational models, remains highly concentrated and is dominated by only a few firms. This concentration risk raises barriers to market entry, limiting innovation and exacerbating global digital divides. Smaller firms, particularly in developing economies, can face steep challenges in accessing high-quality datasets, interoperable platforms and affordable computing resources. In the absence of sufficient competition, there is a risk that the benefits of AI are being concentrated among a limited number of actors, potentially limiting broader inclusiveness (see Philippe Aghion's opinion piece).

While differences in national approaches are to be expected, limited coordination on AI-related competition may lead to trade frictions that risk undermining efforts to make AI more inclusive. Approaches to addressing competition challenges in AI vary significantly across economies. While some governments may invest in public infrastructure, open-source models or national datasets, others may face institutional or technical constraints. As a result, dominant AI firms can operate across jurisdictions with little coordinated oversight, increasing the risk of fragmentation and inconsistent enforcement. Although some of these regulatory differences may reflect legitimate domestic priorities and capacities, and, in some cases, national security considerations, they can spill over into trade tensions, particularly if governments adopt conflicting rules or restrict access to AI inputs and technologies. Such tensions could undermine global inclusiveness, especially if digitally constrained economies are forced to rely on inferior or more expensive AI options. In the absence of a more coherent international approach, disparities in AI development and deployment could widen, leaving some economies at the margins of the AI transformation.

International cooperation could play an important role in addressing AI-related competition challenges, but concrete efforts remain limited and largely concentrated among advanced economies. International cooperation could help to foster a shared understanding of AI-related competition challenges, promote more consistent enforcement and offer a platform for knowledge exchange and capacity-building, especially for governments with fewer resources. Cooperation could also facilitate the resolution of cross-border disputes involving global AI firms. Yet, international cooperation addressing anti-competitive behaviour remains relatively limited, and AI is no exception. Some recent efforts – such as those of the OECD and the G7 – call for regulatory frameworks to be adapted, best practices to be shared and common standards to be developed to ensure competitive AI markets, yet concrete cooperation is still in the early stages.[36] International debates sometimes point to open-source and open-weight AI models – where open-source models disclose their architecture, code and training data, and open-weight models release only the trained parameters[37] – as potential tools to promote competition and inclusiveness by lowering entry barriers, enabling broader participation and enhancing transparency, though they also raise concerns about how they are to be overseen and how they might potentially be misused (UN, 2024). As discussed above, efforts to promote open public data and digital infrastructure can also help to level the playing field by lowering barriers to entry and enabling broader participation in AI development. However, to move beyond early-stage initiatives, broader and more sustained engagement, including from developing economies, is needed if cooperation on AI-related competition challenges is to become more inclusive.

International trade cooperation can also help to strengthen competition in AI-related markets, but additional efforts are needed to ensure more firms can enter these market and more customers can benefit. As noted earlier, uncoordinated competition policies can lead to trade tensions, potentially worsening market concentration and undermining the inclusiveness of AI. While the WTO does not have a comprehensive agreement on competition policy, it does contribute to enhancing the coordination of competition policies by keeping markets open through existing agreements and through instruments such as accession protocols (Anderson et al., 2018). In parallel, RTAs have become the main venue for trade-related cooperation on competition policy. An increasing number of RTAs include provisions that promote fair market conditions through cooperation among authorities, commitments to uphold national competition laws, and, in some cases, rules governing state-owned enterprises (Mattoo, Rocha and Ruta, 2020). A much more limited number of recent RTAs and digital economy agreements, mainly among high-income economies, incorporate competition provisions specific to digital markets, focusing on information exchange, capacity-building and enforcement cooperation, though these provisions do not specifically address AI (Burri, Callo-Müller and Kugler, 2023). As this area of trade cooperation continues to evolve, broader participation by developing economies will be essential to ensure that the benefits of AI are more inclusively shared. The WTO could help with the coordination of competition policies through further collaboration with other international organizations to support more dialogue, information-sharing and capacity-building on competition issues relevant to the AI-driven economy.

AI, innovation and inclusive growth

By Philippe Aghion

Professor of Economics at the Collège de France and INSEAD (Institut Européen d'Administration des Affaires) and visiting professor at the London School of Economics

AI has the potential to foster significant economic growth by automating tasks in goods and services production, and in the generation of ideas, improving technological innovation. That, in turn, accelerates creative destruction – new technologies replacing old ones.

While automation may reduce the incentive to outsource some tasks, developing economies can still benefit from AI by leapfrogging in technology adoption and improving education delivery, much like mobile technology did in the past.

However, access to data and infrastructure is critical. Developing economies need support in building capabilities, such as access to data and computing power. Global cooperation is essential to ensure inclusive access to AI's inputs, as highlighted by the AI Summit in Paris earlier this year.[38] Sound competition policy is also essential, as dominant firms may use AI to entrench market power. Automation may reduce outsourcing incentives and displace jobs, but productivity gains can boost demand and employment. Education and labour market policies are key to helping workers adapt.

As to whether AI may drive more outsourcing from developed to developing economies, or rather a trend toward reshoring, this is complex. Automation could reduce the need to outsource, particularly for tasks that can now be done more cheaply at home, potentially slowing the convergence process for developing economies. However, I don't believe AI will completely upend the existing division of labour in global value chains.

For example, ChatGPT and similar technologies mainly affect services. Over the short to medium term, I expect existing trade patterns – where emerging countries focus on manufacturing and advanced economies on services – to persist. But we need to monitor this closely.

Concerning the kinds of policies needed to ensure that AI promotes employment and reduces inequality in both developed and developing economies, the most important starting point is education. A strong, inclusive education system ensures that more people can benefit from AI rather than be replaced by it. More educated workers are more likely to be complemented by AI, not substituted.

Beyond education, active labour market policies are crucial. I'm a strong advocate of the Danish "flexicurity" model, where workers receive generous support and retraining if they lose their jobs. This combination of flexibility for firms and security for workers helps economies adapt to technological change. Elements of this approach can be scaled regionally in larger countries.

The growing concentration of AI capabilities among a few dominant firms and countries is a serious issue. As with the IT revolution, AI is currently dominated by a few big tech firms – especially those that control the cloud infrastructure. To counterbalance this, we need robust competition policy.

I support open-source models and caution against excessive regulation, which established firms can navigate more easily than new entrants. Governments also have a role to play in subsidizing access to data and computing power for smaller firms to ensure a level playing field.

Disclaimer

Opinion pieces are the sole responsibility of their authors. They do not necessarily reflect the opinions or views of WTO members or the WTO Secretariat.

(c) Managing labour market disruptions from AI is important to supporting AI-enabled trade

In response to potential labour market disruption from AI, governments may try to protect jobs by adopting unilateral measures that ultimately affect trade with other economies and risk undermining the benefits of AI-enabled trade. As discussed in Chapter B, AI may affect jobs and wages directly through automation and indirectly by reshaping comparative advantages. These changes in trade patterns would impact labour markets in complex ways, creating both opportunities and risks for firms and workers, with outcomes depending on sectoral dynamics and investment in AI-related infrastructure and skills. Adjustment policies, such as training and job search assistance or unemployment benefits, can help to facilitate labour movements from contracting to expanding sectors without resorting to trade-distorting measures (WTO, 2017b, 2024b). However, governments could also respond to AI-related labour market disruption, including its trade-related effects, by adopting trade measures, such as tariffs and subsidies, that risk harming other economies. While not specific to AI, empirical evidence suggests that unilateral digital trade restrictions can have broader development implications, disproportionately affecting lower-income economies and potentially constraining their ability to benefit from AI-related opportunities (IMF et al., 2023).

Uncoordinated national approaches to regulating AI-driven platforms that supply work across borders can hinder more inclusive participation in AI-enabled economic opportunities. While informal employment is still widespread globally, accounting for nearly 60 per cent of the workforce, it tends to be even more prevalent in sectors relying on digital labour platforms – online marketplaces that connect workers with clients for tasks (ILO, 2021). Workers providing cross-border services through these digital labour platforms can fall into “regulatory blind spots”, as they may be excluded from both home and host country labour protections, such as minimum wages, overtime pay or health insurance, due to non-standard employment status and misalignments between national labour systems, raising concerns about fairness and inclusion (UN and ILO, 2024). This exclusion is not necessarily a product of national inaction in itself, but of the difficulty in adapting territorial labour regimes to digitally mediated, location-independent work. Uncoordinated policy responses to these challenges can create further distortions for market participants and constrain broader access to the economic opportunities enabled by AI.

International trade cooperation already offers some avenues to help address AI-related labour market challenges while preserving the benefits of an open trading system. While the International Labour Organization (ILO) plays a central role in promoting decent work through international labour standards, the multilateral trading system is also relevant for addressing trade-related labour impacts, including those driven by AI. While potentially trade-distortive measures, such as subsidies, adopted in response to increased import competition, are subject to WTO rules, the multilateral trade system allows the adoption of non-discriminatory labour and social policies to address trade-related labour-market disruptions (WTO, 2024b, 2017b). RTAs are also increasingly incorporating labour provisions aimed at upholding certain ILO standards and promoting cooperation, including on labour market adjustment. Sometimes negotiated as part of RTAs, mutual recognition agreements of digital skills and credentials have been found to facilitate smoother labour market adjustments and reduce protectionist pressures (OECD, 2023). While these mechanisms are not specific to AI, they provide a useful foundation for more inclusive and coordinated responses to potential AI-related labour market disruptions.

Better coordination across international organizations could help address AI-driven labour market disruptions and promote more inclusive AI, while limiting the risk of protectionist responses. Although it is ultimately the responsibility of governments to ensure that their AI, trade and labour policies are coherent and mutually supportive, international cooperation can play an important complementary role. Although trade and labour data collection is well established, analysis of the interlinkages between trade and employment in response to technological changes, such as AI, remains limited. Greater international cooperation on collecting AI-specific data could support more informed and coherent policymaking. Advancing international discussions on how to address gaps in labour protection for workers operating virtually across jurisdictions is also important, as AI is accelerating the growth of cross-border digitally delivered services. Further international cooperation on skills recognition, reskilling and labour mobility could also help to align workforce development with the evolving trade and employment patterns driven by AI. Building on its existing functions, the WTO could help to support more coherent policy responses to AI-driven trade and labour market disruptions by facilitating dialogue on the trade-related aspects of these impacts through its existing bodies, enhancing transparency via mechanisms such as trade policy reviews, and contributing to joint analysis and information-sharing with other international organizations.

(d) Addressing the environmental impact of AI can help to make its development and deployment more sustainable and inclusive

Uncoordinated efforts to manage the environmental impact of AI risk creating trade tensions, potentially undermining environmental protection. As discussed in Chapter B, while AI can help improve energy and resource efficiency and promote environmental innovation, its current development and use consume large amounts of energy and resources, including rare minerals and water, and generate electronic waste (Kshetri, 2024; OECD, 2022). For instance, data centres, cryptocurrencies and AI accounted for around 2 per cent of global electricity demand in 2022. Electricity demand from data centres alone is projected to more than double by 2030 (IEA, 2025). Without some degree of regulatory alignment, governments are likely to adopt different environmental regulations based on national circumstances and priorities, potentially placing those with stricter rules at a competitive disadvantage. This could result in downward pressure on environmental standards, or prompt the use of trade measures, such as tariffs or subsidies, to offset perceived imbalances. Such actions may shift environmental burdens to other economies, undermine international cooperation and worsen overall environmental outcomes (WTO, 2022a). In contrast, open trade supported by appropriate environmental policies can contribute to environmental gains by allowing green comparative advantages to materialize (WTO, 2023).

International cooperation on the environmental impact of AI is still at an early stage, with most efforts so far focused on high-level declarations and few voluntary initiatives. Statements such as those made in the contexts of the UN's Global Digital Compact,[39] the G7 or the OECD increasingly acknowledge the need to minimize the environmental footprint of AI systems, particularly by reducing energy and resource consumption in data centres and related infrastructure. Recent multi-stakeholder initiatives, including those led or supported by the UN – such as the AI for Good platform[40] and the Coalition for Environmentally Sustainable AI[41] – reflect growing recognition of the issue, but concrete commitments remain limited. Some technical guidance and pilot projects have been launched, such as the ITU Focus Group on Environmental Efficiency for Artificial Intelligence and Other Emerging Technologies,[42] but these efforts often fall under broader sustainable development goals, and systematic cooperation on mitigating the environmental impact of AI has yet to emerge. Existing initiatives also tend to give little attention to the role of trade and trade policy in enabling more sustainable AI development and deployment.

Promoting coherence between trade-related and environment-related aspects of AI can help to support a more inclusive and sustainable AI transition. Greater alignment between trade and environmental policies can help to ease regulatory frictions, lower the risk of environmental degradation and support the effective use of natural resources such as affordable renewable energy, which might otherwise be constrained by fragmented rules. In that context, international trade cooperation can help facilitate resource-sharing and technology transfer, and can enhance transparency and accountability with regard to environmental protection. International trade in environmental goods and services can also help to mitigate some of the environmental impacts of AI, for instance, by improving access to energy-efficient cooling systems and low-carbon energy technologies for data centres, and by supporting sustainable AI development and deployment. These efforts are needed to help manage the environmental impacts of AI more effectively across borders, while also creating trade opportunities for broader participation in AI value chains.

Greater trade cooperation among international organizations could further help make AI more sustainable and inclusive. While potentially trade-distortive measures adopted to address the environmental impact of AI, such as tariffs and subsidies, are subject to WTO disciplines, the multilateral trading system does not preclude governments from adopting non-discriminatory environmental policies (WTO, 2022b). By keeping markets open, the WTO can help to ensure that there are environmental gains from trade when economies specialize based on their environmental comparative advantage (Le Moigne et al., 2025). By promoting transparency, facilitating dialogue and supporting policy coherency, the WTO can also help to build mutual understanding around trade-related measures aimed at addressing the environmental impact of AI. However, as discussed above, the environmental dimensions of AI are being addressed mainly in separate digital governance and sustainability forums. Greater engagement – both within the WTO and in collaboration with other international organizations and the private sector – could help members to gain a better understanding of how trade policy interacts with these issues, and to support more coherent, mutually reinforcing approaches.

3. Conclusions

The WTO contributes to the development and deployment of AI by maintaining a more open and predictable trading environment. Open, predictable, transparent, forward-looking, and flexible trade-related AI policies can not only support the deployment of AI technologies, but also benefit AI developers and creators by facilitating market access, knowledge exchange and cross-border collaboration. Existing WTO rules help reduce trade barriers and promote non-discriminatory access to AI-related goods and services. WTO rules also support innovation by protecting IP rights relevant to AI innovation and creation, and encouraging technology diffusion and collaboration. Furthermore, the WTO promotes international regulatory coherence and standards for AI-related goods. Transparency and dialogue on trade-related AI policies are supported through WTO mechanisms that allow WTO members to monitor and comment on relevant regulatory developments. WTO bodies promote cooperation on trade-related AI issues and offer a platform for members to build shared understanding and raise and address concerns.

Although existing WTO rules can be applied to AI-related trade, a business-as-usual approach is unlikely to ensure that the benefits of AI are more widely shared. Four areas for consideration stand out: (1) improving market access conditions for AI-related trade; (2) addressing regulatory fragmentation in AI; (3) using AI responsibly in the implementation of WTO disciplines; and (4) promoting more “trade-and” international cooperation for inclusive AI.

Easing access to markets for AI-related goods and services can help to make the benefits of AI more widely available. Lowering bound tariffs on AI-related raw materials and goods, which would be helped by an increased number of WTO members acceding to the ITA and ITA 2, would improve trade predictability and contribute to making AI-related tools more affordable, thereby facilitating the development and deployment of AI, especially for firms and economies with limited resources. Similarly, improving services commitments in AI-related sectors, whether by binding the applied trade regime or through further openness, would provide firms with greater assurance that market conditions are likely to remain stable long enough to justify investments and the scaling of AI-related operations. However, striking an appropriate balance between binding commitments, aligned with each member’s capacity to implement them, and policy flexibility is important to preserve the stability and predictability associated with credible commitments, and to promote inclusive AI.

Addressing regulatory fragmentation in AI through more informed discussion can help to identify less trade-restrictive approaches that contribute to more inclusive AI. WTO discussions could help find balanced and interoperable approaches to cross-border data flows, the use of training data, and IP rights related to AI-generated contents. In this context, a group of WTO members participating in the Joint Initiative on E-commerce recently reached a stable draft of an agreement covering some areas related to AI. However, more could be done at the WTO level. This includes strengthening the organization’s role in fostering transparency and dialogue in AI-related services regulations. There is also scope for further discussion on the treatment of subsidies and safeguards linked to AI, some of which may not fall under existing disciplines, potentially making it more difficult to keep AI markets more open and to address related disruptions.

Further efforts are needed to promote the use of AI in implementing WTO disciplines, while addressing associated risks that can undermine trust and inclusiveness. Provided that confidentiality concerns are effectively addressed, machine learning applications, in line with members’ WTO obligations, could help to streamline customs procedures and public procurement processes, facilitate IP enforcement and the timely notification of trade policy to the WTO, and support compliance with technical and health requirements, thereby reducing trade costs, particularly for smaller firms and economies. Safe and trustworthy

AI tools could also potentially enhance some of the WTO's core functions, including monitoring, negotiations and dispute settlement, by improving information management, streamlining processes and supporting more timely and inclusive decision-making. However, biased AI algorithms could reinforce forms of discrimination that WTO agreements are intended to address. In this context, more discussion is needed on how to manage these risks, including the potential role that open-source AI solutions could play in supporting transparency, accountability and broader access.

Several challenges that shape the inclusiveness of AI lie partly outside the WTO's mandate, highlighting the need for greater policy coherence and collaboration. Addressing these challenges requires a "trade and" approach. In that context, enhanced cooperation between the WTO and other international organizations and initiatives could help to ensure that the growing role of AI, and the trade it enables, benefits more people. Closing the digital divide, managing AI-related labour market adjustments, aligning trade with environmental goals and addressing market concentration are some of the key areas in which international cooperation can help to ensure that AI-related trade contributes to more inclusive and sustainable outcomes. While some initiatives already exist, enhanced international cooperation is still needed to help close digital divides by supporting sustained investment in digital infrastructure, AI skills development and regulatory capacity. Greater collaboration among international organizations working on AI, labour and trade could promote complementary policies that preserve the benefits of open trade, while managing AI-led labour market adjustments. More international cooperation could also promote more environmentally sustainable AI value chains by addressing the risk of trade tensions arising from uncoordinated trade-and-environment-related policies relevant to AI and enabling benefits for economies stemming from production specializations related to green comparative advantages. Finally, improved coordination between trade and competition policies could help to address market concentration in AI-related sectors and support more inclusive participation in AI-driven growth.

Endnotes

1 WTO official document number WT/MIN(24)/38 – available from https://www.wto.org/english/thewto_e/minist_e/mc13_e/documents_e.htm.

2 Unlike other IP rights, the protection granted to trade secrets is not time-limited.

3 See, for instance, WTO official documents IP/C/R/TTI/CAN/2; IP/C/R/TTI/CAN/3; IP/C/R/TTI/CAN/4; IP/C/R/TTI/EU/2; IP/C/R/ TTI/EU/4; IP/C/R/TTI/CHE/2; IP/C/R/TTI/CHE/3; IP/C/R/TTI/CHE/4; IP/C/R/TTI/USA/2; IP/C/R/TTI/USA/3; IP/C/R/TTI/USA/4, available via https://docs.wto.org/.

4 See https://www.wto.org/english/tratop_e/tbt_e/principles_standards_tbt_e.htm.

5 The ISO/IEC Joint Technical Committee 1, Subcommittee 42 on artificial intelligence is one of the main global processes adopting standards that address various aspects, including explainability, transparency, bias and governance of AI systems (WTO, 2024a).

6 Other transparency provisions relevant to AI governance include those in the GATS and in the TRIPS Agreement.

7 Available at https://eping.wto.org/.

8 See, for instance, WTO official documents G/TBT/N/CHN/1921; G/TBT/N/EU/850; G/TBT/N/KEN/1604, available via https://docs.wto.org/.

9 See, for instance, WTO official documents WT/TPR/S/438/Rev.1; WT/TPR/S/442; WT/TPR/S/455; WT/TPR/S/458, available via https://docs.wto.org/.

10 See https://www.wto.org/english/tratop_e/tbt_e/tbt_0711202310_e/tbt_0711202310_e.htm.

11 High-income economies, as defined by the World Bank income group classification, that are not part of the ITA include Antigua and Barbuda; Barbados; Brunei Darussalam; Chile; Guyana; Saint Kitts and Nevis; Trinidad and Tobago; and Uruguay. See https://blogs.worldbank.org/en/opendata/understanding-country-income--world-bank-group-income-classifica.

12 Some WTO members have imposed export restrictions on products entering the AI value chain, invoking the security exception of GATT Article XXI as justification. More information can be found in the WTO trade concerns database, available at https://tradeconcerns.wto.org.

13 See www.wto.org/english/tratop_e/serv_e/gatsqa_e.htm.

14 See https://www.wto.org/english/tratop_e/devel_e/a4t_e/aid4trade_e.htm.

15 The full text of the Agreement on Subsidies and Countervailing Measures is available at https://www.wto.org/english/docs_e/legal_e/scm_e.htm.

16 The full text of the Agreement on Safeguards is available at https://www.wto.org/english/docs_e/legal_e/sg_e.htm.

17 As of December 2024, 71 members had confirmed their support for the so-called "stabilized" text of the Agreement on Electronic Commerce. See https://www.wto.org/english/tratop_e/ecom_e/xcom_e/joint_statement_e.htm.

18 See https://www.wto.org/english/tratop_e/devel_e/dev_special_differential_provisions_e.htm.

19 See https://www.unilu.ch/en/faculties/faculty-of-law/professorships/burri-mira/research/taped/.

20 See https://www.wto.org/english/tratop_e/devel_e/dev_wkgp_trade_transfer_technology_e.htm.

21 See, for instance, WTO official documents WT/GC/W/868; G/C/W/825; WT/COMTD/W/270; IP/C/W/695; WT/WGTTT/W/33, available via https://docs.wto.org/.

22 The group of WTO members co-sponsoring the IFD Agreement requested its incorporation into the WTO framework as a plurilateral agreement, open for all WTO members to join. More information is available at https://www.wto.org/english/tratop_e/invfac_public_e/invfac_intro_e.htm.

23 See https://www.wto.org/english/docs_e/legal_e/gats_e.htm#art3.

24 The number of notifications has been determined based on a keyword search. Documents were identified as relevant if they contained any of the following terms: digital, cyber, internet, e-commerce, computer, cloud, online, virtual, fintech, blockchain, network, platform. Notifications in goods trade are of a much higher order of magnitude. In 2024, the volume of notifications of technical regulations and conformity assessment procedures submitted to the TBT Committee only reached a new annual record of 4,334. Given the limited number of GATS notifications, parallel efforts have emerged, notably through the release of the WTO Director-General's Monitoring Report and the I-TIP services database to enhance members' awareness of services measures. More information available at https://itip-services-worldbank.wto.org/SearchApplied.aspx.

25 See www.industry.gov.au/publications/seouldeclaration-countries-attending-ai-seoul-summit-21-22-may-2024.

26 For instance, the World Bank (2025) has several digital projects worth US$ 450.8 million, including one in Chad to expand broadband access and strengthen digital public services, and another in Togo focused on broadband connectivity, digital skills and entrepreneurship. The European Investment Bank has invested US$ 20 million in a US$ 250 million digital infrastructure fund for Sub-Saharan Africa (https://www.eib.org/en/products/equity/funds/convergence-partners-digital-infrastructure-fund). The Inter-American Development Bank has various projects worth US$ 11 million to improve digital connectivity and support digital transformation in Latin America and the Caribbean (https://www.iadb.org/en/project-search). Through the Open Source Ecosystem Enabler project (https://www.itu.int/en/ITU-D/ICT-Applications/Pages/Initiatives/OSEEPSI/home.aspx), the International Telecommunication Union (ITU) and the United Nations Development Programme (UNDP) (2025) support the adoption of open-source technologies for digital government services.

27 For instance, the ITU's AI Skills Coalition provides open training on generative AI, machine learning and AI for sustainable development through an inclusive online platform. The Commonwealth Artificial Intelligence Consortium (https://caic.thecommonwealth.org) AI Academy offers free AI courses and works with private firms to boost infrastructure in member states (CAIC, 2025). WIPO also supports informed policymaking on AI and IP through resources and practical guidance.

28 See https://www.wto.org/english/tratop_e/devel_e/a4t_e/aid4trade_e.htm.

29 See https://enhancedif.org/en.

30 The pilot economies for the "Digital Trade for Africa" project are Benin, Côte d'Ivoire, Ghana, Kenya, Nigeria and Rwanda.

31 The OECD and UNESCO, while not standard-setting bodies *per se*, have also developed international AI policy frameworks, such as the OECD AI Principles and the UNESCO Recommendation on the Ethics of AI, respectively.

32 See https://www.un.org/en/ai-advisory-body.

33 For instance, until the 2024 launch of the Global Dialogue on AI under the UN Global Digital Compact, 118 economies, mostly developing ones, were not party to any intergovernmental discussions on AI governance according to the UN AI Advisory Body (2024). Only a few high-income economies participate in most or all AI-related initiatives.

34 See https://www.un.org/en/ai-advisory-body.

35 The final report of the UN AI Advisory Body also calls for the creation of a "Global AI Data Framework" involving different actors, such as economies and relevant international organizations, including the WTO. See https://www.un.org/en/ai-advisory-body.

36 Several recent initiatives address anti-competitive behaviour in AI, including the International Competition Network call for action against anti-competitive conduct in AI, the amended OECD Recommendation on AI (2024), the G7 Digital Competition Communiqués (2023 and 2024), the joint statement of the European Union, United Kingdom and United States, and the EU-US Joint Roadmap.

37 According to https://opensource.org/ai/open-weights, "Open Weights refer to the final weights and biases of a trained neural network. These values, once locked in, determine how the model interprets input data and generates outputs".

38 See https://www.elysee.fr/en/sommet-pour-l-action-sur-l-ia.

39 See https://www.un.org/digital-emerging-technologies/global-digital-compact.

40 See https://aiforgood.itu.int/.

41 See https://www.sustainableaicoalition.org/.

42 See https://www.itu.int/en/ITU-T/focusgroups/ai4ee/Pages/default.aspx.

ANNEX A: LIST OF AI-ENABLING PRODUCTS AND ECONOMIC SECTORS

Annex A.1: Non-exhaustive list of AI-enabling products

HS Code	HS Description	Explanation	Type
280461	Silicon; containing by weight not less than 99.99% of silicon	Key raw material for making insulating layers in transistors and integrated circuits.	Raw materials
280421	Gases, rare; argon	Argon cleans metals, prevents oxidation, and enables non-reactive etching and deposition.	Raw materials
280429	Gases, rare; other than argon	Critical raw materials used in semiconductor manufacturing, often as a cleaning or reducing agent.	Raw materials
280440	Oxygen	Ultra-high purity oxygen is a critical raw material acting as an oxidizing agent in processes such as silicon layer deposition, etching and reactive gas neutralization.	Raw materials
711021	Metals; palladium, unwrought or in powder form	Key raw material for catalysts and components in AI hardware manufacturing.	Raw materials
281111	Hydrogen fluoride (hydrofluoric acid)	Specialty chemical used for cleaning and etching silicon wafers, removing silicon dioxide and preparing surfaces for further processing.	Processed chemicals
290919	Ethers; acyclic, and their halogenated, sulphonated, nitrated or nitrosated derivatives, other than diethyl ether	Solvents used in semiconductor manufacturing, including photoresist formulations and cleaning agents.	Processed chemicals
292990	Nitrogen-function compounds; n.e.c. in chapter 29, excluding isocyanates	A specialty chemical used in semiconductor manufacturing, often for deposition or etching processes.	Processed chemicals
280469	Silicon; containing by weight less than 99.99% of silicon	Essential raw material in AI semiconductor manufacturing with slightly lower silicon purity.	Processed chemicals
281119	Inorganic acids; other than hydrogen fluoride	Specialty chemical used for etching polysilicon to create fine grooves and holes on silicon wafers for electronic circuits.	Processed chemicals
281122	Silicon dioxide	Essential for AI chip manufacturing as a key insulating and protective material in semiconductors.	Processed chemicals
281129	Inorganic oxygen compounds; of non-metals, n.e.c. in item no. 2811.2	A specialty chemical used in semiconductor manufacturing, often for deposition or etching processes.	Processed chemicals

HS Code	HS Description	Explanation	Type
282560	Germanium oxides and zirconium dioxide	Used in AI semiconductor manufacturing for enhancing optical and electronic properties of devices.	Processed chemicals
284920	Carbides; of silicon, whether or not chemically defined	Essential in AI semiconductor production for creating durable, high-performance components.	Processed chemicals
285000	Hydrides, nitrides, azides, silicides and borides, whether or not chemically defined, other than compounds which are also carbides of heading no. 2849	Key chemicals for AI semiconductor fabrication, enabling advanced material properties and device performance.	Processed chemicals
391000	Silicones; in primary forms	Essential materials in AI chip manufacturing for insulation and protection.	Processed chemicals
711029	Metals; palladium, semi-manufactured	Essential intermediate for manufacturing AI hardware components and catalysts.	Processed chemicals
811292	Gallium, germanium, indium, niobium (columbium) and vanadium; articles thereof, unwrought, including waste and scrap, powders	Critical intermediate metals and powders for AI semiconductor manufacturing.	Processed chemicals
811299	Gallium, germanium, indium, niobium (columbium) and vanadium; articles thereof, other than unwrought including waste and scrap and powders	Processed metals and articles essential for AI semiconductor device fabrication.	Processed chemicals
847330	Machinery; parts and accessories (other than covers, carrying cases and the like) of the machines of heading no. 8471	Computer components and testing equipment – such as evaluation kits, graphics cards, memory modules, and cooling systems – for building, optimizing and validating AI hardware performance.	Intermediate inputs
852351	Semiconductor media; solid-state non-volatile storage devices, whether or not recorded, excluding products of Chapter 37	Inputs for AI systems as they provide the data storage and retrieval capabilities needed for training, running and storing AI models and datasets.	Intermediate inputs
853630	Electrical apparatus: for protecting electrical circuits, not elsewhere classified in heading no. 8536, for a voltage not exceeding 1000 volts	Circuit protection devices ensuring the safe and stable operation of AI hardware systems such as servers and data centres.	Intermediate inputs
853650	Electrical apparatus: switches not elsewhere classified in heading no. 8536, for a voltage not exceeding 1000 volts	Switches used to control electrical signals essential components in AI hardware for managing data flow and system operations.	Intermediate inputs
853669	Electrical apparatus; plugs and sockets, for a voltage not exceeding 1000 volts	Sockets for semiconductor load boards used for testing purposes.	Intermediate inputs
854110	Electrical apparatus; diodes, other than photosensitive or light-emitting diodes (LED)	Used in printed circuit board assemblies.	Intermediate inputs

HS Code	HS Description	Explanation	Type
854160	Crystals; mounted piezo-electric	Mounted piezoelectric crystals used in AI hardware for sensing, signal processing and precision control functions.	Intermediate inputs
854190	Electrical apparatus; parts for diodes, transistors and similar semiconductor devices and photosensitive semiconductor devices	Processed wafers serving as the foundation for manufacturing integrated circuits and microchips.	Intermediate inputs
854231	Processors and controllers, whether or not combined with memories, converters, logic circuits, amplifiers, clock and timing circuits, or other circuits	Essential components enabling data processing and computation in AI systems	Intermediate inputs
854239	Electronic integrated circuits; n.e.c. in heading no. 8542	Essential components in AI hardware for data storage, processing, and communication functions.	Intermediate inputs
854442	Insulated electric conductors; for a voltage not exceeding 1000 volts, fitted with connectors	Critical inputs for semiconductor equipment maintenance.	Intermediate inputs
854449	Insulated electric conductors; for a voltage not exceeding 1000 volts, not fitted with connectors	Critical inputs for semiconductor equipment maintenance.	Intermediate inputs
900110	Optical fibres, optical fibre bundles and cables	Inputs used for high-speed data transmission in AI data centres and communication infrastructure.	Intermediate inputs
903084	Other, with a recording device	Various equipment or tools needed for measuring or checking semiconductor wafers or devices.	Intermediate inputs
320820	Paints and varnishes; based on acrylic or vinyl polymers, dispersed or dissolved in a non-aqueous medium	Specialty coatings for equipment used in wafer cleaning, etching and rinsing.	Intermediate inputs
320890	Paints and varnishes; based on polymers n.e.c. in heading no. 3208, dispersed or dissolved in a non-aqueous medium	Specialty coatings for equipment used in wafer cleaning, etching and rinsing.	Intermediate inputs
340590	Polishes, creams and similar preparations; n.e.c. in heading no. 3405, excluding waxes of heading no. 3404	Specialty coatings for equipment used in wafer cleaning, etching and rinsing.	Intermediate inputs
370199	Photographic plates and film; (for other than colour photography), in the flat, sensitised, unexposed, with no side exceeding 255mm, of any material other than paper, paperboard or textiles	Photomask blanks used to transfer circuit patterns onto silicon wafers.	Intermediate inputs
370790	Photographic goods; chemical preparations other than sensitised emulsions, put up in measured portions or put up for retail sale in a form ready for use	Photoresists and related materials used in photolithography to create patterned coatings for transferring circuit designs onto silicon wafers.	Intermediate inputs

HS Code	HS Description	Explanation	Type
381800	Chemical elements; doped for use in electronics, in the form of discs, wafers or similar forms; chemical compounds doped for use in electronics	Silicon wafers.	Intermediate inputs
392310	Plastics; boxes, cases, crates and similar articles for the conveyance or packing of goods	Plastic trays and containers used for handling and protecting semiconductor components during manufacturing and testing.	Intermediate inputs
392390	Plastics; articles for the conveyance or packing of goods n.e.c. in heading no. 3923	Packaging supplies for semiconductors.	Intermediate inputs
392690	Plastics; other articles n.e.c. in chapter 39	Packaging supplies for semiconductors.	Intermediate inputs
401693	Rubber; vulcanised (other than hard rubber), gaskets, washers and other seals, of non-cellular rubber	Packaging supplies for semiconductors.	Intermediate inputs
401699	Rubber; vulcanised (other than hard rubber), articles n.e.c. in heading no. 4016, of non-cellular rubber	Packaging supplies for semiconductors.	Intermediate inputs
621143	Track suits and other garments n.e.c.; women's or girls', of man-made fibres (not knitted or crocheted)	Cleanroom garments that prevent contamination and maintain a controlled environment to ensure high-quality semiconductor manufacturing.	Intermediate inputs
680421	Millstones, grindstones, grinding wheels and the like; of agglomerated synthetic or natural diamond	Diamond dresser discs used to condition and restore polishing pads and ensure uniform surface profiles.	Intermediate inputs
690912	Ceramic wares; for laboratory, chemical or other technical uses, articles having a hardness equivalent to 9 or more on the Mohs scale	Ceramic Semiconductor Production Components/Parts that have high strength, thermal, and electrical insulation and corrosion resistance.	Intermediate inputs
702000	Glass; articles n.e.c. in chapter 70	Quartz components such as reactor tubes and holders used in semiconductor manufacturing for thermal processing and maintaining clean environments.	Intermediate inputs
841350	Pumps; reciprocating positive displacement pumps, n.e.c. in heading no. 8413, for liquids	Pumps essential for handling fluids like corrosive chemicals and ultra-pure water in semiconductor manufacturing.	Intermediate inputs
841410	Pumps; vacuum	Pumps crucial for vacuum creation and gas handling in deposition and etching processes.	Intermediate inputs
841459	Fans; n.e.c. in item no. 8414.51	Fans and compressors essential for cooling, cleanroom control and maintaining semiconductor process purity.	Intermediate inputs

HS Code	HS Description	Explanation	Type
841480	Pumps and compressors; for air, vacuum or gas, n.e.c. in heading no. 8414	Compressors and vacuum pumps used in semiconductor manufacturing to maintain cleanroom conditions, control gases and support critical processes like etching and deposition.	Intermediate inputs
841490	Pumps and compressors; parts, of air or vacuum pumps, air or other gas compressors and fans, ventilating or recycling hoods incorporating a fan	Parts of compressors and vacuum pumps used in semiconductor manufacturing to maintain cleanroom conditions, control gases and support critical processes like etching and deposition.	Intermediate inputs
841950	Heat exchange units; not used for domestic purposes	Heaters essential for controlled temperature processes in semiconductor manufacturing, such as wafer processing and thin-film deposition.	Intermediate inputs
841989	Machinery, plant and laboratory equipment; for treating materials by change of temperature, other than for making hot drinks or cooking or heating food	Specialized heating or cooling equipment used in semiconductor manufacturing processes requiring precise thermal control.	Intermediate inputs
842121	Machinery; for filtering or purifying water	Water purification systems essential for maintaining ultra-clean environments in semiconductor manufacturing.	Intermediate inputs
842129	Machinery; for filtering or purifying liquids, n.e.c. in item no. 8421.2	Filtration systems used to purify specialty chemicals and process fluids critical for semiconductor fabrication.	Intermediate inputs
842139	Machinery; for filtering or purifying gases, other than intake air filters, catalytic converters or particulate filters for internal combustion engines	Gas filtration systems essential for ensuring the purity of process gases in semiconductor manufacturing environments.	Intermediate inputs
844391	Printing machinery used for printing by means of plates, cylinders and other printing components of heading 8442; parts and accessories	Include heatsink – device attached to a heat-generating component to prevent overheating.	Intermediate inputs
847160	Units of automatic data processing machines; input or output units, whether or not containing storage units in the same housing	Input/output units critical for connecting and controlling AI and semiconductor devices during data processing and testing.	Intermediate inputs
847180	Units of automatic data processing machines; n.e.c. in item no. 8471.50, 8471.60 or 8471.70	Specialized data processing units essential for AI computation, control and processing tasks in semiconductor manufacturing and AI systems.	Intermediate inputs
847950	Machinery and mechanical appliances; industrial robots, n.e.c. or included	Robots that automate certain tasks to increase efficiency in semiconductor manufacturing.	Intermediate inputs
848180	Taps, cocks, valves and similar appliances; for pipes, boiler shells, tanks, vats or the like, including thermostatically controlled valves	Valves for controlling fluids in precise, corrosive, or semiconductor manufacturing processes.	Intermediate inputs

HS Code	HS Description	Explanation	Type
848190	Taps, cocks, valves and similar appliances; parts thereof	Parts of valves used to control the flow of liquids and gases in various semiconductor manufacturing processes.	Intermediate inputs
848640	Machines and apparatus of a kind used solely or principally for the manufacture or repair of masks and reticles, assembling semiconductor devices or electronic integrated circuits, or for lifting, handling, loading or unloading items of heading 8486	Equipment for processing semiconductor wafers, such as photolithography tools and wafer cleaning systems.	Intermediate inputs
848690	Machines and apparatus of heading 8486; parts and accessories	Parts and accessories for semiconductor manufacturing tools, including pellicles that protect photomasks during lithography.	Intermediate inputs
850132	Electric motors and generators; DC, of an output exceeding 750W but not exceeding 75kW	Motors used in the automation of semiconductor manufacturing processes such as wafer handling and positioning.	Intermediate inputs
850432	Transformers; n.e.c. in item no. 8504.2, having a power handling capacity exceeding 1kVA but not exceeding 16kVA	Power supplies used to power various semiconductor manufacturing equipment.	Intermediate inputs
850440	Electrical static converters	Power supplies used to power various semiconductor manufacturing equipment.	Intermediate inputs
853400	Circuits; printed	Used in printed circuit board assemblies.	Intermediate inputs
853690	Electrical apparatus: not elsewhere classified in heading no. 8536, for switching or protecting electrical circuits, for a voltage not exceeding 1000 volts	Electrical apparatus for switching or protecting electrical circuits, essential for controlling semiconductor equipment and ensuring operational safety.	Intermediate inputs
853710	Boards, panels, consoles, desks and other bases; for electric control or the distribution of electricity, (other than switching apparatus of heading no. 8517), for a voltage not exceeding 1000 volts	PCB assemblies serve as the foundation for mounting and connecting various semiconductor components.	Intermediate inputs
853810	Electrical apparatus: parts (e.g. boards, panels, consoles, desks, cabinets, other bases), for goods of heading no. 8537, not equipped with their apparatus	Lighting and signalling devices essential for AI hardware systems.	Intermediate inputs
854121	Electrical apparatus; transistors, (other than photosensitive), with a dissipation rate of less than 1W	Transistors that enable AI chip processing and computations.	Intermediate inputs
854129	Electrical apparatus; transistors, (other than photosensitive), with a dissipation rate of 1W or more	Semiconductor switches used in AI circuits for signal control.	Intermediate inputs

HS Code	HS Description	Explanation	Type
854130	Electrical apparatus; thyristors, diacs and triacs, other than photosensitive devices	LEDs used in AI device displays and indicators.	Intermediate inputs
854151	Electrical apparatus; photosensitive semiconductor devices, semiconductor-based transducers	Photovoltaic cells supporting energy needs in AI sensors.	Intermediate inputs
854159	Electrical apparatus; photosensitive semiconductor devices n.e.c. in heading no. 8541	Photosensitive semiconductors for AI vision and sensing.	Intermediate inputs
854232	Electronic integrated circuits; memories	Integrated circuits powering AI processors and memory.	Intermediate inputs
854233	Electronic integrated circuits; amplifiers	Specialized integrated circuits for AI applications.	Intermediate inputs
854290	Parts of electronic integrated circuits	Miscellaneous semiconductor components used in AI hardware.	Intermediate inputs
854390	Electrical machines and apparatus; parts of the electrical goods of heading no. 8543	Critical inputs for semiconductor equipment maintenance.	Intermediate inputs
854420	Insulated electric conductors; co-axial cable and other co-axial electric conductors	Critical inputs for semiconductor equipment maintenance.	Intermediate inputs
854470	Insulated electric conductors: optical fibre cables	Electronic capacitors critical for AI circuit performance and stability.	Intermediate inputs
854710	Insulating fittings; of ceramics, for electrical machines, of insulating material only (except minor assembly parts), excluding those of heading no. 8546	Insulating fitting for semiconductor production equipment/tool.	Intermediate inputs
854790	Insulating fittings; (other than of ceramics or plastics), for electrical machines, appliances and equipment, excluding insulators of heading no. 8546	Insulating fitting for semiconductor production equipment/tool.	Intermediate inputs
902519	Thermometers and pyrometers; (other than liquid filled, for direct reading), not combined with other instruments	Crucial for monitoring and controlling semiconductor manufacturing processes such as thin film deposition, annealing and lithography.	Intermediate inputs
902620	Instruments and apparatus; for measuring or checking pressure	Instruments that control the flow and distribution of ultra-high purity gases and liquids used for semiconductor manufacturing.	Intermediate inputs
902730	Spectrometers, spectrophotometers and spectrographs; using optical radiations (UV, visible, IR)	Used for process monitoring and material analysis in semiconductor manufacturing.	Intermediate inputs

HS Code	HS Description	Explanation	Type
903090	Instruments, apparatus for measuring, checking electrical quantities, not meters of heading no. 9028; parts and accessories, for measuring or detecting alpha, beta, gamma, x-ray, cosmic and other radiations	Evaluation kits/boards used for testing performance and functionality.	Intermediate inputs
960350	Brushes; constituting parts of machines, appliances or vehicles	Chemical mechanical polishing brushes for cleaning and slurry distribution.	Intermediate inputs
847149	Automatic data processing machines; presented in the form of systems, n.e.c. in item no. 8471.30 or 8471.41	Tools and equipment used for the design, verification, optimization, debugging and testing of semiconductors.	Equipment
847150	Units of automatic data processing machines; processing units other than those of item no. 8471.41 or 8471.49, whether or not containing in the same housing one or two of the following types of unit: storage units, input units or output units	Tools and equipment used for the design, verification, optimization, debugging and testing of semiconductors.	Equipment
847170	Units of automatic data processing machines; storage units	Data storage units required to handle the massive datasets and model outputs used in AI training and inference processes	Equipment
847989	Machines and mechanical appliances; having individual functions, n.e.c. or included in this chapter	Machines often used in AI hardware manufacturing and integration to support the assembly, testing or deployment of AI-enabled equipment.	Equipment
848620	Machines and apparatus of a kind used solely or principally for the manufacture of semiconductor devices or of electronic integrated circuits	Highly specialized equipment for producing the semiconductor chips that power AI hardware.	Equipment
903040	Instruments and apparatus; specially designed for telecommunications (e.g. cross-talk meters, gain measuring instruments, distortion factor meters, psophometers)	Tools and equipment used for the design, verification, optimization, debugging and testing of semiconductors.	Equipment
903082	Instruments and apparatus; for measuring or checking semiconductor wafers or devices (including integrated circuits)	Various equipment or tools needed for measuring or checking semiconductor wafers or devices.	Equipment
903141	Optical instruments and appliances; for inspecting semiconductor wafers or devices or for inspecting photomasks or reticles used in manufacturing semiconductor devices, n.e.c. in chapter 90	System level test equipment to test the operation of semiconductors in final user environments.	Equipment

HS Code	HS Description	Explanation	Type
847130	Automatic data processing machines; portable, weighing not more than 10kg, consisting of at least a central processing unit, a keyboard and a display	Devices serving as platforms for developing, testing or running lightweight AI models locally, and accessing AI tools and performing computations.	Equipment
847141	Automatic data processing machines; comprising in the same housing at least a central processing unit and an input and output unit, whether or not combined, n.e.c. in item no. 8471.30	Systems used for training, developing or deploying AI applications.	Equipment
848610	Machines and apparatus of a kind used solely or principally for the manufacture of semiconductor boules or wafers	Machines for making semiconductor wafers, essential for producing AI chips like GPUs and accelerators.	Equipment
851762	Communication apparatus (excluding telephone sets or base stations); machines for the reception, conversion and transmission or regeneration of voice, images or other data, including switching and routing apparatus	Essential machines for AI systems that rely on high-speed data exchange, cloud computing and connected devices.	Equipment
851769	Communication apparatus (excluding telephone sets or base stations); machines for the transmission or reception of voice, images or other data (including wired/wireless networks), n.e.c. in item no. 8517.6	Other communication devices supporting AI applications.	Equipment

Source: WTO Secretariat compilation. The list of AI-enabling raw materials and chemical elements is based on Baskaran and Schwartz (2024). The list of AI-enabling semiconductors and intermediate inputs is based on comments submitted by the Semiconductor Industry Association (SIA) as part of the Section 232 investigation on semiconductors (SIA, 2025). More detailed HS codes have been aggregated to the sub-heading six-digit level.
Note: n.e.c. stands for "not elsewhere classified".

Annex A.2: List of sectors by AI intensity

Sector	Industry (ISIC Rev.4)	AI intensity – summary indicator
Computer & electronics	26	High
Media	58-60	High
Telecommunications	61	High
IT services	62-63	High
Finance & insurance	64-66	High
Legal & accounting	69-71	High
Scientific R&D	72	High
Chemicals	20	Medium
Pharmaceuticals	21	Medium
Electrical equipment	27	Medium
Machinery & equipment	28	Medium
Transport equipment	29-30	Medium
Other manufactures	31-33	Medium
Wholesale & retail	45-47	Medium
Transportation & storage	49-53	Medium
Real estate	68	Medium
Other business services	73-75	Medium
Admin. & support services	77-82	Medium
Food products	10-12	Low
Textiles & apparel	13-15	Low
Wood & paper	16-18	Low
Rubber, plastics, minerals	22-23	Low
Metal products	24-25	Low
Construction	41-43	Low
Hotels & food services	55-56	Low

Source: Calvino et al. (2024)

Annex B: Key AI terms

The report makes references to several key concepts in AI. To facilitate comprehension of these terms, we provide definitions for the following key concepts:

- **General AI** or **artificial general intelligence (AGI)** represents a type of AI system that possesses a broad range of capabilities that matches or outmatches those of humans (Morris et al., 2024). True AGI systems do not yet exist. The concept of AGI remains a visionary goal, but the rapid pace of development of AI hints at the possibilities and potential directions that AGI might take.
- **Narrow AI** refers to a type of AI system that is designed to address specific tasks or solve particular problems. Unlike AGI, which aims for broad capabilities, narrow AI focuses on defined tasks and exhibits expertise within a limited domain. Narrow AI systems are tailored to excel in specific applications or problem domains.
- **Generative AI**, also known as gen AI, is a type of AI that creates new content, such as text, images, audio, videos or software code, based on prompts or inputs. Generative AI relies on sophisticated machine learning models, called deep learning models, that simulate the learning and decision-making processes of the human brain. It works by learning patterns from large datasets and subsequently generating new content that mimics those patterns.
- **Agentic AI** refers to AI systems composed of autonomous agents that can make decisions and act independently to achieve specific goals, often with limited human supervision. It consists of AI agents – machine learning models that mimic human decision-making to solve problems in real time. Examples include an AI-powered trading bot that analyses real-time stock prices and economic indicators to generate predictions and execute trades, or an AI system that streamlines supply chain management by automating processes, such as placing orders with suppliers or adjusting production schedules, to maintain optimal inventory levels.

AI technologies

- **Machine learning** is a subset of AI that focuses on the development of algorithms and statistical models which enable computers to perform tasks without being explicitly programmed to do so. In other words, machine learning algorithms learn from data, identify patterns, and make decisions or predictions based on that data.
- A **neural network** is a computational model inspired by the structure and function of the human brain, composed of interconnected nodes, or artificial neurons, organized in layers. Through a process called training, neural networks learn from examples by adjusting the weights of connections to minimize the difference between predicted and actual outputs, thereby enabling them to recognize patterns, make predictions, and perform complex tasks across a wide range of domains.
- **Deep learning** is a subset of machine learning that involves training artificial neural networks with many layers of processing units, or neurons, to learn representations of data. The term “deep” refers to the depth of the neural networks, which typically consist of multiple hidden layers between the input and output layers.
- **Large language models (LLM)** are advanced AI systems that are trained on massive amounts of text data to understand and generate human-like language. These models are characterized by their vast size, often containing hundreds of millions to billions of parameters, which enables them to capture intricate patterns and nuances in language.

Supervised versus unsupervised learning

- **Supervised learning** is a machine learning approach defined by its use of labelled datasets. These datasets are designed to train or “supervise” algorithms into classifying data or predicting outcomes accurately. Using labelled inputs and outputs, the model can measure its accuracy and learn over time.
- **Unsupervised learning** uses machine learning algorithms to analyse and cluster unlabelled data sets. These algorithms discover hidden patterns in data without the need for human intervention.
- **Reinforcement learning** is a type of machine learning whereby an agent learns to make decisions by interacting with an environment and receiving feedback in the form of rewards or

punishments. The goal is for the agent to learn an optimal policy – a strategy for making decisions – that maximizes its cumulative reward over time.

Openness in AI models

- **Open-source AI** is an AI system that is made available according to certain terms that allow users free use of the system for any purpose and without having to ask for permission; that allow users to study how the system works and to inspect its components; that allow users to modify the system for any purpose, including changing its output; and that allow users to share the system for others, to use with or without modification, for any purpose (OSI, 2025).
- **Open-weight AI** refers to foundation models (see below) with publicly available trained weights (i.e., numbers that determine the importance of any connection within a model's artificial neural network, which shapes the model's behaviour). These models can generate content and perform a variety of tasks across different applications. Examples include the recently launched DeepSeek R1, OpenAI's GPT-OSS, and Alibaba's Qwen (OECD, 2025c).

Other terms

- **Foundation models** are large-scale, pre-trained models that serve as the basis or foundation for developing more specialized AI applications or models. These foundation models are typically trained on vast amounts of data using techniques such as unsupervised learning. Developers can fine-tune these pre-trained foundation models on specific datasets or tasks to create more specialized AI models tailored to particular applications or domains.
- **Source code** refers to the human-readable instructions written by programmers to define the behaviour, algorithms and models used in AI systems.
- **Natural language processing (NLP)** is a field of AI that focuses on enabling computers to understand, interpret, and generate human language, both written and spoken.
- **Artificial Intelligence of Things (AIoT)** refers to the integration of AI technologies with Internet of Things (IoT) devices and systems. AIoT combines the capabilities of AI algorithms with the vast amounts of data generated by IoT devices to create intelligent and autonomous systems.
- **Intelligent automation** combines AI technologies, such as machine learning, computer vision, natural language processing and robotics process automation, to automate and optimize processes, tasks and workflows in various domains and industries.

Annex C: Data and methodology for AI patent citation analysis

This annex documents the data construction procedures for analysing cross-border diffusion of AI-related knowledge using patent citations. It specifies sources, definitions and assumptions applied in assembling the analytical dataset.

Defining AI patents

The data are sourced from PATSTAT Online (Autumn 2024 edition),[1] a database of bibliographical and legal event patent data from a number of industrialized and developing economies provided by the European Patent Office. The unit of observation is the individual patent application, which is classified using the Cooperative Patent Classification (CPC) system.[2]

To identify AI-related patents, a two-step approach is used. First, the WIPO (2019) AI taxonomy is adopted as the baseline, which specifies CPC codes relevant to AI. Since CPC codes are updated twice a year, this baseline is extended by reviewing the 2024 CPC master headings for AI-related terms, using regular expressions based on the keyword list in Table 2. These keywords are used only to identify potential new CPC headings, not to retrieve patents directly. All matches are manually checked to remove irrelevant entries.

Patent applications are classified as AI-related if they contain at least one CPC code listed in Table 1.

Identifying AI patent citation flows

To analyse AI knowledge diffusion, all patent citations received by AI-related patents are tracked, regardless of whether the citing patents are themselves AI-related. This approach captures how AI innovations influence other technological domains both within and beyond AI.

Patent citation data are drawn from PATSTAT (table TLS228_DOCDB_FAM_CITN), with self-citations within the same family excluded. A knowledge flow from country j to country i in year t is recorded when a patent with priority year t (priority country = i) cites an AI-related patent whose priority country is j (Thomas and Murdick, 2020).

The origin of an AI knowledge flow is determined by the filing of the cited patent by the country of priority, hence circumventing the problem of missing values

Table 1: AI patent classification codes

WIPO 2019 baseline G06N codes:
G06N-003, G06N-005/003:G06N-005/027, G06N-007/005:G06N-007/06, G06N-099/005, G06N-003/004:G06N-003/008, G06N-007/046

Extended CPC class list, defined as G06N codes that contain an AI-related keyword:
G06N 20/00, 20/10, 20/20; G06N 3/00, 3/02, 3/04, 3/042, 3/043, 3/044, 3/0442, 3/049, 3/0499, 3/06, 3/08, 3/084, 3/086, 3/088, 3/0895, 3/09, 3/091, 3/092, 3/094, 3/096, 3/098, 3/0985, 3/10, 3/12, 3/126; G06N 5/00, 5/02, 5/04, 5/043, 5/045, 5/048; G06N 7/00, 7/02.

Table 2: List of AI-related keywords

neural, learning, deep, fuzzy, inference, supervised, unsupervised, reinforcement, backpropagation, autoencoder, feedforward, recurrent, lstm [long short-term memory], gru [gated recurrent unit], embedding, representation, artificial intelligence, computational intelligence, neural network, bayesian network, chatbot, data mining, decision model, deep learning, genetic algorithm, inductive logic, machine learning, natural language, reinforcement learning, supervised learning, swarm intelligence, unsupervised learning, semi-supervised learning, expert system, fuzzy logic, transfer learning, support vector machine, random forest, decision tree, gradient tree boosting, xgboost [eXtreme Gradient Boosting], adaboost [Adaptive Boosting], rankboost, logistic regression, stochastic gradient descent, multilayer perceptron, latent semantic analysis, Latent Dirichlet Allocation, multi-agent system, hidden Markov model.

for inventor and applicant country of residence. According to Thomas and Murdick (2020), this simplified procedure accurately captures the first inventor country for AI-related patents in over 80 per cent of cases.

Gravity model specification

The sample covers patent citations from 2010 to 2022, with subsequent citations left out of the sample to avoid a potential truncation bias. The resulting dataset is an 84-country balanced dyad-year panel with annual flows, retaining zero-citation pairs for Poisson Pseudo-Maximum Likelihood estimation. Domestic flows are excluded.

Bilateral AI knowledge flows were estimated using a Poisson Pseudo-Maximum Likelihood model, following the approach of Silva and Tenreyro (2006), which is robust to heteroskedasticity and the presence of zero flows:

$$Citation\ Flow_{ijt} = Exp(\beta_1 \log(Trade_{ijt}) + \beta_2 RTA_{ijt} + \gamma_{it} + \delta_{jt} + \Phi_{ij} + \varepsilon_{ijt})$$

where $Citation\ Flow_{ijt}$ represents citations from country i to AI patents originating in country j during year t.

Origin-year fixed effects γ_{it} and destination-year fixed effects δ_{jt} are included to control for multilateral resistance and other time-varying country-specific factors affecting citation intensity, as well as directional country-pair fixed effects Φ_{ij} to account for potentially asymmetric knowledge flow frictions between country i and j. Only cross-border flows ($i \neq j$) are included when trade variables are used as regressors. Standard errors are clustered at country-pair level.

Five alternative trade specifications are tested:

1. Digitally deliverable services trade only
2. Other services trade (total services minus digitally deliverable services)
3. Goods trade only
4. Digital services + goods trade
5. All trade (digital + other services + goods).

Data on goods trade are taken from the International Trade and Production Database (ITPD-Ev2024), expressed in current US dollars, with zero trade flows retained. Services trade data are sourced from the OECD-WTO Balanced Trade in Services dataset (OECD–WTO BaTIS, 2023 release). Measures of bilateral distance and regional trade agreement (RTA) coverage are taken from the Centre d'Études Prospectives et d'Informations Internationales (CEPII), with distance calculated as population-weighted and all values corresponding to the 2023 release.

Annex D: WTO AI Trade Policy Openness Index (AI-TPOI): methodology

1. Introduction

This annex documents the construction of the AI Trade Policy Openness Index (AI-TPOI), a composite indicator designed to summarize how trade policies and regulatory frictions shape an economy's AI readiness and integration into the global AI ecosystem. The index captures the degree of policy openness across three key dimensions: services trade, goods trade and cross-border data flows. Together, these components reflect policy instruments that influence economies' ability to access, develop and diffuse AI and AI-related goods and services. The composite index aggregates these elements to provide a standardized measure of AI-related trade policy openness.

The AI-TPOI covers 108 economies and is reported on a 0–1 scale, where higher values denote less openness, and therefore greater restrictiveness and potential barriers to AI-related trade.

2. Conceptual framework

The AI-TPOI is structured around three pillars, each reflecting a policy domain relevant to AI diffusion: (i) services trade restrictiveness in AI-salient sectors; (ii) trade measures on AI-related goods; and (iii) cross-border data flow restrictions. The index assigns equal weight to these dimensions, reflecting the view that services, goods and data flows are complementary enablers of AI development, deployment and scaling.

Formally, the index for economy is computed as:

$$AI\text{-}TPOI_i = ⅓\cdot STRI_i + ⅓\cdot TRM_i + ⅓\cdot CBP_i$$

where:

$STRI_i$: restrictiveness in AI-salient services;

TRM_i : trade measures on AI-related goods;

CBP_i : restrictiveness of cross-border data policies.

Each component is normalized to the [0,1] interval, with higher values indicating more restrictive policy regimes and, thus, lower openness to AI and AI-related trade.

i. Services trade restrictions

The services component is based on the World Bank–WTO Services Trade Restrictiveness Index (STRI),[3] which classifies measures affecting foreign service suppliers on a 0–1 scale, where 0 indicates full openness and 1 indicates a complete restriction.

Given the focus on AI preparedness, the index includes services subsectors particularly salient for AI development and deployment. These comprise telecommunications (fixed-line, mobile and internet), audio-visual services, computer and related services (including data processing and database services) and professional services highly complementary to AI deployment, such as engineering and research and development (R&D) services. These sectors are selected because they either directly provide AI services, supply critical inputs to AI development, or represent key areas of application for AI technologies. This targeted approach ensures that the index captures the most relevant policy barriers while maintaining parsimony.

The STRI for each economy is calculated as a weighted average, using as weights sectoral value-added shares (or regional averages if unavailable).

$$STRI_i = \sum_s w_{i,s} \cdot STRI_{i,s}$$

The underlying STRI aggregation follows a CES (constant elasticity of substitution) functional form, capturing the imperfect substitutability between different types of regulatory barriers. This approach recognizes that overall restrictiveness depends not only on individual measures, but also on their interaction effects.

ii. Trade-related measures on AI goods

While AI is a digital technology, it depends heavily on physical infrastructure, including servers, computing hardware and telecommunications equipment. Trade policies affecting access to these goods can significantly hinder AI trade and development.

The index combines three types of trade barriers – tariffs, quantitative restrictions (QRs) and trade remedies – each weighted according to its expected impact on AI-related trade flows.

$$TRM_i = 0.5\cdot Tariff_i + 0.4\cdot QRs_i + 0.1\cdot TRs_i$$

Tariffs:

Based on simple average applied tariff rates on AI-related products from the WTO Tariff & Trade

Data (TTD),[4] averaged over 2019-23 and normalized to [0,1] using min-max scaling. Covered AI-related products include computers and processing units, telecommunications equipment, scientific instruments and other ICT hardware identified through HS codes.

Quantitative restrictions (QRs):

This component is drawn from the Digital Trade Integration (DTI) database (Ferracane, González Ugarte and Rogaler, 2025),[5] averaging indicators 10.1 through 10.4, which capture import and export restrictions on ICT hardware, including licensing requirements and local content requirements for ICT systems. The DTI is used instead of the WTO QRs database[6] because it offers slightly broader data coverage and a structure more conducive to index construction.

Trade remedies:

This covers contingent protection measures – such as anti-dumping, countervailing duties and safeguards measures – applied to ICT-related products as reported in the DTI database. Though these measures may address legitimate trade concerns, they can increase trade uncertainty and raise costs for AI technology importers.

iii. Cross-border data policy

Data are a fundamental input for AI development and deployment. Restrictions on cross-border data flows can significantly fragment digital ecosystems and constrain AI innovation and trade.

The cross-border data policy is calculated as a simple average of five regulatory indicators from the DTI database (items 6.1 to 6.5). These comprehensively cover data localization requirements, restrictions on cross-border data transfers, mandates for local processing, conditional flow regimes and local storage requirements, and commitments in RTAs on data governance.

$$CBP_i = ⅕ \sum_{k=1}^{5} \mathrm{DTI}_{i,k}$$

All sub-components are scaled so that higher values indicate more restrictive regimes.

3. Normalization and robustness

All sub-indicators are normalized to [0,1], and thus higher values always indicate greater restrictiveness. The STRI and DTI databases already follow this convention by design. Tariff data are min-max normalized across the full sample of 108 economies.

Where time-series data are available, multi-year averages are used to smooth possible short-term fluctuations. Tariff data are averaged over a five-year period (2019-23). Services and data policies, which typically change less frequently, are measured at the most recent available year.

Endnote

1 See https://www.epo.org/en/searching-for-patents/business/patstat.

2 See https://www.cooperativepatentclassification.org/home.

3 See https://itip-services-worldbank.wto.org/.

4 See https://ttd.wto.org/en.

5 The Digital Trade Integration (DTI) index is still under development. Some values may change in the final version, which will be released on the DTI website: https://dti.eui.eu/.

6 See https://qr.wto.org/en.

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World Trade Report 2025

Artificial intelligence (AI) has the potential to lead to a new era of growth. By transforming how goods and services are produced, exchanged and consumed, AI can bring about substantial changes in the global economy. Yet the future trajectory of AI remains uncertain, raising critical questions about trade and inclusive growth.

The *World Trade Report 2025* explores the complex and fast-evolving relationship between AI and international trade and how this relationship can shape inclusive growth. AI offers new opportunities to reduce trade costs, boost productivity and expand access to global markets. In addition, trade can help to render AI more accessible by spreading knowledge, fostering innovation and promoting participation in AI value chains. However, unequal access across the world to digital infrastructure, appropriate skills and capabilities could increase the digital divide. Also, the impact of AI on the labour market presents additional challenges.

Whether AI-enabled trade translates into broad-based, inclusive growth will depend on the design and implementation of trade and trade-related policies. WTO rules on trade in goods, services, data, intellectual property and public procurement can shape the availability, affordability and diffusion of AI. Complementary policies regulating competition, data infrastructure, energy, education and government support can also help to determine whether and how economies benefit from AI-enabled trade. The WTO can play a central role in ensuring that AI supports more inclusive trade-led growth by administering WTO rules, by fostering dialogue, transparency and capacity-building, and by deepening collaboration on AI and digital trade with other international organizations.

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