

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.

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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 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

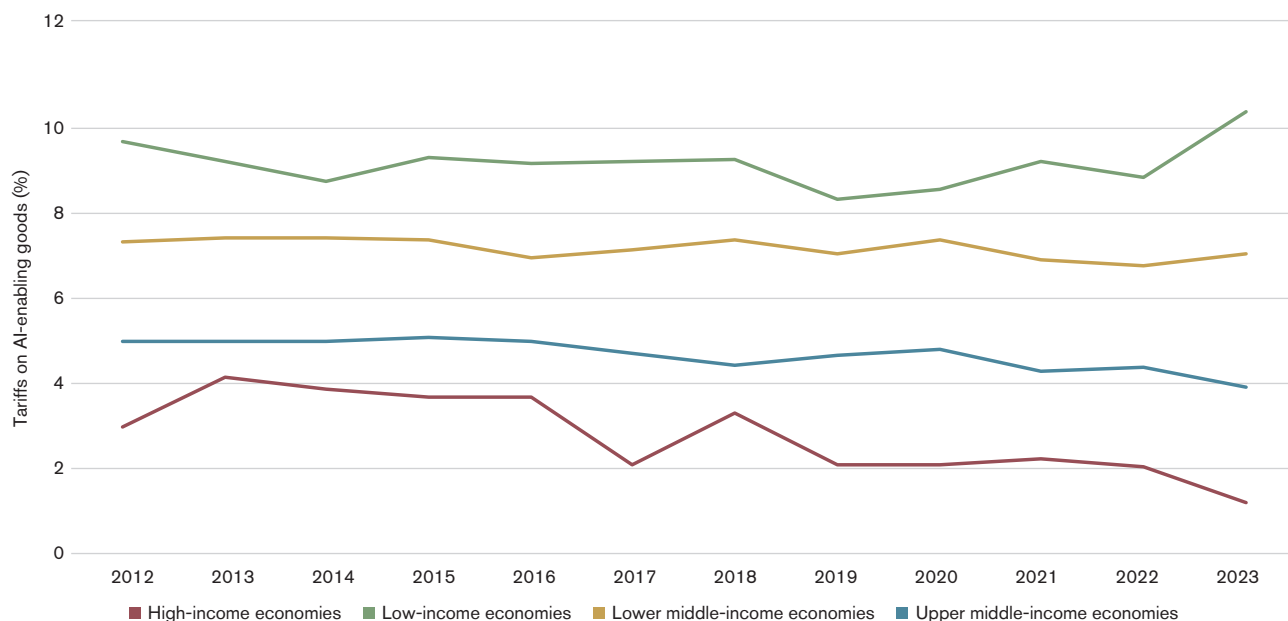
AI ecosystem. These range from the use of tariffs to import and export restrictions, including full bans or licensing systems. Reasons for relying on these measures are diverse. They cover both economic and non-economic considerations, including environmental and national security concerns, not least 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.

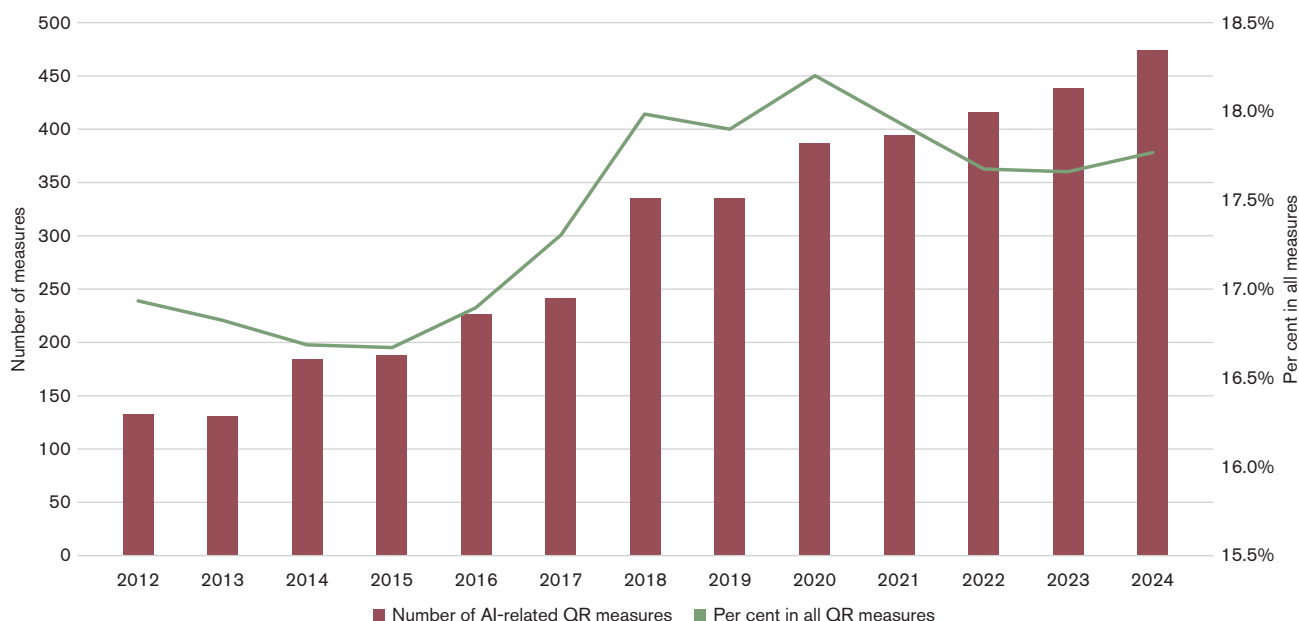
QRs are typically, but not exclusively, applied to dual-use goods, reflecting the fact that these goods may potentially have both a civil and a military use. The products most frequently covered by these restrictions include nitrogen function compounds, ethers, inorganic acids and non-metallic oxygen 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.

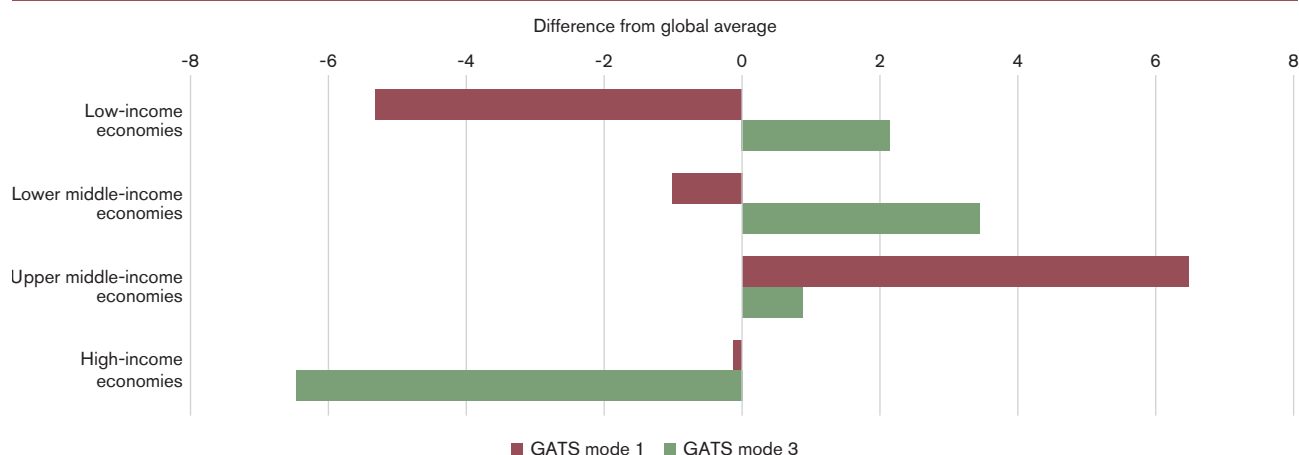
The level of services restrictions in different economies differs according to income and across modes of supply. As illustrated in Figure C.3, the cross-border supply of services (GATS mode 1) tends to be less regulated in low-income economies, and the highest levels of restriction are observed in upper 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 Treffer, 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).

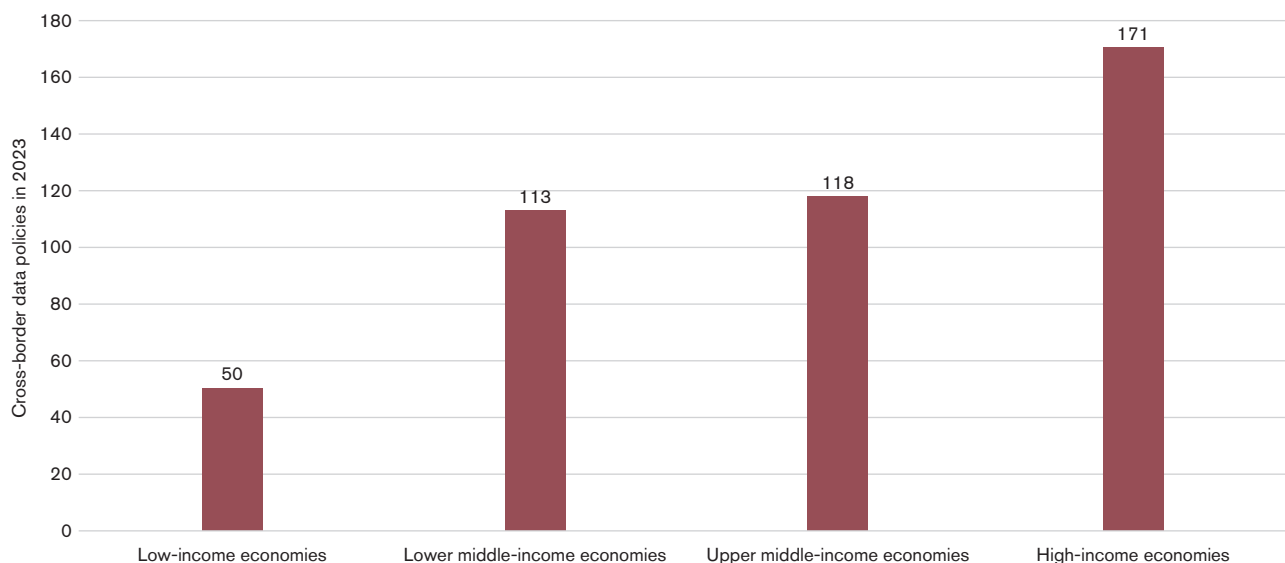
The last decade has seen a rapid rise in data regulation, much of which restricts the flow of data.

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, Amini⁶

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) database⁷ (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

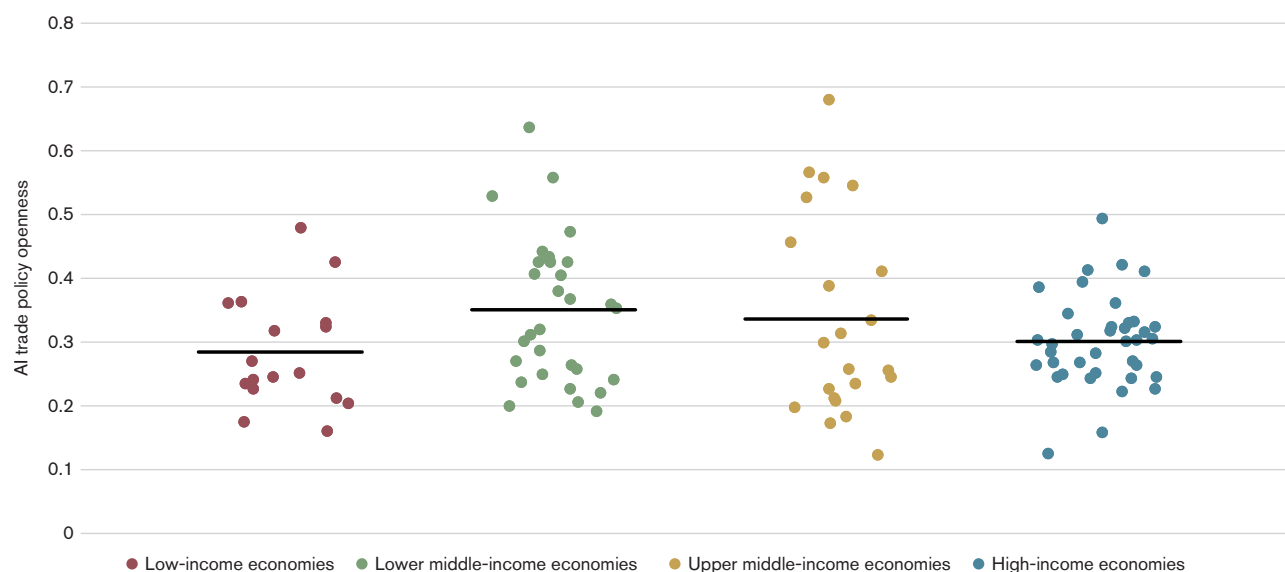
Figure C.5: Composition of the AI Trade Policy Openness Index



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).

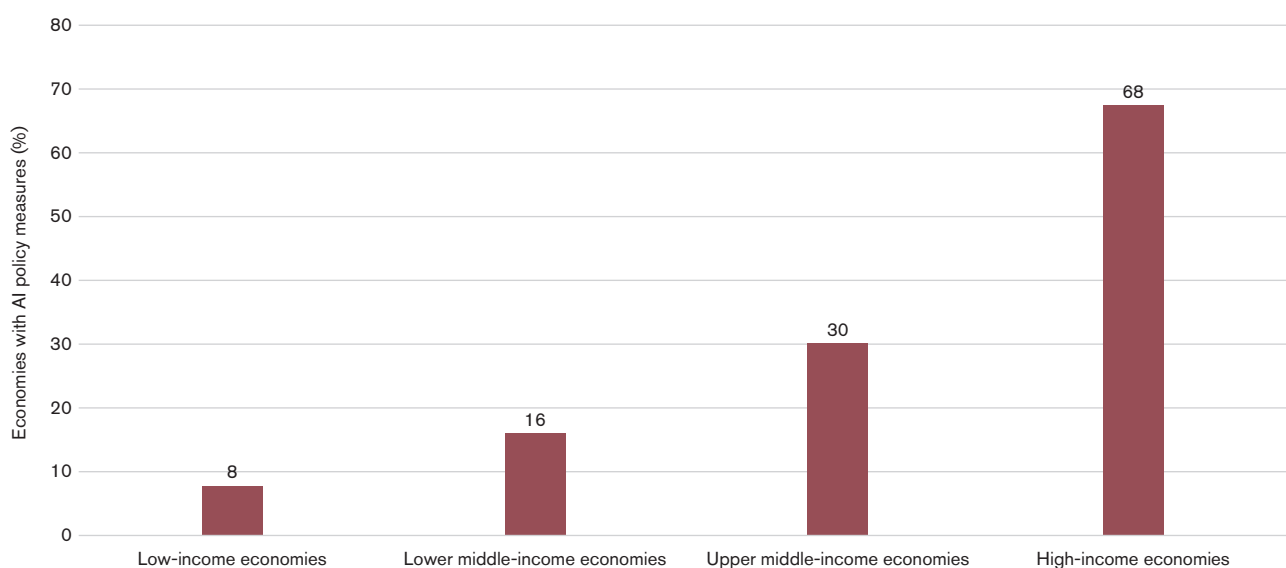
High-income and upper middle-income economies are leading in terms of AI regulation. Only 36 per cent of economies globally have adopted AI policy measures. Most of these measures are implemented either by high-income or upper middle-income economies, which together account for 92 per cent of the policies 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

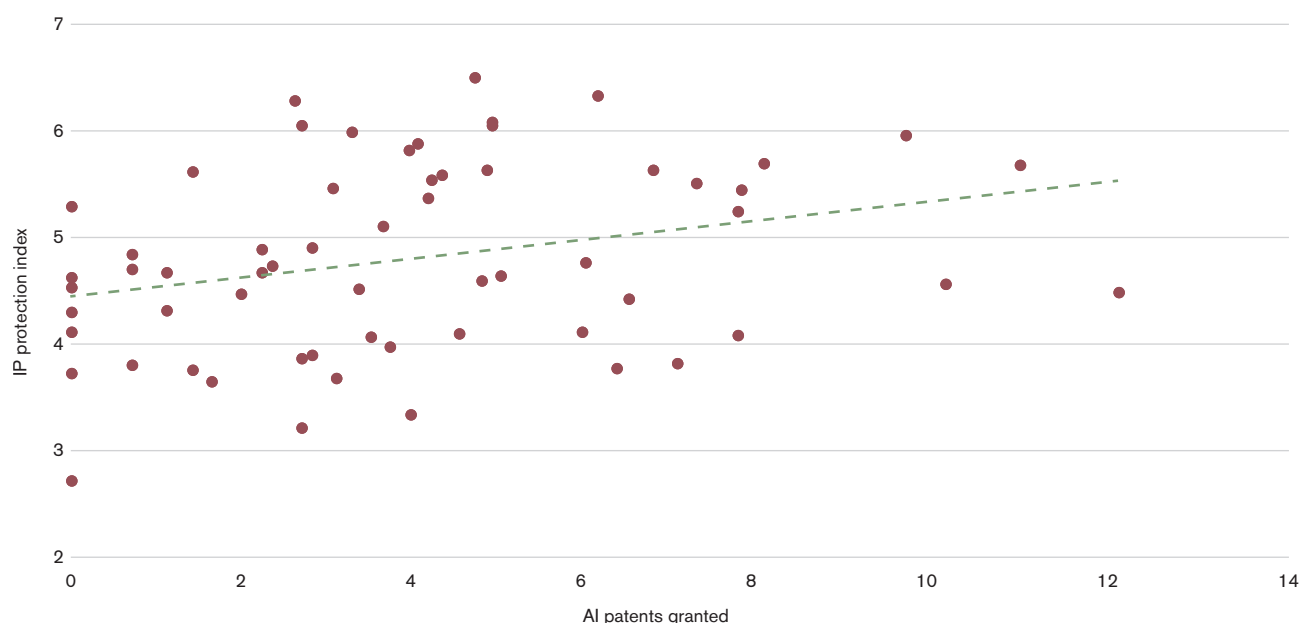
Trade-related IP rules play a critical role in shaping how technologies are shared across borders, with important implications for inclusive innovation. While comprehensive studies on the impact of IP protection on inclusive innovation in AI are not yet available, initial economic analysis suggests that 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

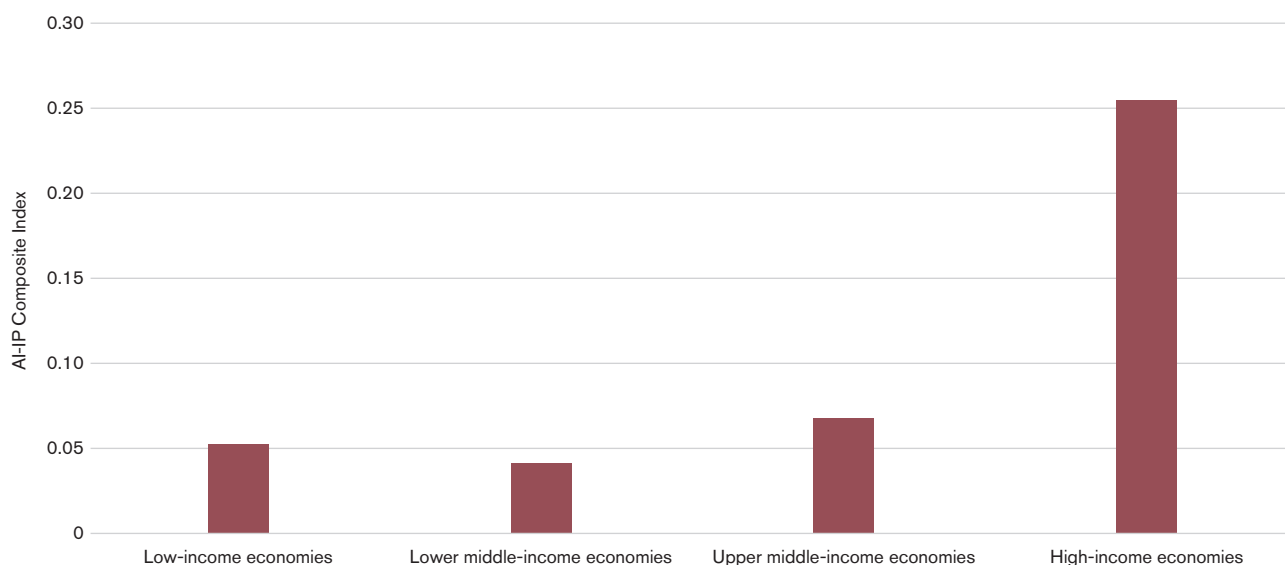
forthcoming AI-IP Composite Index,¹⁰ developed by Cáceres (2025), provides a systematic comparison of how national regimes address five key areas: protection for AI-generated works and inventions; governance of training data use; regulation of algorithms and models; the use of AI tools within IP offices; 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 Concorrência, 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

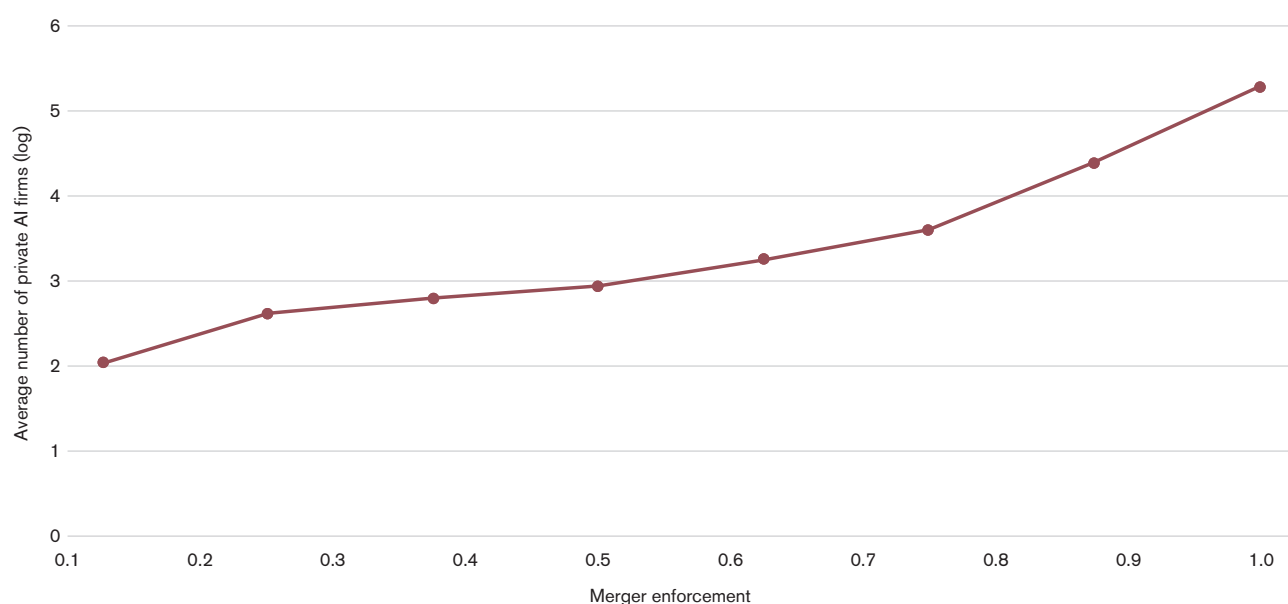
acquisitions may generate such welfare-enhancing scale effects (Petit Schrepel, and Heiden, 2024). Moreover, in highly dynamic sectors, monopoly power may be less of a concern, as leadership positions are unstable and contingent on continued innovation (Teece, 2023). Effective competition policy must 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 Alert¹⁴ – 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.

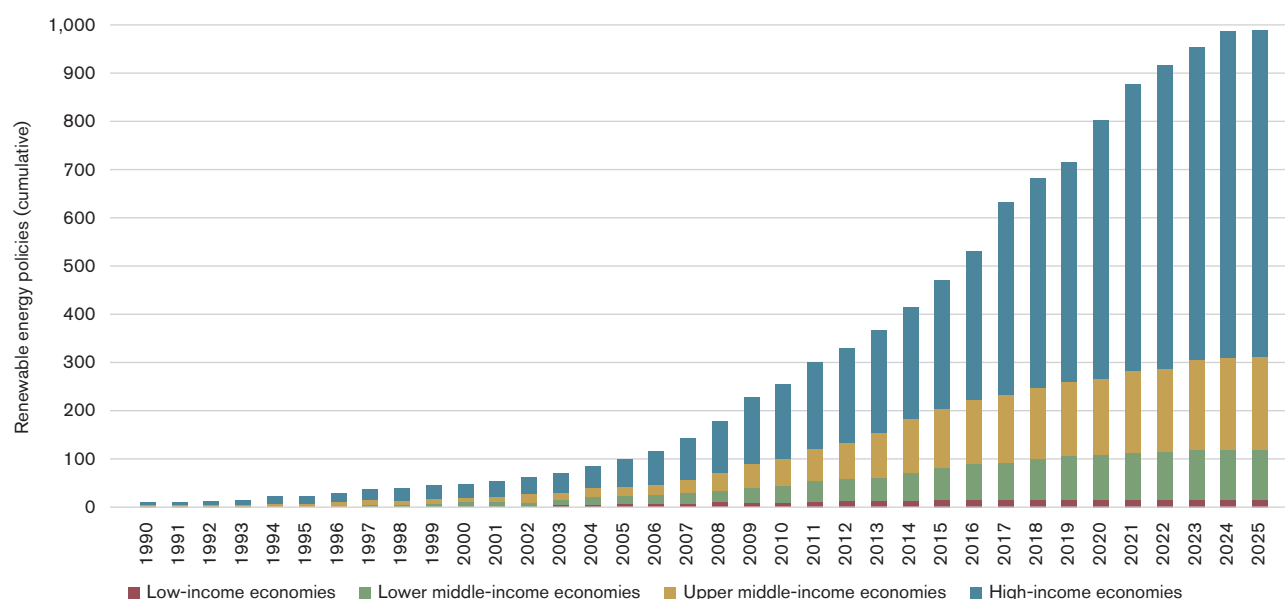
Policy activity on renewable energy is concentrated in high-income economies. The number of renewable energy policies has increased exponentially since the early 1990s, but distribution of these policies is highly uneven, with high-income economies accounting for a large majority of the surge. By 2025, 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).

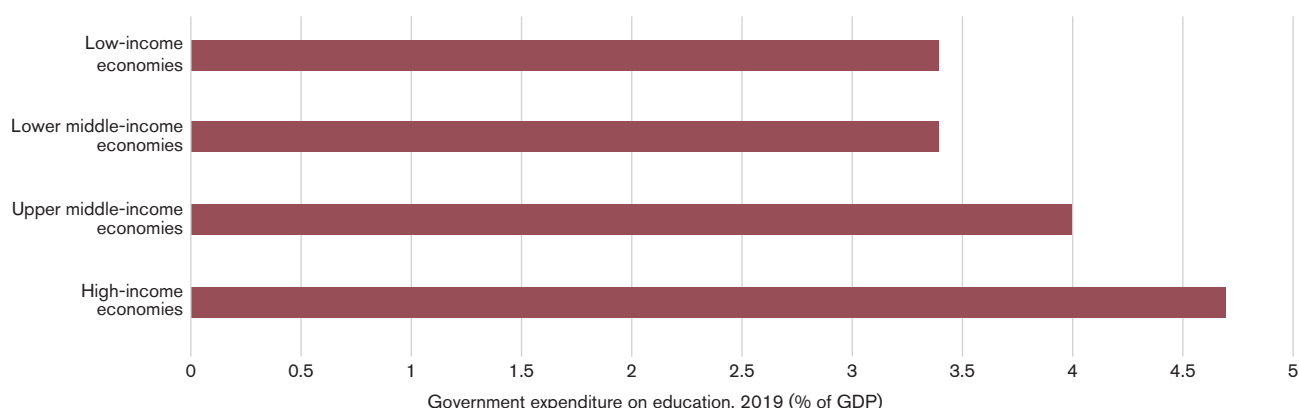
Economies need to support their workforce continuously with labour market policies, as AI may lead to changing patterns in the labour market. AI, reinforced by changes in trade patterns, has the potential to affect the labour market severely (see Section B.1(b)). Given the uncertainty around how AI will 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

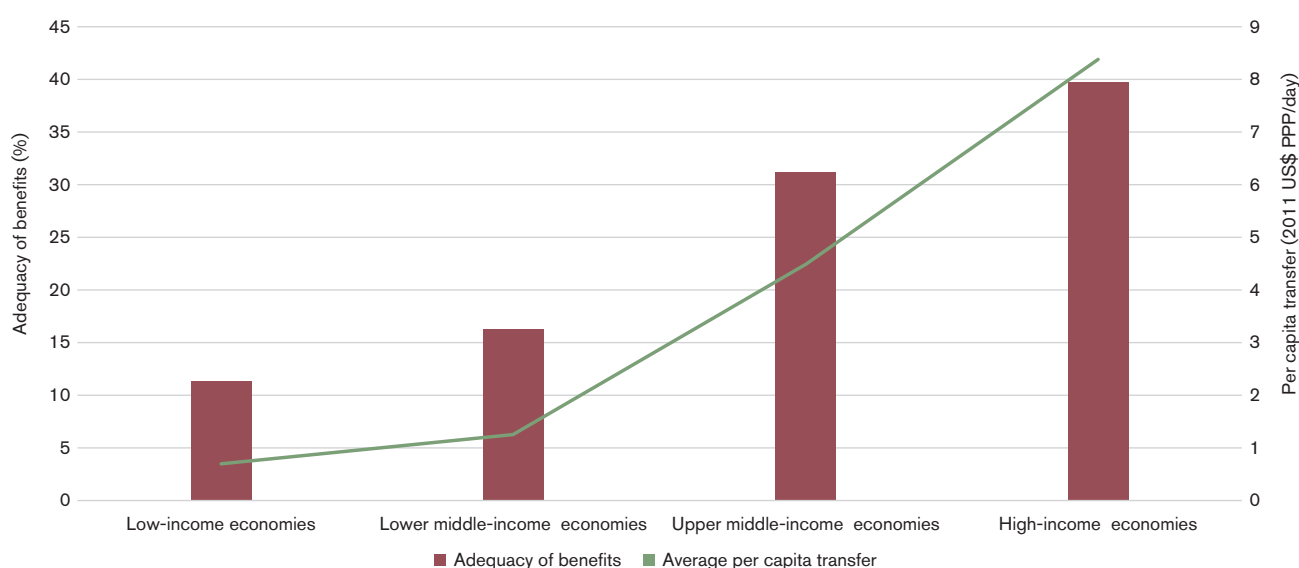
regulations can protect displaced or vulnerable workers, overly stringent employment protections tend to slow job reallocation, particularly in sectors requiring labour adaptation (Haltiwanger, Scarpetta and Schweiger, 2014). While high dismissal costs may mitigate short-term unemployment effects, they 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,

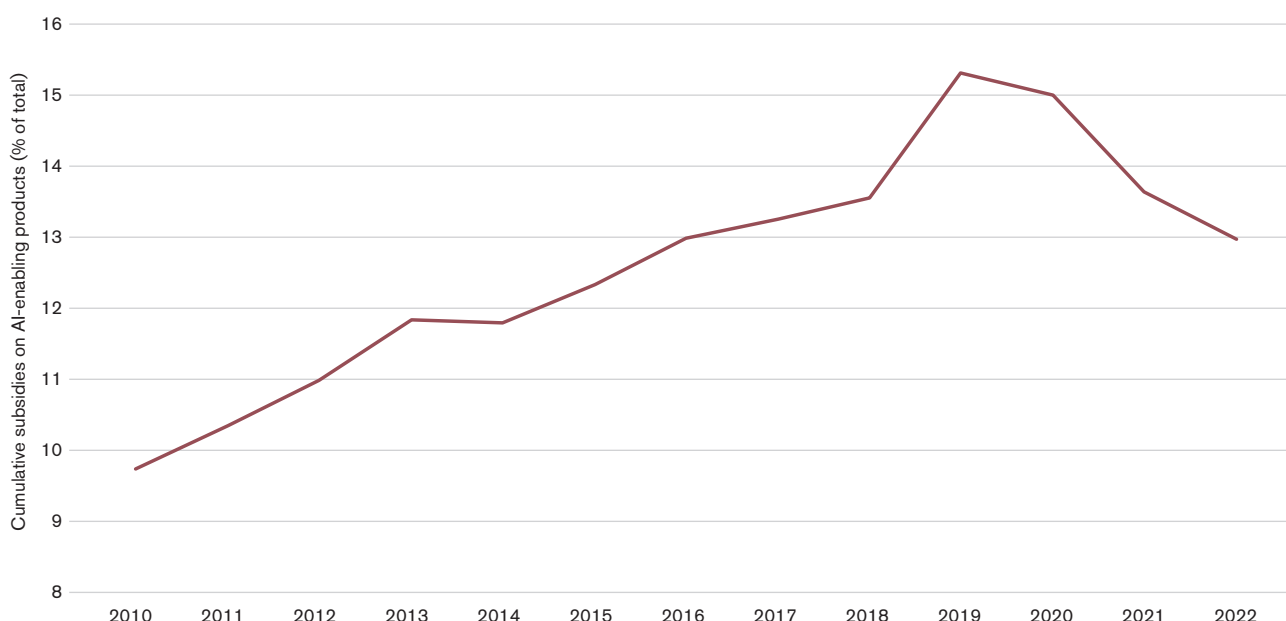
which was launched in 2014, and of which the third phase was launched in 2024) (Goldberg et al., 2024). Government support has also been found to be more effective when it targets upstream sectors, as support to these sectors diffuses downstream along the value chain (Liu, 2019; Lane, 2025). This also 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.

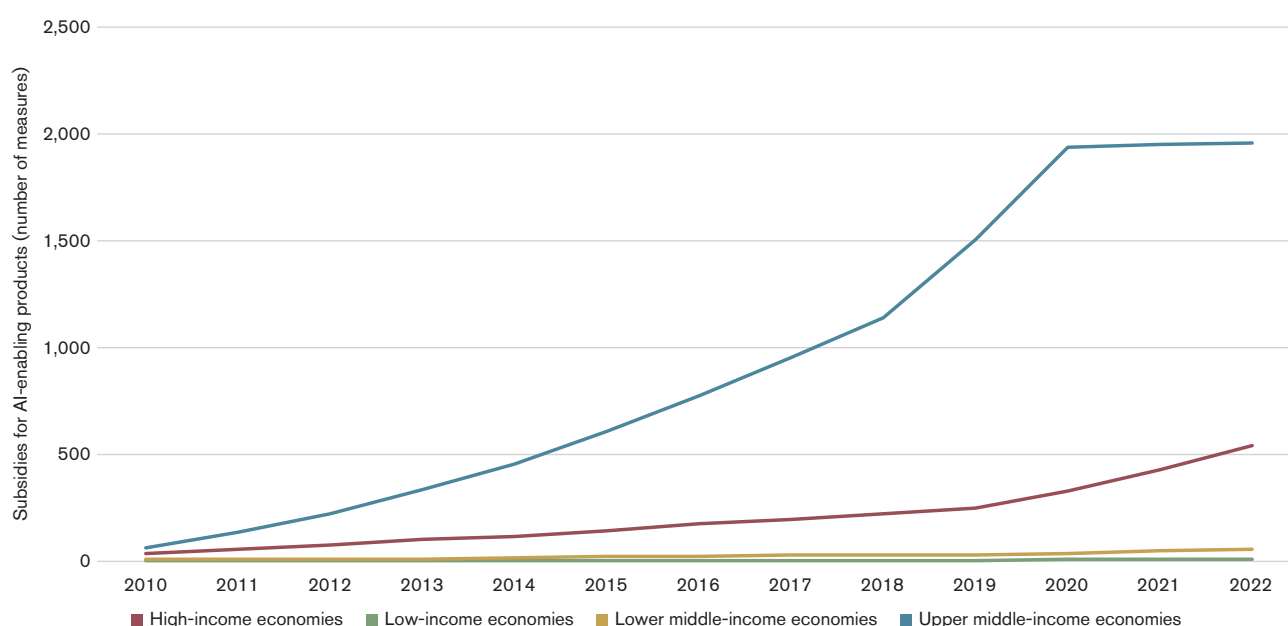
Public procurement is another major source through which governments can accelerate AI development and uptake. According to estimates, global public procurement amounts to US\$ 13 trillion per year, and in some economies, public procurement accounts for over one third of GDP, making it a key tool to 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.eu.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.