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# ARTIFICIAL INTELLIGENCE AND INTERNATIONAL TRADE

## SOME PRELIMINARY IMPLICATIONS

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# Artificial Intelligence and International Trade: Some Preliminary Implications

Janos Ferencz, Javier López-González, and Irene Oliván García

Artificial intelligence (AI) has strong potential to spur innovation, help firms create new value from data, and reduce trade costs. Growing interest in the economic and societal impacts of AI has also prompted interest in the trade implications of this new technology. While AI technologies have the potential to fundamentally change trade and international business models, trade itself can also be an important mechanism through which countries and firms access the inputs needed to build AI systems, whether goods, services, people or data, and through which they can deploy AI solutions globally. This paper explores the interlinkages between AI technologies and international trade and outlines key trade policy considerations for policy makers seeking to harness the full potential of AI technologies.

**Key words**: Trade policy, digital trade, innovations, data flows, Regional Trade Agreements

**JEL codes**: F13, F14, O33

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## Key messages

- AI innovations are taking place across many different sectors, but they are most pronounced in those sectors with strong trade exposure, suggesting strong links between trade and AI.
- AI matters for trade because it can lead to greater productivity, better supply chain management and lower trade costs. At the same time, trade, and trade policy, matter for the diffusion of AI systems because they enable access to goods, services, people and data.
- Further enabling the use of AI in international trade could be facilitated through:
  - *Easing barriers to trade in ICT goods*, including existing tariff and non-tariff barriers to trade in computers and related ICT products as well as in network equipment to facilitate access to the hardware needed to deploy AI systems. These measures remain especially high in developing countries.
  - *Providing an enabling regulatory environment for trade in services* to help with the wider adoption and deployment of AI systems. Barriers to digitally enabled services have been rising in recent years, affecting the ability of countries to take advantage of gains from digitalisation more broadly and AI more specifically.
  - *Facilitating access to human expertise*. Not all intelligence is artificial. Indeed, access to trained engineers and programmers is key for the development and deployment of AI solutions. However, barriers to the movement of professionals remain high and lowering these would facilitate the transfer of AI-related knowledge and skills.
  - *Enabling data free flows with trust*. Data is one of the main ingredients of AI systems, but the emerging patchwork of regulatory approaches to data flows risks reducing the ability to deploy AI systems globally by reducing access to data and requiring duplication of activities. More interoperable regulatory approaches that enable the free-flow of data with “trust” are needed to help reap the benefits of AI.
- *Provisions relevant to AI are appearing in regional trade agreements (RTAs)*, featuring binding commitments on data flows, provisions on privacy, prohibitions of local storage requirements and provisions related to source code and cybersecurity. New digital trade arrangements also include specific AI-related provisions recognising the importance of developing ethical governance frameworks for the trusted, safe and responsible use of AI technologies which are also reflected in international instruments such as the OECD AI Principles.
- *Applications of AI in international trade are growing.* For instance, AI powered machine translation has been proven to lower language barriers in trade, helping to foster exports, particularly for e-retailers. AI can also generate efficiencies in the logistics sector, for instance in managing smart warehouses through improved predictions and better coordination of activities within warehouses. Financial services have also benefitted from AI, including in areas such as access to credit, financial risk assessment and anti-money laundering compliance, among others.
- Overall, this work suggests that *the relationship between AI and trade goes in two directions*. On the one hand, AI has the potential to fundamentally change different aspects of trade and international business models. On the other hand, trade can be an important mechanism through which countries access the inputs needed to build AI systems and through which they can deploy AI solutions globally.

## 1. Introduction

Artificial intelligence (AI) is widely considered to be a general-purpose technology with a strong potential to spur innovation, help firms create new value from data, and reduce trade costs (Agrawal, Gans and Goldfarb, 2017[1]).[1] Broadly defined, AI is “a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy” (OECD, 2019[2]). AI uses data to train algorithms and often co-exists with software that can be embedded in hardware such as robots, autonomous cars or appliances based on Internet of Things (IoT). Examples of AI application include smart assistants, translation, self-driving cars, medical diagnosis and robotics. Today, AI is used in many sectors ranging from precision agriculture (Forbes, 2019[3]) to manufacturing (McKinsey, 2019[4]) (Li, Hou and Yu, 2017[5]) and services (Huang and Rust, 2018[6]).

Growing interest in the economic and societal impacts of AI is being matched by growing interest in the issues at the intersection of trade policy and AI (Lee-Makiyama, 2018[6]; Irion and Williams, 2019[7]; Goldfarb and Trefler, 2018[8]). While the larger regulatory and policy environment around AI (e.g. security, privacy, etc.) continues to evolve, it is important to also think about the issues that are specific to trade and AI. This is also important in the context of the current trade policy deliberations, including in the Joint Statement Initiative on e-commerce discussed at the WTO or in regional trade agreements.

Previous OECD work has outlined the profound implications that digitalisation has had for trade and market openness, as well as how policy makers approach trade in goods and services in the context of rapid technological developments (López González and Ferencz, 2018[9]). The COVID-19 pandemic further accelerated the digital transformation underscoring the importance of digital trade for mitigating the economic slowdown and speeding up recovery (OECD, 2020[10]). This paper focuses on the specific applications for AI with a view to helping policy makers better understand the benefits and challenges that AI brings for trade and to outline key trade policy considerations for harnessing the full potential of this technology.

The paper begins with a brief description of AI technologies and shows what existing data can tell us about the adoption and proliferation of AI. This is followed by a deeper discussion on the policy issues at the intersection of trade and AI: looking at what AI means for trade and what trade means for AI. Three case studies then discuss specific applications of AI technologies in international trade. The last section provides some concluding remarks.

The paper is intentionally short and focused on the broad issues that might be worthy of consideration by trade policy-makers. The field of AI is fast evolving and has many different important, and indeed contentious, facets. This paper aims to provide an initial framework for thinking about the implications of AI for trade without delving into a number of important but broader regulatory concerns which are being discussed in the context of the work of the OECD Science Technology and Innovation Directorate.

## 2. The adoption and proliferation of AI technologies

The study of AI was first established as an academic discipline in the 1950s but remained of limited interest for most of the 20th century. Basic forms of AI systems, such as pre-programmed expert knowledge solutions, have been around for several decades (Zweben and Fox, 1994[11]). However, the exponential rise in computing power in the past two decades, vastly improving communication networks and the increase in the volume of data being collected have lifted AI to the forefront of business activities and the public policy agenda worldwide.

There are two main subfields of AI, artificial “narrow” intelligence (ANI) and artificial “general” intelligence (AGI). Machine vision, speech recognition and automated translation are examples of “narrow” AI. They

[1] The term AI is used to refer to a number of technologies, including machine learning or deep learning.

cover narrowly defined tasks where AI can perform specific problem-solving or reasoning tasks that, in some cases, can outperform humans. Such “narrow” AI uses large data samples to generalise pattern recognition in images, text or language. By contrast, AGI refers to (hypothetically) advanced AI systems that can potentially go beyond specific tasks in well-defined contexts to enable autonomous learning, decision making and action-taking functions across a range of tasks that are much closer to human cognitive functions. The commercial application of AI today is ANI rather than AGI.

Machine learning (ML) is a subset of AI but with slightly different scope. ML allows machines to learn in an automated manner through patterns and inferences rather than through explicit instructions from a human (OECD, 2019[12]). ML approaches often teach machines to reach an outcome by showing them many examples of correct outcomes. However, they can also define a set of rules and let the machine learn by trial and error. Deep learning (DL) is a more advanced form of ML, based on neural networks, to approximate complex relationships by learning to classify input examples to output examples based on large quantities of training data. DL is typically applied to unstructured data such as images or voice. (OECD, 2021[13])

AI systems can be applied across a vast range of commercial activities. Some examples include:

- *Logistics*: AI systems can help optimise warehouse usage by predicting demand, organising inventories, improving efficiency across supply chains, and tracking the movement of parcels.
- *Customs*: AI is being used to read and understand descriptions of commercial goods and classify these against customs codes in the Harmonised System to help companies identify requirements related to customs procedures and duties.[2] AI is also increasingly used to identify counterfeited products.[3]
- *Transport:* AI systems are at the heart of autonomous vehicles, using complex machine learning systems to interpret road signs, read maps, and recognise and react to danger factors. In other applications, ML and human inputs are combined to optimize navigational software using real-time traffic data and historic information to predict the best route options for road users. Beyond the automotive industry, AI is also used in other transport operations, including air and maritime transport to improve scheduling, optimise use of load space and capacity, and analyse other real-time input into the transport process.
- *Financial services:* financial institutions leverage AI systems to improve financial decisions, generate efficiencies through greater automation, personalize financial services, assess credit-worthiness, detect fraud, and reduce customer service costs, among others.
- *Professional services:* Professionals such as lawyers, engineers and architects can leverage AI systems to create efficiencies in their work. For instance, “lawbots” can analyse large volumes of case law, saving crucial time for the lawyers.
- *Virtual assistants:* AI systems empower software that relies on natural language processing and can respond to spoken or written commands and questions. Virtual assistants are employed to reduce costs in consumer relations, and improve tailoring and customisation of services.
- *Marketing and advertising*: AI systems help to augment consumer experience and personalise content, while making more accurate predictions for targeted advertising for goods and services.
- *Agriculture:* AI systems can help analyse farm data in real time, predicting the consequences of weather conditions, water usage, soil health and other variable factors. This can help farmers increase crop yield and quality and identify what to plant, how, where, and when.
- *Health care:* AI systems are increasingly used in medical diagnostics, prevention of disease outbreaks, and development on new drugs, among others.

[2] See https://www.forbes.com/sites/stevebanker/2017/10/07/global-trade-is-powered-by-artificial-intelligence/.

[3] See https://www.wsj.com/articles/ai-is-a-new-weapon-in-the-battle-against-counterfeits-11596805200; https://www.researchgate.net/publication/339983307_IMPROVING_FAKE_PRODUCT_DETECTION_USING_AI-_BASED_TECHNOLOGY.

- *Language learning and automated translation*: Developments in natural language processing improve automated language learning, translation processes, and facilitate the automation of simple communications.
- *Entertainment services:* AI systems can be leveraged to improve user experience of online streaming services through better tailoring and customisation of content suggestions. Moreover, AI can also reduce poor image quality in case of increased bandwidth usage.

Although AI offers many opportunities across a range of different applications and sectors, it also raises a number of challenges, including with respect to its governance and use (for instance, potential societal, consumer or security risks). The OECD has been pioneering work in this field, helping policy-makers respond to the challenges raised by AI, including through the development of a set of AI Principles (OECD, 2019[2]). These promote the use of AI that is innovative, trustworthy and that respects human rights and democratic values. These values-based principles focus on how governments and other actors can shape a human centric approach to trustworthy AI (Box 1).[4] The OECD has also set up a platform to share and shape AI policies through the OECD AI Policy Observatory and AI network of experts (Box 2).

### Box 1. The OECD Principles on AI

The OECD Principles on Artificial Intelligence promote AI that is innovative and trustworthy and that respects human rights and democratic values. They were adopted in May 2019 and are the first such principles signed up to by governments.[5]

The OECD AI Principles set standards for AI that are practical and flexible enough to stand the test of time in a rapidly evolving field. They complement existing OECD standards in areas such as privacy, digital security risk management and responsible business conduct.

The instrument identifies five complementary values-based principles for the responsible stewardship of trustworthy AI:

- AI should benefit people and the planet by driving inclusive growth, sustainable development and well-being.
- AI systems should be designed in a way that respects the rule of law, human rights, democratic values and diversity, and they should include appropriate safeguards – for example, enabling human intervention where necessary – to ensure a fair and just society.
- There should be transparency and responsible disclosure around AI systems to ensure that people understand AI-based outcomes and can challenge them.
- AI systems must function in a robust, secure and safe way throughout their life cycles and potential risks should be continually assessed and managed.
- Organisations and individuals developing, deploying or operating AI systems should be held accountable for their proper functioning in line with the above principles.

In addition to and consistent with these value-based principles, the instrument also provides five recommendations to policy-makers pertaining to national policies and international co-operation for trustworthy AI, namely:

- investing in AI research and development
- fostering a digital ecosystem for AI
- shaping an enabling policy environment for AI

[4] See https://oecd.ai/en/ai-principles.

[5] In addition to OECD countries, Argentina, Brazil, Costa Rica, Malta, Peru, Romania and Ukraine, *inter alia*, have adhered to the OECD Principles on AI. It is expected that new countries will adhere (see also https://oecd.ai/en/ai-principles).

- building human capacity and preparing for labour market transformation, and
- international co-operation for trustworthy AI.

The instrument also includes a provision for the development of metrics to measure AI research, development and deployment, and for building an evidence base to assess progress in its implementation.

Source: https://oecd.ai/en/ai-principles

### Box 2. The OECD.AI Policy Observatory and AI network of experts

In February 2020, the OECD launched OECD.AI Policy Observatory, a platform to share and shape AI policies that provides data and multidisciplinary analysis on artificial intelligence. The Observatory provides practical guidance on implementing the OECD AI Principles and proposes an online database of AI policies that compiles relevant resources on AI topics including AI trends and data, national AI policies and initiatives, and AI research across different policy area. This database was developed jointly with the European Commission.

Also in early 2020, the OECD's Committee on Digital Economy Policy tasked the OECD.AI Network of Experts on AI with proposing practical guidance for implementing the OECD AI principles for trustworthy AI through the activities of three working groups and one taskforce on *AI Compute*. The working group on the classification of AI systems is developing a user-friendly framework to classify and help policy makers navigate AI systems and understand the different policy considerations associated with different types of AI systems. The working group on implementing trustworthy AI is identifying practical guidance and shared procedural approaches to help AI actors and decision-makers implement effective, efficient and fair policies for trustworthy AI. The working group on national AI policies developed a report titled State of Implementation of the OECD AI Principles: insights from national AI policies where it identified good practices for implementing the five recommendations to policy makers contained in the OECD AI Principles.

With the creation of a specific section for the OECD.AI Network of Experts (ONE AI) and "The AI Wonk" blog, OECD.AI has also become a space for dialogue and the sharing of ideas among AI experts from all stakeholder groups.

Source: https://oecd.ai/en/network-of-experts, www.oecd.ai/policies, www.oecd.ai/tools, www.oecd.ai/classification.

Beyond the OECD AI principles, governments are also putting in place domestic instruments that aim to set principles, guidelines, and strategies for the development of human-centric and trustworthy AI.[6] Regulatory approaches across countries and regions continue to evolve rapidly, including through new legislative initiatives that build on and further define the regulatory environment for implementing human-centric AI systems.[7] In addition, discussions are also taking place in the business community, including through the World Economic Forum (WEF).[8]

[6] On the various national AI strategies see the OECD.AI Policy Observatory's repository available at https://oecd.ai/en/dashboards. At the time of writing, the repository included over 700 AI policy initiatives across 60 countries.

[7] For instance, on 21 April 2021, the European Commission published a package of AI-related instruments, including a Proposal for a Regulation laying down harmonised rules on artificial intelligence, and updated Coordinating Plan with Member States, and a Proposal for a Regulation on Machinery Products. The proposed Regulation on AI adopts a risk-based regulatory approach that differentiates between uses of AI systems based on their risk levels. See https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A52021PC0206.

[8] See https://www.weforum.org/topics/artificial-intelligence-and-robotics.

Regulations on specific uses of AI technologies, such as autonomous vehicles or AI-powered medical systems, complement this emerging regulatory environment, often setting industry-level standards and other requirements for the implementation and use of AI systems (OECD, 2021[13]).

More specific discussions on technical standards that matter for AI, including ICT technical standards, are being developed in several international fora, such as the International Telecommunication Union (ITU), the International Standards Organisation (ISO), the International Electrotechnical Commission (IEC) or the Institute of Electrical and Electronics Engineers (IEEE). In this regard, the (ITU) has published several technical standards related to AI, including standards to provide an architectural framework for the integration of machine learning into 5G and future networks,[9] a framework to evaluate intelligence levels across different parts of the network[10] and a framework for data handling in support of ML.[11] ISO/IEC is also currently developing standards on specific aspects of the AI lifecycle, including ML classification, quality of data, explicability of ML and controllability of automated AI systems, to cite just a few.[12] The OECD has also been playing a role in facilitating trust for trade in agricultural products through international codes and standards. As AI has the potential to improve precision agriculture machines, standardised testing and certification procedures will be key in promoting the use of AI, for instance in the context of autonomous agricultural and forestry tractors (OECD, 2021[14]).

As countries grapple with different aspects of the technology, the proliferation of national and international regulatory instruments on AI is likely to rise in the near future. This also raises questions about the relationship between regulation and innovation.[13] Finding a balance between promoting innovation and ensuring that it is undertaken with appropriate regulatory oversight can be difficult. It will be important that reforms aim to help ensure that regulations remain responsive to changes in AI technologies, promoting the economic and social benefits of such technologies while minimising their risks. Effective cooperation between regulators and innovators will be key in this regard.

Moreover, as new regulations on AI continue to be adopted, it will be important to limit regulatory fragmentation across countries that could increase the costs of trade for AI businesses. Indeed, future domestic regulations aimed at setting standards for AI could consider and prioritise the adoption of international standards to enable easier use of AI across countries.[14] In addition, policy experimentation through regulatory sandboxes promote the flexible application or enforcement of policies that could provide the basis for knowledge sharing among countries, and identification of best practices (Attrey, Lesher and Lomax, 2020[15]).

## 2.1. Firms that develop AI solutions are concentrated in the ICT sector across developed and emerging economies

Measuring advances and developments in AI technologies, including in the context of adoption and use, is difficult. A number of methodological challenges emerge, including related to how best to define the technology for statistical purposes (Montagnier and Ek, 2021[16]).[15] Although new data gathering efforts

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**9** Architectural framework for machine learning in future networks including IMT-2020 (ITU-T Y.3172 (06/2019)) https://www.itu.int/ITU-T/recommendations/rec.aspx?rec=13894&lang=en

10 Framework for evaluating intelligence levels of future networks including IMT-2020 (ITU-T Y.3173 (02/2020) https://www.itu.int/ITU-T/recommendations/rec.aspx?rec=14133

11 Framework for data handling to enable machine learning in future networks including IMT-2020 (ITU-T Y.3174 (02/2020)). https://www.itu.int/ITU-T/recommendations/rec.aspx?rec=14134.

12 https://www.iso.org/committee/6794475/x/catalogue/.

13 There is a longstanding literature on the impact of regulation on innovation. See (Blind, Petersen and Riillo, 2017[54]) or more recent empirical evidence from France in (Aghion, Bergeaud and Van Reenen, 2021[55]).

14 See also Principle 2.5 of the OECD AI Principles: “Governments should promote the development of multi-stakeholder, consensus-driven global technical standards for interoperable and trustworthy AI”, available at: https://oecd.ai/en/dashboards/ai-principles/P14.

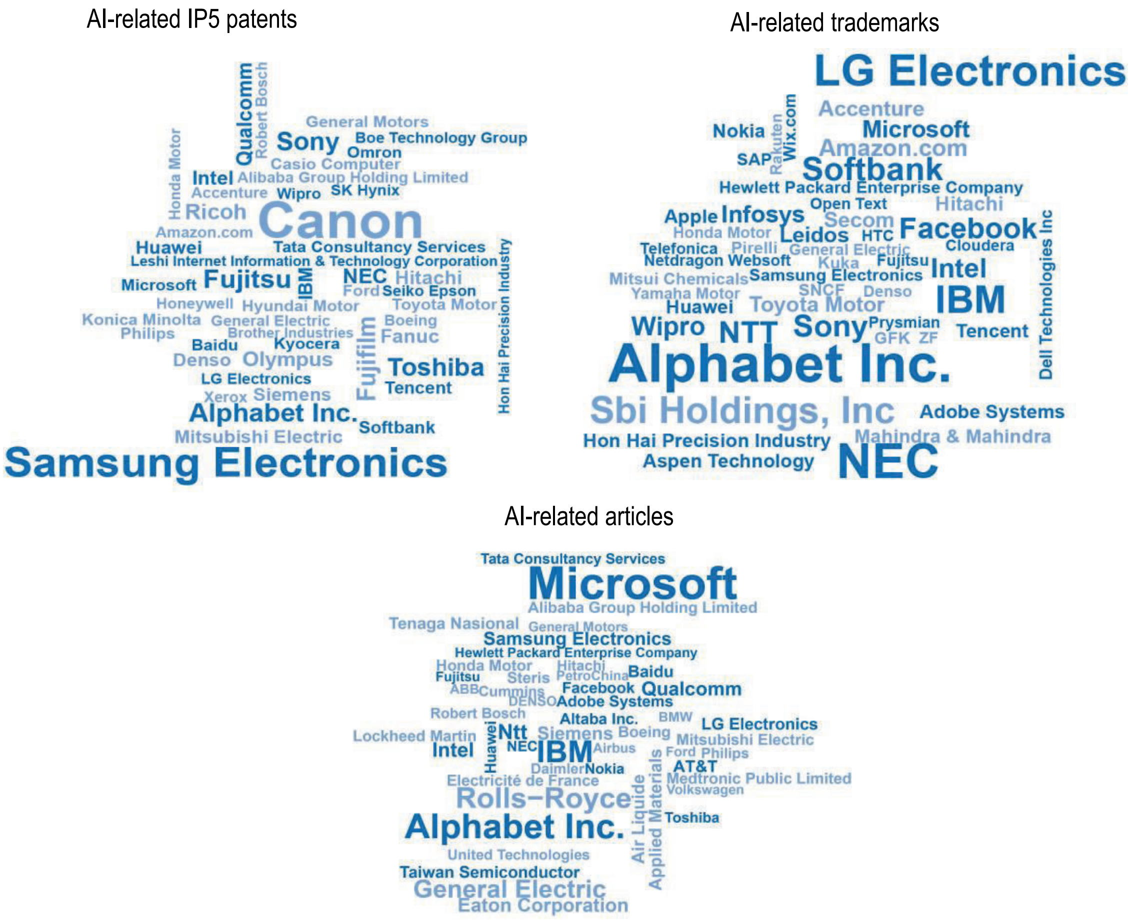
15 Statistical agencies have started using generic definitions of AI in the context of efforts to improve the coverage of AI-related technologies in existing statistical surveys. For instance, Eurostat defines AI as “systems that use technologies such as: text mining, computer vision, speech recognition, natural language generation, machine

are underway (e.g. OECD AI Policy Observatory),[16] measurement efforts remain in their infancy, making it difficult to get a clear picture of ongoing adoption. That said, insights can be gleaned from existing indicators on AI-related patents, trademarks, and scientific publications (Baruffaldi et al., 2020[17]). Patents and trademarks in this section cover items that are relevant when using AI but that are not specific to AI only.

Companies in the ICT sector are the most prominent players in AI innovations (patent, trademarks and publications), although other companies, for instance in the automotive sector, also appear active (Figure 2.1). Most of these are large companies headquartered in the United States, Japan, Korea or China. Companies based in Europe feature more prominently in AI-related scientific publications than in patents or trademarks.

## Figure 2.1. Top innovators in Artificial Intelligence, 2014-16

Top 50 companies with IP5 patent applications, AI-related trademarks, and AI-related publications




Note: ICT-related companies are shown in darker blue.
Source: JRC-OECD, COR&DIP© database v.2., 2019. (Dernis H., 2019[18]).

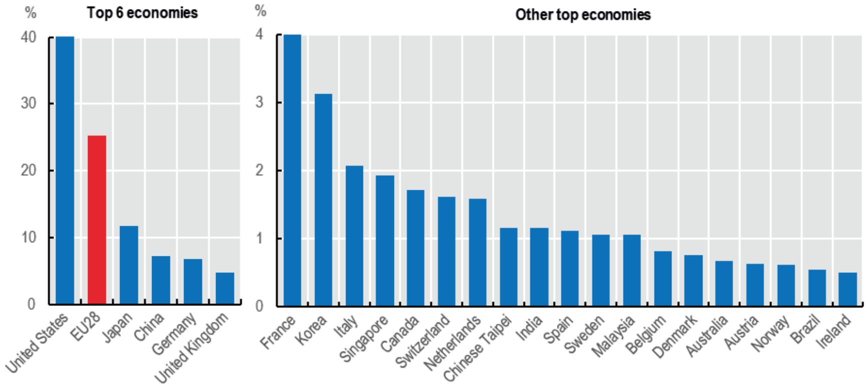
learning, deep learning to gather and/or use data to predict, recommend or decide, with varying levels of autonomy, the best action to achieve specific goals". Statistics Canada refers to AI as "systems that display intelligent behaviour by analysing their environment and taking actions – with some degree autonomy – to achieve specific goals. AI-based systems can be purely software-based or embedded in a device." Israel's Central Bureau of Statistics refers to AI as "activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment." See also (Montagnier and Ek, 2021[16]).

[16] See https://oecd.ai/en/data-from-partners?selectedArea=ai-research.

The geographical concentration of AI activities is also apparent from data on publications by R&D investors according to the author's affiliation (Figure 2.2). Indeed, the United States, European Union and Japan occupy 75% of the share of top performers, with very few entries for developing or emerging countries.

### Figure 2.2. AI related publications by country of author affiliation, 2014-2016

Share of total publications by world's top R&D investors, by author's affiliation location, 2014-16



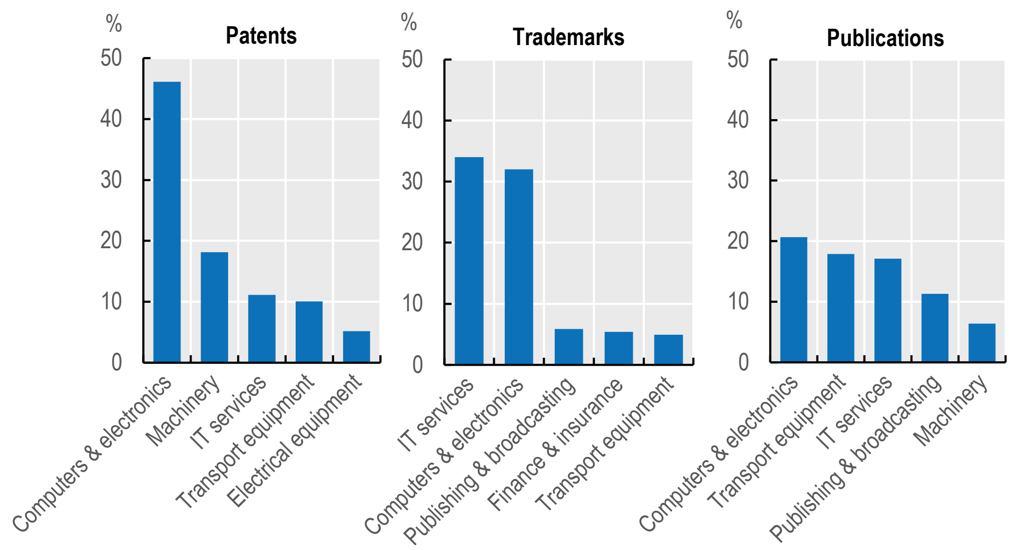

Note: Data relate to economies with over 1 000 publications by the top 2 000 corporate R&D sample in 2014-16.
Source: JRC-OECD, COR&DIP© database v.2., 2019.

## 2.2. Advances in AI are most prominent in highly tradable sectors

Almost 91% of AI-related patent filings are concentrated in five sectors, of which close to half are filed in "Computer and electronics". The remaining are filed in the "Machinery", "IT services", "Transport equipment", and "Electrical equipment" sectors (Figure 2.3). AI-related trademarks are also highly concentrated, with the top five sectors representing 82% of total AI-related trademark registrations, and "IT services" and "Computer and electronics" jointly accounting for about 70%. Indicators based on scientific publications related to AI are somewhat less concentrated but identify a similar pattern, with most publications in "Computer and electronics", followed by "Transport equipment" and "IT services". Jointly, these represent close to 60% of all AI-related publications.

### Figure 2.3. Top 5 sectors in Artificial Intelligence, 2014-2016

Share in total AI-related patents, trademarks, and publications

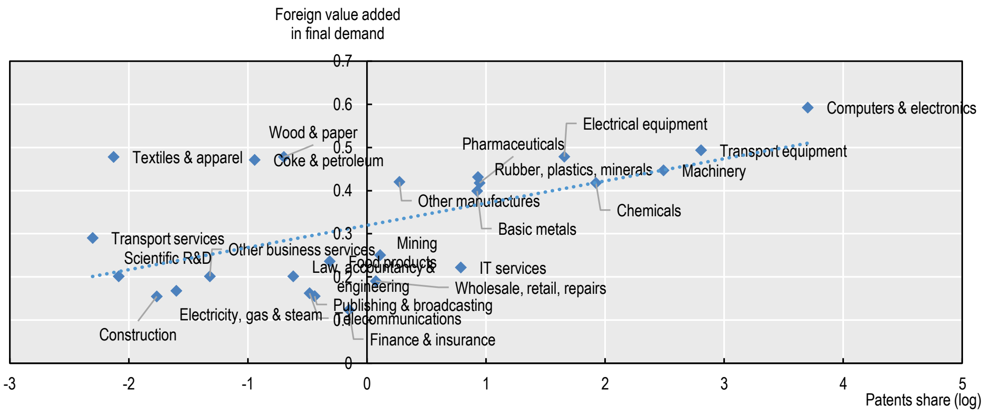



Note: Classification based on ISIC Rev. 4.
Source: JRC-OECD, COR&DIP© database v.2., 2019. Dernis (2019[18]).

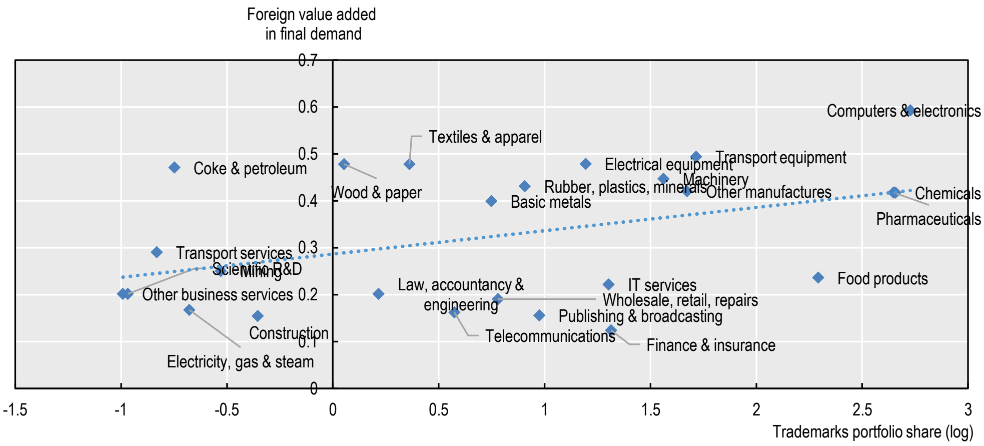
Many of these sectors are strongly embedded in international trade and global value chains (GVCs). Indeed, whether patents, trademarks or publications, the higher the foreign value added content of final demand, a proxy measure for a sector's foreign exposure, the higher the levels of innovation in AI (Figure 2.4). This relationship also holds for investment in AI. That is, more tradeable sectors are those that invest most in AI (Figure A1). The data therefore suggest that AI innovation and investment are highly correlated with trade.

## Figure 2.4. AI innovations are highest in more tradable sectors

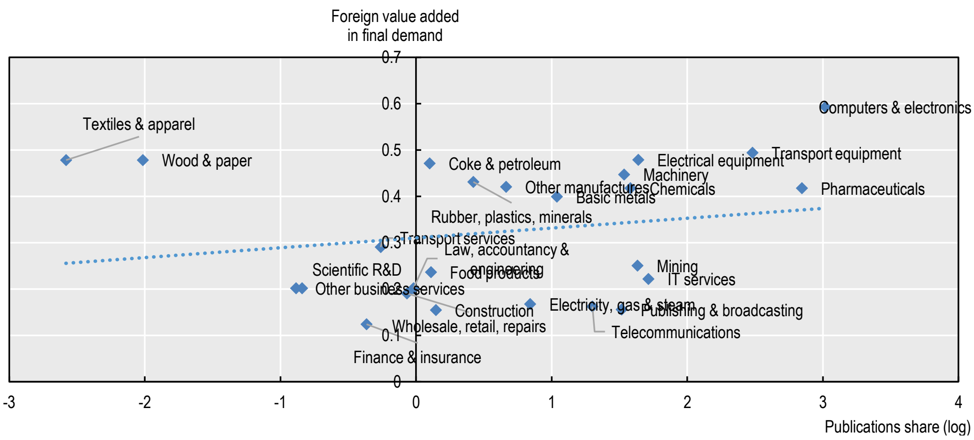
a. Patents




b. Trademarks




c. Publications




Note: Foreign value added in final demand captures the share of value added in the production of a particular sector that comes from foreign sources. It is calculated from the OECD TIVA database for the year 2015 Data on patents, trademarks and publications are for the year 2016.
Source: Own based on TiVA (2018) and JRC-OECD, COR&DIP© database v.2., 2019. (Dernis H., 2019[18]).

# 3. AI and international trade

## 3.1. Why does AI matter for trade?

While AI technology is still evolving and subject to limitations, it has the potential to enhance international trade in various ways. One is through increases in the *productivity* of adopters, which is associated with greater benefits from trade through exports.[17] However, empirical evidence on the links between AI and productivity is only just emerging.[18] While there is a deepening and broadening use of AI technologies in specific companies and sectors, especially data-intensive sectors such as finance, insurance and on-line consumer platforms, on aggregate, the benefits of transformative technologies like AI remain elusive in the productivity statistics. This has been referred to as the “modern productivity paradox” (Brynjolfsson, Rock and Syverson, 2017[19]).[19]

Potential explanations behind this paradox include false hopes, mismeasurement, redistribution and implementation lags. Brynjolfsson, Rock and Syverson (2017[19]) suggest that the latter might be the biggest contributor to the lack of evidence on improved productivity, and thus positive effects are expected to appear once AI capabilities are diffused more widely and complementary innovations are developed and implemented.

Another channel contributing to enhancing trade relates to the potential for AI to enable greater *supply chain efficiency* (Meltzer, 2018[20]). This includes more streamlined and automated ‘smart’ manufacturing; improved predictions about consumer demand; and better decision-making about the location of production. AI has also the potential to help with other policy objectives such as lowering greenhouse gas emissions in supply chains by optimising logistics operations (Tsolakis et al., 2021[21]). Adoption of AI can therefore enable firms to reduce production costs and to be more nimble in responding to changes in consumer demand.

AI also promises to *reduce trade costs*. This can arise partly through greater logistical efficiency but also by better connecting supply and demand and reducing language barriers. Use of AI in customs and other border agencies for trade facilitation may also contribute to further trade cost reductions arising at the border (WCO, 2019[22]). More concrete case studies on how AI can affect trade are provided in Section 4.

## 3.2. Why does trade matter for AI?

Trade also matters for the wider adoption of AI technologies, interacting with different elements of an AI system’s lifecycle. Recent OECD work identifies four separate phases in an AI system’s lifecycle (OECD, 2019[12]):

- *Design, data and modelling* including the planning and design of an AI system, data collection and processing, as well as model building and interpretation.
- *Verification and validation* including executing and fine-tuning models.
- *Deployment* into live production, including piloting, compatibility assessment, ensuring regulatory compliance, managing organisational change, and evaluating user experience.
- *Operation and monitoring,* including continuous monitoring of outputs in light of the desired objectives.

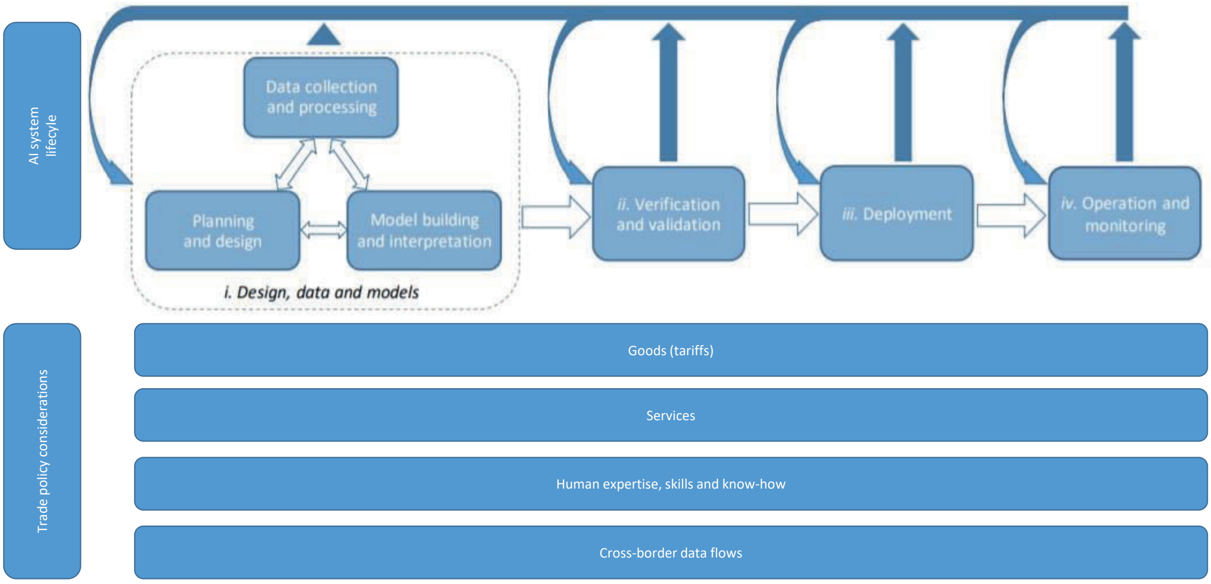
[17] It is well established that firms that are more productive are better able to face the costs associated with exporting (see Melitz and Redding, 2013)

[18] While there is growing case-by-case evidence highlighting the importance of AI for productivity, there are very few studies that rely on larger populations of firms. While the field is advancing quickly – the National Statistics Offices are putting AI modules in the field – in much work, AI is proxied by other digital technologies.

[19] Referring back to the Solow Paradox in 1987 which was that “You can see the computer age everywhere but in the productivity statistics”.

Trade, and by extension, trade policy, can play an important role in each phase through facilitating access to goods, services, people and data (Figure 3.1). Other policy disciplines, such as the protection of intellectual property rights or international standards, would also be of importance.[20]

### Figure 3.1. Illustrative examples of the policy intersections between an AI system lifecycle and international trade




Note: The figure represents a non-exhaustive illustrative examples of some of the key intersections between AI systems and trade.
Source: Authors' elaboration based on OECD (2019[12]).

Tariffs on ICT equipment are likely to affect access to, and cost of, essential hardware, as well as the price of final consumer goods, including devices. Services are fundamental to the development and use of AI; firstly, due to the role that ICT services such as telecommunications and computer services play in establishing the communication networks needed to develop AI systems, and secondly, due to the opportunities that services markets present as channels to monetise AI technology (e.g. improving existing services and providing the basis for new ones).

In a knowledge intensive field such as AI, specialised expertise will be needed to design the models and algorithms driving AI system's operational logic. Enabling the movement of experts across countries could therefore help increase access to the best data scientists. Additionally, issues related to the *movement of data*, the raw input into all AI systems, will be of key importance.

Other trade policy areas will also play a role, often in a more overarching horizontal manner. For instance, since training data for AI models needs collecting, copying and editing, clarity on regulations related to intellectual property rights (IPR), notably copyright, protection and enforcement will be essential. As training datasets are organised and processed, existing rules related to the protection of databases could also play a role. In addition, existing IPR protection and enforcement regimes related to copyrights, patents, and trade secrets will remain relevant to protect AI innovations. The software or computer programme behind an AI will most often be protected under copyright law. Patents will be relevant to protect AI inventions that provide a novel product or process, although they may be less relevant for protecting software (Gonzalez, 2006[23]). Regulations related to trade secrets may offer further protection for AI in certain cases, notably for information that is secret, that has commercial value because it is secret and

[20] See also the recent report on the state of implementation of the OECD AI Principles for further information on progress in other policy areas (OECD, 2021[13]).

that has been subject to reasonable steps to keep it secret.[21] The protection of trade secrets prevents the unauthorised use or disclosure of the protected information. Moreover, trade secrets would generally have a broad subject matter scope that could provide protection against unlawful misappropriation of AI innovations that otherwise would fall outside the ambit of copyright or patent protection.

## 3.3. Trade measures affecting AI deployment

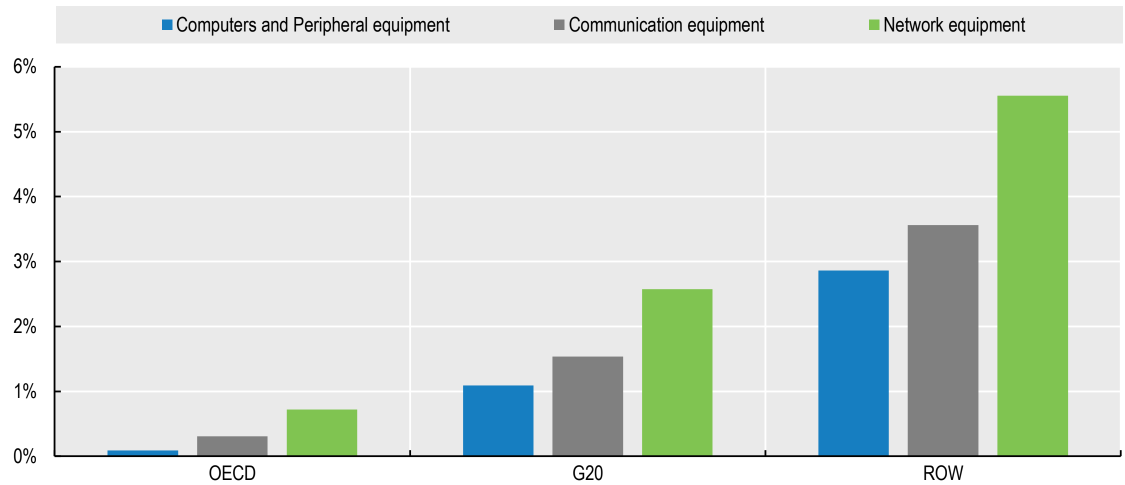
### *3.3.1. Easing barriers to trade in goods can foster the deployment of AI systems*

The successful development, deployment and implementation of AI systems hinges on access to hardware, including high performance computing equipment, data sensors, communication units and adequate network equipment to ensure seamless information flow and interlinkages between units in the AI system.

ICT equipment are among the most highly traded goods, with most manufacturing concentrating in a few Asian countries, notably China. Tariffs imposed at the border can increase costs and act as a deterrent for AI adoption, especially for countries without domestic substitutes for these goods. While on average, tariffs for ICT equipment tend to be low (Figure 3.2), the hardware used for AI is very specific and can be more expensive than ordinary computing hardware due to the high performance components on which it relies. Thus, even relatively low tariffs can lead to substantial increases in prices of specialised AI-related ICT equipment. At the same time, higher prices on devices through which AI solutions are deployed, from smart phones to smart speakers and laptops, can lead to higher costs for consumers, affecting demand for AI solutions.

Tariff rates vary across regions but are highest in developing countries (Figure 3.2.), many of which do not participate in the WTO Information Technology Agreement (ITA). This constitutes an obstacle for the adoption of AI technologies via trade by these countries and also for the development of their own AI capacity. This might be especially important in the context of leveraging AI for development (International Finance Corporation, 2020[24]) and to help developing countries rebuild after the pandemic (see (Sonneborn and Graf, 2020[25]).

**Figure 3.2. AI-related ICT equipment are subject to varying degrees of tariffs**




Note: Simple average applied tariffs for the years 2017-2018 for 133 countries. G20 grouping includes OECD countries. 'ROW' refers to 'Rest of the World'.
Source: TRAINS and WTO-IDB databases. See also, OECD (2020[10]).

[21] Article 39 of the WTO Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS).

### 3.3.2. Lowering trade restrictions for services matters for AI systems

Services have been instrumental in the digital transformation of modern economies. Telecommunications services, for instance, provide the backbone upon which digital networks are built and computer services provide the software that gives meaning to communication on these networks. Transport, logistics, distribution and courier services are instrumental for efficient e-commerce activities (trade in parcels), while financial services enable secure transactions for online purchases. Most services can now be partially or wholly traded on digital networks, and AI systems are increasingly becoming a component in either the input or output of services (see examples of services activities using AI discussed in Section 2 above).

The adoption of AI technologies can be significantly accelerated through an enabling trade regulatory environment that facilitates market access and foreign investment related to new technologies, limits undue barriers on the uptake and use of AI, and safeguards competition and a level playing field in the market. At the same time, barriers to trade could significantly slow down this process.

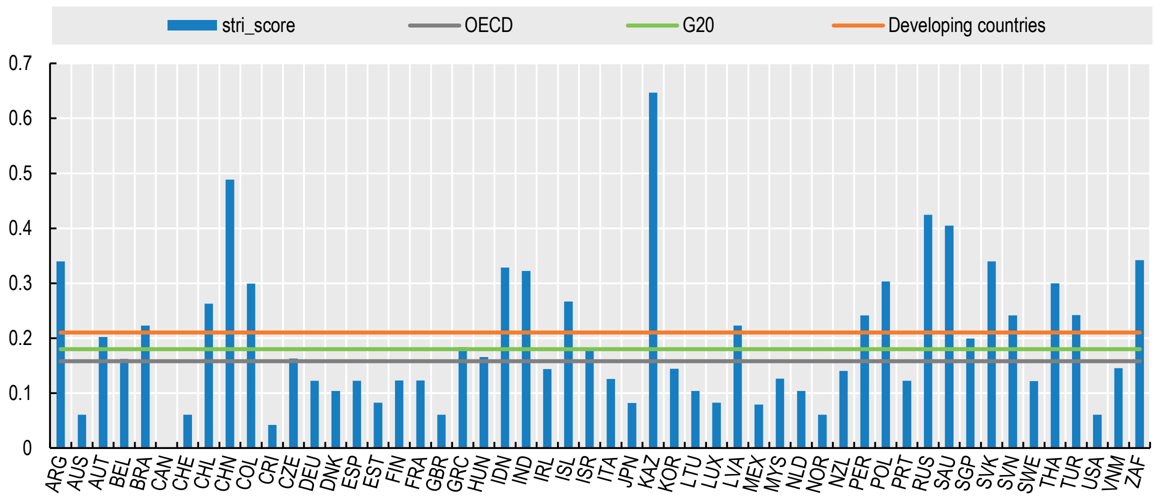
On the international level, existing services commitments under the WTO General Agreement on Trade in Services (GATS) or regional trade agreements apply in a technologically neutral way, meaning that such commitments would be relevant when AI solutions are used for the provision of services.

With respect to the applied regulations on a domestic level, evidence from the OECD's Services Trade Restrictiveness Index (STRI) and Digital STRI suggests that there is room for improving the global regulatory environment by lowering existing barriers (Figure 3.3.), especially in communication infrastructure and data connectivity where they are highest (Figure 3.4). This is especially important for developing countries which tend to have higher barriers, presenting challenges for accessing AI technologies via trade and for deploying their own domestic AI solutions.

The global regulatory environment for digitally enabled services trade has increasingly become more restrictive over the past years (Figure 3.5), particularly in service sectors that are at the frontier of the digital transformation, such as telecommunications and computer services, but also beyond in sectors such as financial services, transport and distribution services (OECD, 2021[26]).

## Figure 3.3. Easing regulatory barriers could help foster the uptake of AI technologies

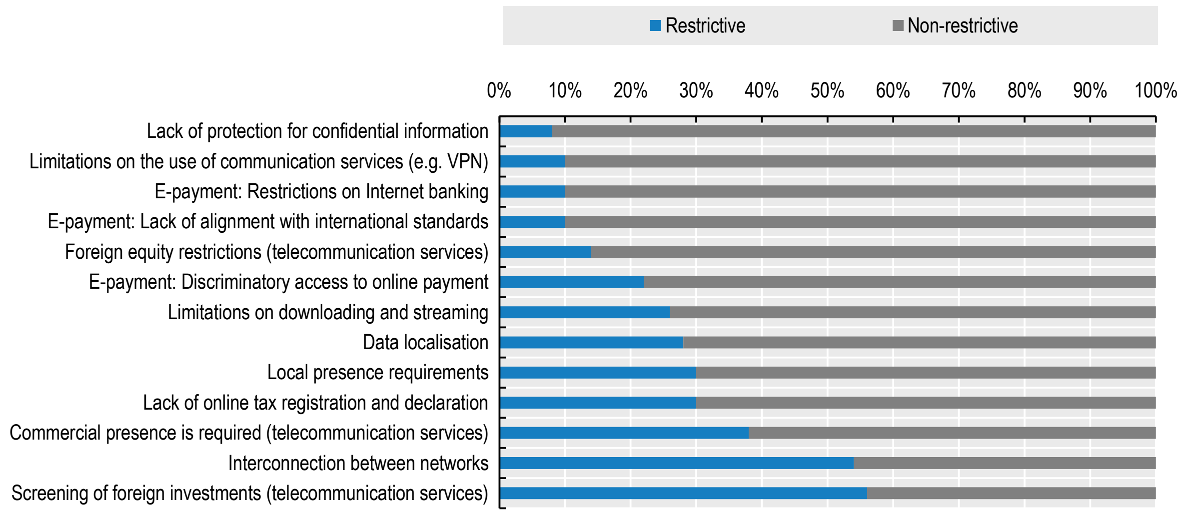
OECD Digital STRI, 2021




Note: The DSTRI values range between 0 and 1, where 1 represents the most restrictive regulatory environment for digitally enabled services. The figure shows developing countries as covered in the DSTRI.
Source: OECD STRI database, 2020.

### Figure 3.4. Regulatory measures affecting digital trade are likely to affect the deployment and use of AI

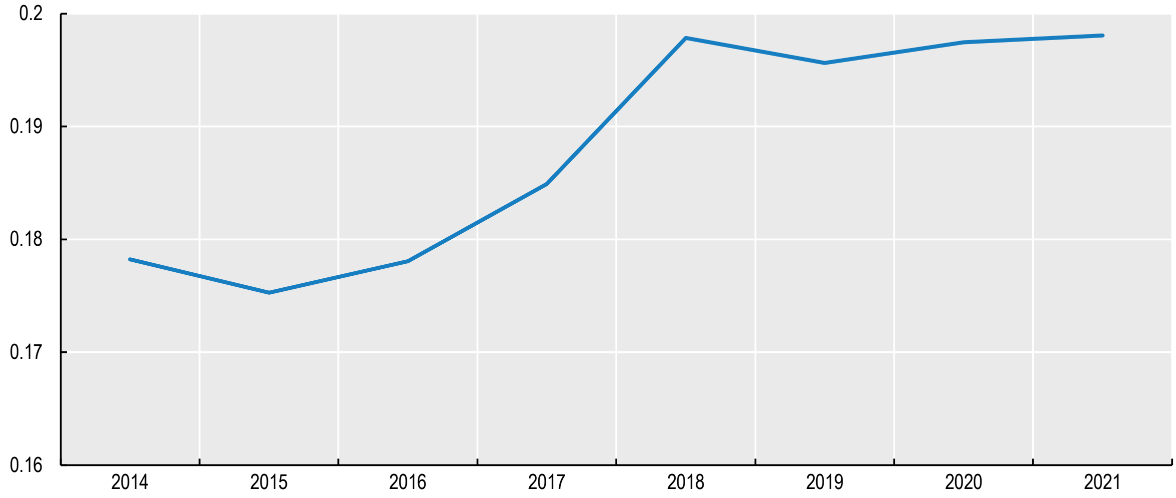
Distribution of answers in selected measures of the OECD Digital STRI and telecommunications services STRI, 2021




Source: OECD STRI database, 2021.

### Figure 3.5. Evolution of global regulations affecting digital trade

Changes in the Digital STRI averages over time, 2014-2021




Source: OECD Digital STRI Database, 2014-2021.

### *3.3.3. Not all intelligence is artificial: Trade is a conduit for the transfer of skills, human expertise and knowledge*

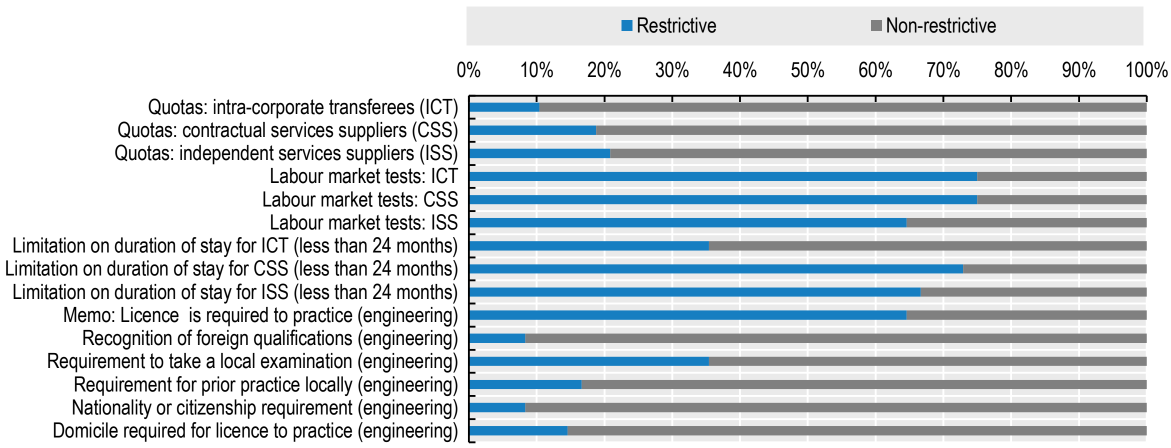
Much of the physical infrastructure and computing capacity can be purchased through cloud services today, but building AI capability relies heavily on employing the right AI expertise (Goldfarb and Trefler, 2018[8]). While knowledge-sharing services can more easily be delivered over digital networks, the technical know-how, installation, and maintenance of AI systems often requires the physical presence of professionals in the country where the AI systems will operate.

Common professions related to AI include computer or software engineering, specialists in robotics, program developers, cloud solution architects, digital security experts and data scientists. Some of these are also regulated professions (e.g. certain computer engineering activities) and thus obtaining a license is required for professionals to practice in a large number of countries. Increasingly, voluntary certifications for AI engineers are becoming available. These attest professional aptitude for a range of skills related to AI systems.[22]

Trade policy, along with migration policy, plays a substantial role in enabling the cross-border flow of AI talent, skills and knowledge, especially for developing countries, and could facilitate the cross-border movement of AI professionals by eliminating existing barriers (Figure 3.6). Technical experts usually travel to the client's home country, either as a self-employed professional providing tailored services on their own, or as part of contracted services from a foreign firm where the professional is employed. While the COVID-19 pandemic facilitated remote working, including for certain professions related to AI, highly skilled AI talents are mostly hired from abroad and thus will be affected by migration and entry policies. Evidence shows that entry conditions for AI professionals remains affected by barriers such as requirements to demonstrate the lack of suitable local labour supplies and burdensome application procedures (Figure 3.6). Short permitted duration of stay for professionals can also be an issue, especially for longer and more complex projects. Where a license is required for AI-related engineering professions, recognition of foreign qualifications and easing requirements related to local qualifications (e.g. on local examinations) would be key factors in enabling easier market access in the destination country.

## Figure 3.6. Trade measures affecting the movement of AI professionals

Barriers on the movement of people in the STRI for computer and engineering services, 2021




Source: OECD STRI Database, computer and engineering services, 2021.

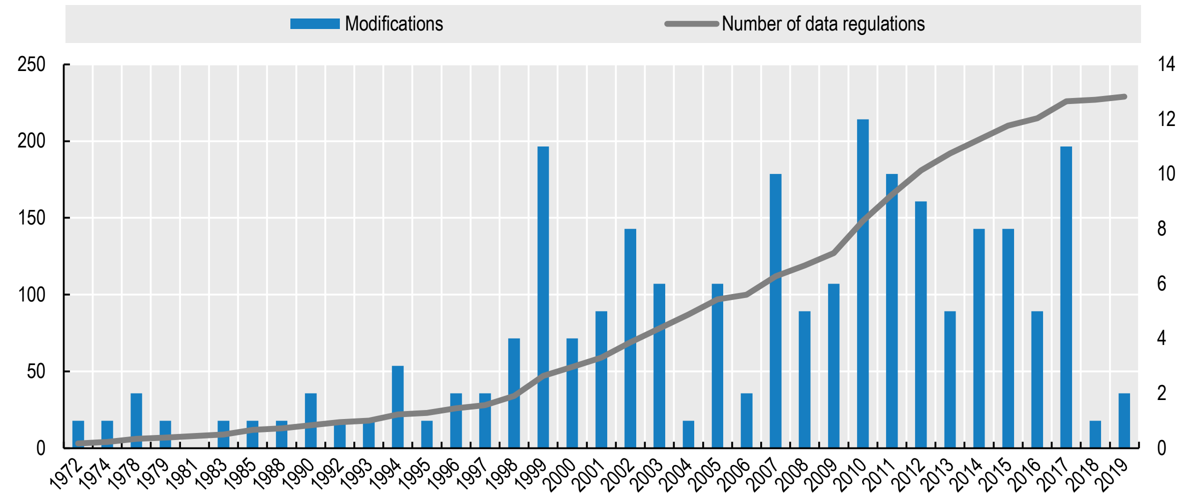
### *3.3.4. Data, a key ingredient for AI systems*

Data is one of the main inputs into AI systems. Indeed, "companies that have more observations will generate more accurate predictions" (Goldfarb and Trefler, 2018[9]). Beyond the volume of data, veracity and variance are also key (Box 3). AI systems are data hungry and access to larger and more varied datasets often involves gathering data from a number of countries, in turn, raising issues related to cross-border data flows (Lee-Makiyama, 2018[6]).

[22] For instance, see the Artificial Intelligence Engineer Certification from the Artificial Intelligence Board of America (ARTIBA): https://www.artiba.org/certification/artificial-intelligence-certification

However, the emerging landscape as it relates to data and, in particular, cross-border data flows, is becoming increasingly complex. Concerns about privacy protection, cybersecurity, national security, regulatory reach, competition and industrial policy have led to growing data regulation which either conditions the transfer of data abroad or which mandates that data is stored domestically (Casalini and López González, 2019[27]) (Figure 3.7).

## Figure 3.7. Regulation affecting the movement of data across borders is on the rise



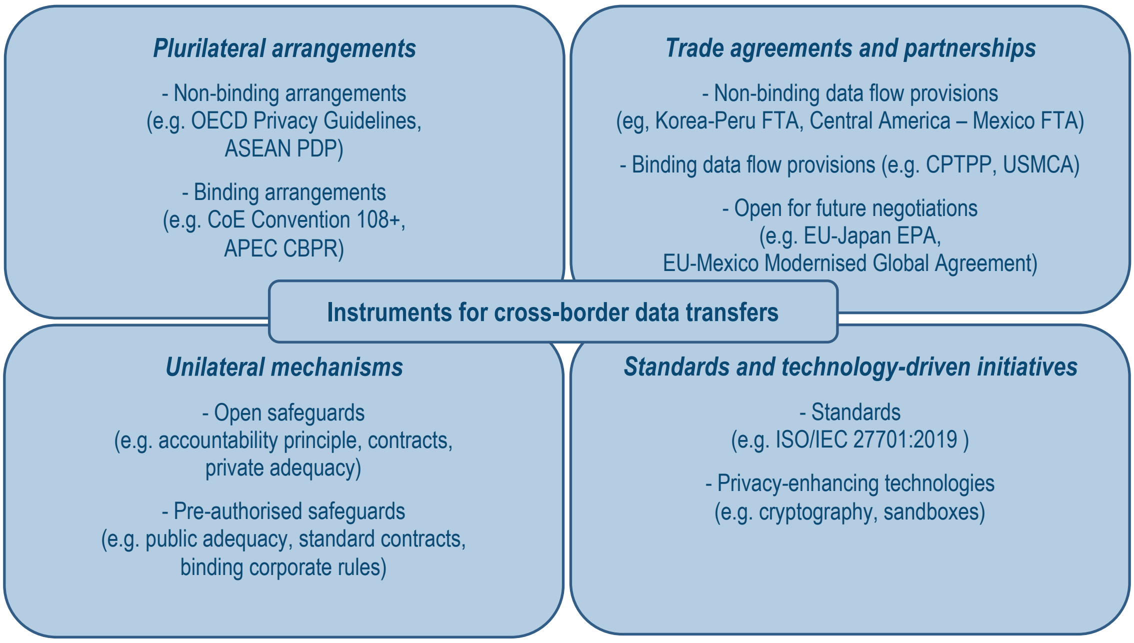

Source: Casalini and López González (2019[27]).

While there are legitimate reasons for cross-border data regulation, the existing diversity of approaches (Casalini, López González and Nemoto, 2021[28]) will affect the ability of firms to access the data they need to efficiently deploy AI solutions.[23] In some cases, it will imply duplicating activities across different regions. Beyond higher costs for firms, this may also mean lower precision of AI systems, owing to limited access to bigger and more diverse datasets.

More fragmented cross-border data regulation risks stalling the delivery of the promised benefits of AI, including, but not limited to, those related to trade. Existing instruments can play an important role in facilitating transfers and promoting interoperability amongst different regulatory approaches. Indeed, building on "commonalities, complementarities and convergences" (Casalini, López González and Nemoto, 2021[28]) across a range of existing instruments – from unilateral approaches, to plurilateral arrangements and trade agreements – may enable more interoperable combinations of data free flows with "trust" which would be more conducive to more efficient AI deployment (Figure 3.8).

[23] That said, new developments in federated learning techniques (Bonawitz et al., 2019[51]) may reduce the issues associated with cross-border data flows. These enable actors located in different places to develop machine learning models without having to share data. It is the algorithm that moves, not the data.

## Figure 3.8. Existing instruments for facilitating cross-border data transfers




Source: Casalini, López González and Nemoto (2021[28]).

### Box 3. The economics of data and AI

Data is the lifeblood of AI systems. It is the raw material on which algorithms are trained to perform narrowly defined tasks. By itself, data is useless. It only becomes valuable when it is processed using a combination of software, hardware and expertise to inform or automate action.

Data is also different. Unlike 'traditional goods', data is non-rivalrous. This means that the consumption by one user does not reduce the ability of another to use that same data. If a particular unit of data can be used by a number of users for a number of purposes without being depleted, then it can support many different value-generating activities. This implies strong economies of scale and scope when data can be shared, including across borders.

However, the characteristics of data matter. While more data can mean more precise recommendations, there are diminishing returns to data (Bajari et al., 2018[29]). Volume is not all, variance matters too. Goldfarb and Trefler (2018[8]) provide an example of how Google's search engine can outperform Microsoft's due to wider access to rarer queries. At the margin, the variance in the data and, in particular, its ability to capture more rare events are also important for making better predictions.

There are also important positive feedback loops, or network effects to data. That is, more and better data can attract more customers, in turn generating more data.

Overall, the economics of data for AI imply that there are considerable economies of scale and scope from being able to access large volumes of data from different sources. From a global welfare perspective, unrestricted access to more data would support more competition and greater economic gains for consumers. However, this can also lead to greater misuse of data. This is why policies that can promote greater use and re-use of data, including across borders, but which also enable data to be safeguarded against abuse are needed.

## 3.4. Provisions in RTAs and emerging digital trade agreements relevant for AI systems

The regulatory landscape for digital trade is becoming increasingly complex (Nemoto and López-González, 2021[30]), including in the context of provisions in regional trade agreements (RTAs) with potential impacts on the development and diffusion of AI systems.[24]

For instance, trade agreements are increasingly including provisions on *data flows*. As of June 2021, according to the updated TAPED dataset (Burri and Polanco, 2020[31]), 32 agreements (out of 188 agreements in the dataset) included some form of data flow provision.[25] However, not all provisions have the same depth – only 40% have binding (hard) commitments on enabling data flows (of all types of data).

Provisions regarding the *protection of personal information and privacy* are also widely included in RTAs, with potential implications for how and what data can be used in AI systems. Indeed, the TAPED database identifies 93 agreements that include provisions on data protection. Among these, 17 agreements recognise principles such as security safeguards, transparency and accountability with respect to personal data. Moreover, 39 agreements also recognize international standards in the area of data protection. For example, the United States–Mexico–Canada Agreement (USMCA) refers to the APEC Privacy Framework and the Singapore-Australia FTA (SAFTA) to the APEC Cross-border Privacy Rules System (CBPR System). Both these agreements also mention the OECD Privacy Guidelines as references that parties should take into account in the development of legal frameworks for personal information protection.

A number of RTAs (17 in all) include binding commitments regarding the prohibition to subject market access to the location of computing facilities in the country (also known as **data localisation**). Data localisation can potentially force companies to duplicate activities, raising the costs of operating centralised AI systems. Some agreements include this commitment, although it remains subject to the application of general exceptions,[26] while others explicitly include exceptions to achieve a legitimate public policy objective, provided that the violating measure is non-discriminatory and least trade restrictive.[27]

The *cybersecurity* aspects of AI are also increasingly important, particularly as AI applications grow.[28] Cooperation in this area is extensively covered in RTAs. To date, 46 agreements include provisions on cybersecurity, usually comprising cooperation activities, such as building capabilities of national entities, or using existing cooperation mechanisms to identify and mitigate malicious intrusions or dissemination of malicious code affecting the electronic network of the parties.[29]

Protecting the AI algorithm when trading AI products in international markets will also be key. In this regard, 11 RTAs currently include commitments not to require the transfer or access to source code of software as a condition for market access. This provision shall not, however, preclude a regulatory body or a judicial authority for requiring access in the context of a specific investigation or judicial procedure.[30] Some agreements include specific details regarding the scope of this commitment, such as the CPTPP that limits its application to mass-market software or the Singapore-Australia FTA (SAFTA) where the parties agree to extend any new obligations undertaken in a future RTAs on source code disclosure to algorithms

[24] Extensive analysis exists on e-commerce provisions in RTAs (see for example, Burri and Polanco (2020[31]), Monteiro and The (2017[47]), Nemoto and López-González (2021[30]). This section focuses on those provisions closely related to the development and diffusion of AI systems.

[25] The TAPED database includes a number of agreements with relevant provisions for digital trade and e-commerce, including the EU-UK Trade and Cooperation Agreement. It does not include a range of more recent digital economy agreements signed by the United Kingdom at the end of 2021 and beginning of 2022.

[26] For an example of this provision, see Article 32.1(2) of USMCA that covers Article 19.12 of the USMCA.

[27] For an example of this exception, see Article 14.13 of the CPTPP, Article 24 of Chapter 14 of the Singapore-Australia FTA or Article 13.12 of the Australia-Peru FTA.

[28] Analysis of the multifaceted relationship between cybersecurity and AI are beyond the scope of this paper.

[29] Examples of this type of provisions include Article 19.15 of the USMCA, Article 14.16 of the CPTPP or Article 9 of the ASEAN-Australia-New Zealand FTA.

[30] For example, see Article 19.16 of the USMCA or Article 8.73 of the EU-Japan FTA.

expressed in source codes.[31] This extension is particularly important for AI as some AI algorithms are not source code and may therefore be excluded from this protection. Trade secrets is another legal mechanism to protect AI algorithms. In this regard, 70 agreements include binding provisions on the protection of *trade secrets*.[32]

Applying a moratorium on customs duties for electronic transmissions is also an important element enabling digital trade (Andrenelli and López González, 2019[32]), and thus will also be relevant when cross-border activities involve AI solutions. Since 1998, WTO Members agreed on a moratorium on applying customs duties on electronic transmissions, which has been regularly extended, most recently at the General Council Meeting in December 2019, where it was extended until the next WTO Ministerial Conference. Moreover, 56 WTO Members have signed at least one RTA including a provision prohibiting the application of customs duties on electronic transmissions, and many of these provisions bind signatories on a permanent basis (Andrenelli and López González, 2019[32]).

New agreements such as the Australia-Singapore Digital Economy Agreement, the Digital Economy Partnership Agreement (DEPA) between Chile, New Zealand and Singapore, or the Digital Economy Agreement between the United Kingdom of Great Britain and Northern Ireland and the Republic of Singapore include specific commitments supporting data innovation. They also specifically refer to the possibility of using regulatory sandboxes to promote data-driven innovation.[33] These also include provisions which specifically refer to AI and AI technologies, and recognise the increasing importance of the use and adoption of AI technologies within a digital economy, as well as the importance of developing ethical governance frameworks for the trusted, safe and responsible use of AI technologies.[34]

Beyond RTAs, ongoing negotiations in the context of the WTO Joint Statement Initiative on E-commerce will be key in developing multilateral trade rules for digital trade that will also enable the spread of AI. For instance, wider agreement and adoption of international instruments, for example, related to e-transaction frameworks, e-signatures or e-transferable records, can lead to further digitalisation of trade processes. This can enable new opportunities for deploying AI solutions aimed at helping make trade processes more efficient. At the same time, agreement on common approaches to data flows, consumer protection or cybersecurity may lead to less regulatory fragmentation, enabling more efficient deployment of AI solutions.

## 3.5. Can AI enhance trade policy making?

While much attention has focused on how AI can help design more efficient product offerings and firm strategies, there has been less focus on how AI can help governments design better policies (with the notable exception of the role of AI in achieving the Sustainable Development Goals (SDGs)).[35] In the context of a growing number of unexpected events affecting international trade – such as increased exposure to natural disasters, cyberattacks or health crises - AI can become a useful tool to analyse real-time data and provide more timely and granular information to economic agents and policy makers, as well as help understand the impact of uncertainty or specific shocks. Although not specifically related to trade

[31] Article 28 of the SAFTA reads "If both Parties undertake obligations under: (a) an international agreement that enters into force after the date of entry into force of this Agreement; or (b) an amendment to any existing international agreement, to not require the transfer of, or access to, an algorithm expressed in source code of software owned by a person of a Party or non-Party as a condition for the import, distribution, sale or use of that software, or of products containing that software, in their respective territories, this Article shall apply, *mutatis mutandis*, to algorithms expressed in source code of software owned by a person of the other Party". The same provision is found under article 28 of the Australia-Singapore digital economy agreement.

[32] For an example, Article 14.36 of the EU-Japan FTA or article 20.69 of the USMCA.

[33] For an example, see Article 26 of the Australia-Singapore Digital Economy Agreement, Article 9.4 of the DEPA, and Article 8.61-I of the UK-Singapore DEA.

[34] For an example, see article 31 of the Australia-Singapore Digital Economy Agreement, Article 8.2 of the DEPA, and Article 8.61-R of the UK-Singapore DEA.

[35] Different initiatives have studied how AI can accelerate progress towards the 17 UN SDGs, compiling relevant efforts in repositories, including ITU's SDG AI Repository (2021), the AI4SDGs Think Tank (2021) and the database of the University of Oxford's research initiative AIxSDGs (Saïd Business School, 2021).

policy applications, the example of the Valencian Government's use of AI in the context of its fight against COVID-19 (Box 4) highlights how AI is increasingly being deployed to inform policy making (Feras A. Batarseh, 2020[33]).

That said, besides the technical analytical capacities (both in terms of tools and methods, and human capacities), one of the main challenges to develop AI methods in trade policy making is the difficulty of identifying and accessing relevant datasets that are able to provide insights on emerging trade patterns, as well as the difficulty of ensuring the completeness of these datasets. In this regard, progress is being made with the deployment of machine learning techniques with high-frequency data to track economic activity in real time (Woloszko, 2020[34]).

Where trade is concerned:

- AI can improve analytical capacities, helping governments make better choices. For instance, increased data points from earth observation data, port information or financial transactions may be used to increase the accuracy and timeliness of information, including on trade-related issues such as identifying trade volumes and the evolving geographical distribution of trade. Enhanced analysis of data can also provide new insights on regional integration initiatives, identify supply bottlenecks or nowcast trade and GDP. For example, recent OECD work (Jaax, Gonzales and Mourougane, 2021[35]) combines ML techniques with dynamic factor models to "nowcast" aggregate services trade. This work relies on a variety of hard and soft indicators, including unemployment rates, retail sales, goods exports, business and consumer confidence, financial indicators (stock market prices) and Google Trend search indicators.
- AI can also be used to study human dynamics and optimise value chain activities. By improving prediction, optimising operations and resource allocation, the use of AI can be leveraged to identify demand surges or bottlenecks in the international supply chain. A similar approach was proposed by the UN Global Pulse project (Hurricane Odile project) to better understand the economic resilience of people affected by natural disasters by analysing financial transaction data (sale payments and ATM cash withdrawal data).[36]

### Box 4. Use of AI to drive policy: Valencia's AI strategy to fight COVID-19

Before the COVID-19 pandemic hit, the government of the Generalitat Valenciana (Spain) developed a strategy to incorporate AI into its governing methodology, appointing Dr. Nuria Oliver as AI Commissioner for Valencia.[1] In March 2020, at the onset of the pandemic, Dr. Oliver created a multidisciplinary data science workgroup[2] to work with the General Directorate of Analysis and Public Policies of the Presidency. The aim was to leverage data and AI to advise government decisions on issues related to COVID-19.

Based on an existing agreement with Telecom operators and the National Statistics Agency granting access to anonymised data and using a questionnaire, the team was able to identify perceptions of confinement rules and likely concentrations of people, helping anticipate future outbreaks. The data modelling and prediction of outbreaks proved highly accurate and were successfully used to inform containment policy measures and to provide evidence of these to judicial bodies.

Following the success of the models used in Valencia, the deep-learning based "COVID-19 cases predictor" and "policy prescriptor" used were expanded to include global data on COVID-19 infection rates and were submitted to the XPRIZE Foundation challenge. This challenge, launched in October 2020 aimed at fostering the development of data-driven AI systems to predict COVID-19 infection rates and prescribe "intervention plans". Valencia IA4COVID19 coordinated by Dr. Oliver and Dr. Conejero won the contest.[3] The winning models are meant to be made available to policy makers, business leaders and health authorities around the world to be used when evaluating strategies to reopen in a way safe and reactivate the economy.

[36] See https://www.bbvaaifactory.com/odile/.

The Government of Valencia has announced it will continue its use of AI in policy making by creating a Data Scientist division to advise the government in policymaking.

1. See https://presidencia.gva.es/es/web/campanyes/inteligenciaartificialcv.
2. The team is made up of researchers from different universities, in collaboration with Microsoft, ESRI, the Spanish national statistics institute and three most important mobile phone companies in Spain, along with the national Secretariat for Artificial Intelligence.
3. See https://www.xprize.org/challenge/pandemicresponse/winners-results ; Open Data Science to fight COVID-19: Winning the 500k XPRIZE Pandemic Response Challenge.

## 4. Case studies on the application of AI in trade

AI technologies can have a broad scope of application, hence their use and limitations can be illustrated through targeted case studies. This section looks at three illustrative examples of specific application of AI technologies in the context of trade. The first is AI-powered machine translation and its use to facilitate trade transactions. The second relates to AI technologies used in supply chains and the third focuses on the application of AI in the financial sector.

### 4.1. Case study 1: AI-powered machine translation and trade

International trade generally involves tasks that rely on the use of different languages, whether to communicate to consumers, provide product details, research market conditions, or ensure regulatory compliance. Language barriers can impose significant hurdles for international traders raising transaction costs. Several empirical studies have shown that reducing language barriers can have a substantial positive impacts on trade (Lohmann, 2011[36]) (Melitz and Toubal, 2014[37]), (Molnar, 2013[38]), (Egger and Lassmann, 2012[39]).

AI-powered technologies, particularly machine learning, can help overcome language barriers through automated translation systems that can handle large volumes of inputs much faster and cheaper than human translators.

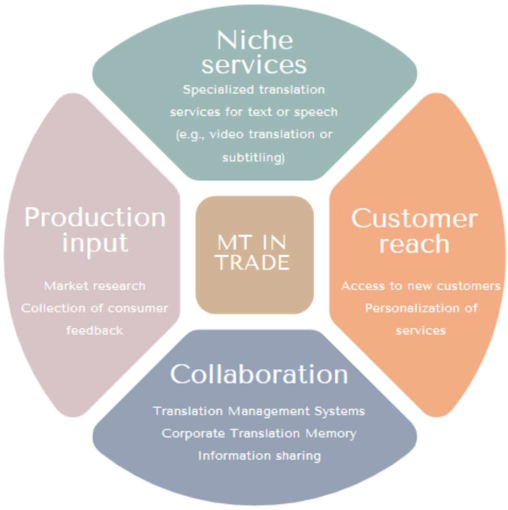
Common forms of machine translation approaches include (Chand, 2016[40]):

- *Rule-based machine translation (RBMT):* Where the translation software uses rules to break down the content and match the source language to the target one. Common uses include simple translations, such as addresses, dictionaries, and other simple text where a linguistic corpus is not part of the translation.
- *Statistics-based machine translation (SBMT):* Where translations rely on statistical methods using existing bilingual corpus (e.g. through analysing existing text or records). SMT typically depends on large volumes of data.
- *Hybrid machine translation:* Where RBMT and SBMT approaches are used within a single machine translation system.
- *Neural network based machine translation (NNMT):* This approach relies on AI neural networks to predict more complex translations using mathematical formulas and applying refinements obtained through trainings on existing data sets.

Most modern machine translation solutions use a combination of different approaches. However, a key challenge remains to ensure acceptable quality translations which are often difficult to achieve given nuances in language structures, differences in meanings of words and contextual influences on meanings. New AI technologies have helped to advance and improve translation quality in recent years due to the increased availability, and better quality, of training data. Nonetheless, skilled human editing is still required for quality outputs, even for advanced machine translations, to eliminate potential errors and ensure seamless flow of translated products.

There are several examples of application of machine translation technologies within the context of international trade (Figure 4.1). Machine translation can help respond to increased demand in niche services traded across borders (e.g. professional document translations, audio-visual content translation, remote event and meeting interpretation etc.). Machine translations can be used more broadly as production inputs (e.g. when conducting market research, market surveys, etc.), as well as to reach new customers or improve the experience of existing ones (e.g. through personalisation of services or tailored customer support in the local language). In addition, translations often form an integral part of multinational corporate structures where multi-lingual communication and information sharing is essential for collaboration, to increase efficiency, lower costs, and ensure consistency.

### Figure 4.1. Example uses of machine translation in international trade




Source: Authors' elaboration

Machine translation could be particularly beneficial for e-commerce retailers that have customers all over the world (eBay, 2016[41]) (Alibaba, 2018[42]). A study by (Brynjolfsson, Hui and Liu, 2018[43]) looked at the impact of introducing eBay's Machine Translation (eMT) to facilitate online sales to foreign markets (eBay, 2016[41]). The eMT learns how to translate among different languages and uses tailored engineering to make it easier for buyers to search for and understand the details of items that are not listed in their language.

The study looked at US exports to Spanish-speaking Latin American countries, and found that the implementation of eMT increased exports on eBay by 17.5% in terms of quantity and 13.1% in terms of revenue. The impact was even larger for non-standard products, as well as cheaper products and listings with more detailed descriptions in the selling advertisement. Moreover, to put this in context, a 10% reduction in distance between countries is estimated to increase trade revenue by 3.51% on eBay (Lendle et al., 2016[44]). This implies that the 13.1% increase in revenue due to the introduction of eMT is equivalent to reducing the distance between countries by 37.3% (Brynjolfsson, Hui and Liu, 2018[43]).

## 4.2. Case study 2: AI applications in logistics and warehousing

With the rapid rise of e-commerce and the growing volume of parcels cross borders across the globe (López González and Sorescu, 2021[45]), the logistics sector has been under pressure to manage increased demand and meet growing expectations for fast, reliable and timely deliveries.

Inherently, logistics activities entail a complex management of goods flows from origin to end point, often employing multiple transport modes, crossing different borders, clearing customs and ensuring seamless last-mile deliveries. Managing these flows is a difficult task. However, AI systems can play a critical role, from helping with the management of inventories and warehouses, to coordination of shipments across countries, predictions of future trends, improving the accuracy of just-in-time delivery, and enhancing customer experience. Moreover, increased use of sensors, tracking codes, and other connected systems can feed into the AI systems in real time, maximising efficiency throughout the process.

A particularly challenging task relates to managing inventories and warehouse space, requiring foresight in identifying changing trends and optimising shipments and schedules. AI systems can help create “smart warehouses” that rely on sensors, computer vision and automated processes to inform decision-making processes related to storage and logistics.

There are several benefits associated with use of AI in warehouse operations, including:

- *Increased productivity*: AI systems can be deployed to streamline and centralise operational processes within the warehouse; speed up the process of receiving, identifying, sorting and pulling of shipment; improve the efficiency of warehouse robots.
- *Improve accuracy and timeliness*: AI systems use advanced neural networks to predict consumer trends, analyse inventories, and plan streamline transportation processes like loading, shipping, unloading and delivery.
- *Improve security:* Recourse to AI systems helps anticipate and prevent security risks, prevent accidents and damage to shipments, and reduce human error in the logistic process.

Some examples of tools feeding into an AI-powered smart warehouses include:

- *Radio-frequency identification (RFID):* RFID technology is used to digitally tag goods and packages, replacing traditional labelling and barcodes that are time consuming to attach and scan. Moreover, RFID works on the basis of radio waves, thus tags can be scanned from a distance, allowing for faster processing and faster locating of items in warehouses. RFID technology also improves inventory control and helps locate misplaced packages. Data from RFID can be fed into a warehouse management system controlled though AI.
- *Robots*: AI-system can effectively instruct robots to carry out tasks around the warehouse such as loading or unloading, storing or pulling items. Robots can move at higher speed and carry heavier loads than humans, which becomes relevant especially in larger warehouses. AI is also used to optimise the route that robots take for finding and pulling goods, reducing the time and distance, which is especially relevant for larger warehouses where considerable time could be spent on searching for items through the aisles.
- *Sensors and other devices (Internet of Things – IoT)*: Sensors help collect data in real time and feed this into a centralised AI-powered decision-making mechanism. IoT devices rely on sensors to collect data, and are capable of communicating with other IoT devices, creating a connected ecosystem throughout an entire warehouse. Real-time data is fed back to a centralised AI powered decision-making system which analyses the data, and returns the appropriate instructions to the IoT enabled devices. This creates new synergies between IoT and AI.

AI may also play a role in lowering greenhouse gas emissions across logistics value chains by delivering advanced data-driven insights on carbon footprint[37] and increasing the efficiency of automated operations at transport terminals (Tsolakis et al., 2021[21]). While the efficiency of automated machines and AI solutions is yet to be proven, and the use of AI has its own carbon footprint,[38] there is a potential for AI and enhanced data analytics to improve the environmental impact of logistics activities in the long term.

[37] The Boston Consulting Group estimates that monitoring and optimising emissions with AI solutions can help reduce greenhouse gas emissions by between 2.6 and 5.3 gigatons of $CO_2$ equivalent. See: https://www.bcg.com/publications/2021/ai-to-reduce-carbon-emissions

[38] This is particularly due to the computational resources that necessitate similarly substantial energy consumption, for instance when training AI systems (Strubell, Ganesh and McCallum, 2019[52]).

## 4.3. Case study 3: AI in the financial sector

AI systems are used in the financial sector to improve and streamline money management. For instance, AI systems help banks improve credit decisions by using machine learning and vast data resources to score borrower risk. Using AI in credit underwriting also has the potential to make access to credit more inclusive for underbanked lenders, although its use is not immune to biases.[39]

Another use for AI solutions in the financial sector is risk assessment. AI systems help make more accurate predictions on financial risks using existing data to pinpoint trends, identify risks, reducing time spent on assessments, help regulatory compliance and anti-money laundering efforts (Box 5).

Other applications of AI systems in financial services include online banking service. Through AI, financial services can be more personalised and tailored to the customer's needs, for instance, through personalised financial advice on spending and savings, and natural language processing solutions to provide automated customer services.

Financial services is one of the most dynamic areas where AI systems have the potential to bring increased efficiency, more secure transactions, and help make financial services more inclusive and accessible to all.

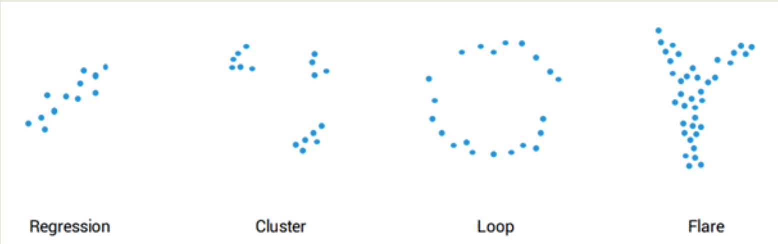
### Box 5. Symphony AyasdiAI: improving risk assessment through the shape of data

Symphony AyasdiAI uses a unique combination of topological data analysis (TDA), ML, and statistical and geometric algorithms to improve financial risk assessment, help businesses understand and manage risks, detect fraud and patterns of potential money laundering.

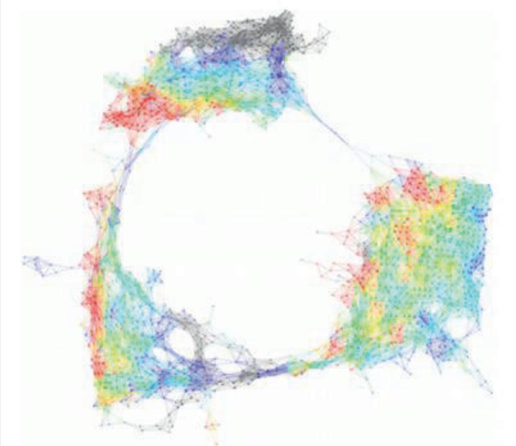
AyasdiAI is also unique in using TDA. TDA is based on topology, the mathematical sub-discipline that studies the notion of shape. TDA refers to the adaptation of this discipline to analyse highly complex data. It draws on the philosophy that all data has an underlying shape and that shape has meaning. This knowledge is widely understood for certain shapes – but data does not restrict itself to certain shapes.

For example, the shape of data on the far left corner of the below image is well known to statisticians, economists and data scientists. It represents a regression line, and provides the qualitative information that the y-variable varies directly with the x-variable (i.e. that y increases as x increases). The second shape is a cluster which shows that the data set breaks into a set of three tightly concentrated clusters while the third one is a loop often associated with periodic or recurrent behaviour in the data set. The last share looks like a "Y". Note that it has a central core and three "flares" extending from it. This might represent a situation where the core represents the most frequently occurring behaviours, and the tips of the flares represent the extreme behaviours in the data.

But data does not have just four shapes. Complex data has endless shapes, all of which encode information. The images below illustrates what complex data sets could look like.




[39] See also https://www.forbes.com/sites/korihale/2021/09/02/ai-bias-caused-80-of-black-mortgage-applicants-to-be-denied/?sh=6e3c948436fe.



TDA uses ML algorithms to determine the shape of data and the information encoded therein. This helps uncover subtle patterns missed by other approaches that rely on a single algorithmic dimension.

Source: https://www.ayasdi.com; Understanding Ayasdi: What we do, how we do it, why we do it, White Paper 2017.

## 5. Conclusions

This paper aims to shed new light on the growing importance of AI for international trade and to identify the role that international trade can play in enabling the uptake of this new technology. AI has enabled the automation of cognitive tasks using complex algorithms and data to make predictions. This already has vast applications in international trade, such as productivity improvements, efficiency gains along supply chains and reductions in trade costs. Indeed, evidence in this paper highlights that AI innovations are particularly important in highly tradable sectors, including ICT goods and services.

This paper also underscores the importance of trade in goods, trade in services, as well as the movement of human expertise and data as essential ingredients for enabling AI. But it also notes that barriers on goods, services, people and data remain, affecting the deployment of AI solutions. For instance, many countries, particularly developing and emerging economies, still have tariffs on ICT goods. This imposes additional costs on the deployment of the necessary hardware and computing facilities to run AI systems. At the same time, barriers to digitally enabled services have been rising in the past years, affecting the ability of countries to take advantage of gains from digitalisation more broadly and AI more specifically.

While AI-related services and goods can be sold across borders, they also need to be explained, installed, and maintained. Indeed, access to trained engineers and programmers is key for the development of AI solutions. However, here too, barriers to the movement of people remain and lowering these would facilitate the transfer of AI-related knowledge and skills.

Data is one of the main ingredients of AI systems, but the emerging patchwork of regulatory approaches to data flows risks reducing the ability to deploy AI systems globally, reducing access to data and requiring duplication of activities. More interoperable regulatory approaches that enable the free-flows of data with trust are needed to help reap the benefits of AI.

Regional trade agreements increasingly feature provisions that are relevant for AI systems. Disciplines related to cross-border data flows, data localisation, source code, or provisions related to cybersecurity are some examples. New digital trade arrangements also include specific AI-related provisions recognising the importance of developing ethical governance frameworks for the trusted, safe and responsible use of AI technologies.

The paper has also shown how AI can enhance international trade through three case studies. Firstly, AI application in machine translation has proven to lower language barriers in trade and foster exports particularly for e-retailers. Secondly, AI can also generate efficiencies in the logistics sector, particularly by managing smart warehouses through improved predictions and better coordination of activities within warehouses. Thirdly, financial services have also benefitted from AI, including in areas such as access to credit, financial risk assessment and anti-money laundering compliance, as well as personalised banking.

The field of AI is fast evolving and has many different important, and indeed contentious, facets. This paper aims to provide an initial framework for discussion among trade policy makers on the intersections between AI and international trade. However, this area remains understudied, and more analysis could be done in the future, including on quantifying the implications of AI for trade.

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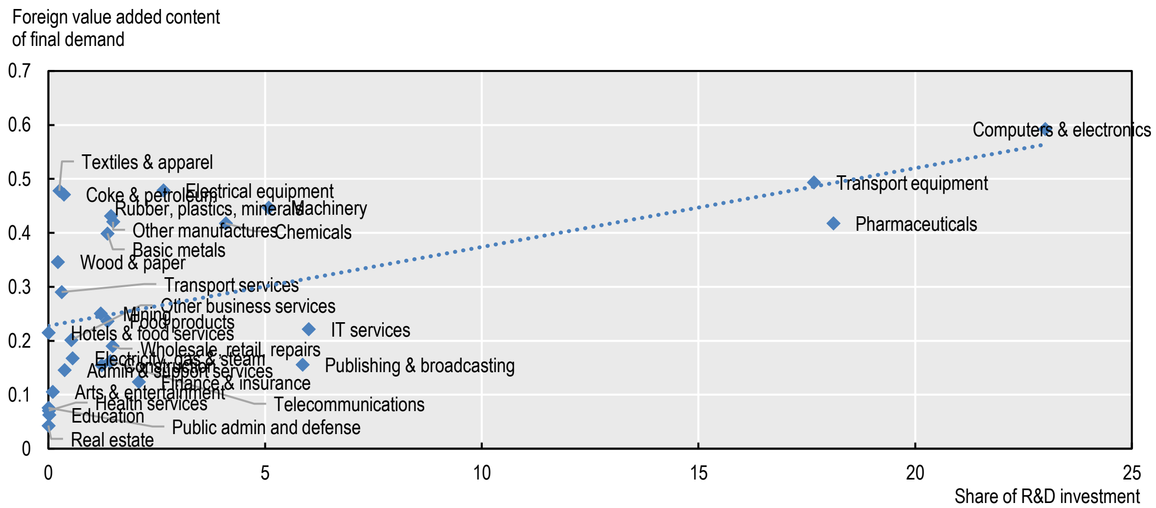
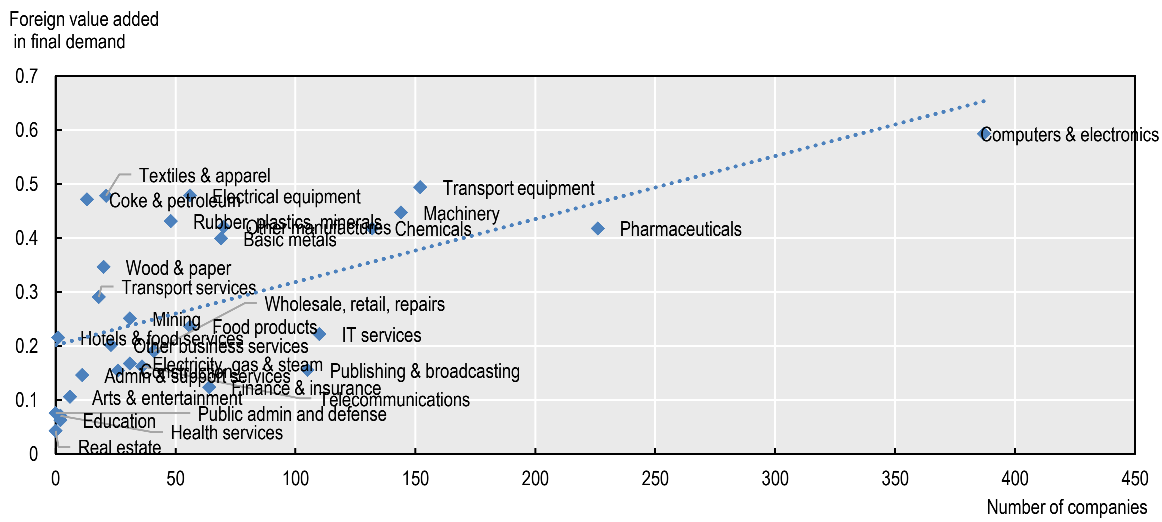
# Annex A.

## Figure A1. Investment in R&D and trade exposure

a. Share of R&D investment in total R&D investment of world's top R&D investors




b. Number of R&D Investments of companies by sector




Note: Foreign value added in final demand captures the share of value added in the production of a particular sector that comes from foreign sources. It is calculated from the OECD TIVA database for the year 2015 Data on investment are for the year 2016.
Source: Own based on TiVA (2018) and JRC-OECD, COR&DIP© database v.2., 2019. Dernis (2019[18]).

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