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Contact information
Address: Edificio Expo, C/ Inca Garcilaso 3, Sevilla 41092, Spain
Email: EC-AI-WATCH@ec.europa.eu

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Contents

Foreword

This report is published in the context of AI Watch, the European Commission knowledge service to monitor the development, uptake and impact of Artificial Intelligence (AI) for Europe, launched in December 2018.

AI has become an area of strategic importance with potential to be a key driver of economic development. AI also has a wide range of potential social implications. As part of its Digital Single Market Strategy, the European Commission put forward in April 2018 a European strategy on AI in its Communication "Artificial Intelligence for Europe". The aims of the European AI strategy announced in the communication are:

- to boost the EU's technological and industrial capacity and AI uptake across the economy, both by the private and public sectors;
- to prepare for socio-economic changes brought about by AI; and
- to ensure an appropriate ethical and legal framework.

In December 2018, the European Commission and the Member States published a "Coordinated Plan on Artificial Intelligence", on the development of AI in the EU. The Coordinated Plan mentions the role of AI Watch to monitor its implementation.

Subsequently, in February 2020, the Commission unveiled its vision for a digital transformation that works for everyone. The Commission presented a White Paper proposing a framework for trustworthy AI based on excellence and trust.

Furthermore, in April 2021 the European Commission proposed a set of actions to boost excellence in AI, and rules to ensure that the technology is trustworthy. The proposed Regulation on a European Approach for Artificial Intelligence and the update of the Coordinated Plan on AI aim to guarantee the safety and fundamental rights of people and businesses, while strengthening investment and innovation across EU countries. The 2021 review of the Coordinated Plan on AI refers to AI Watch reports and confirms the role of AI Watch to support implementation and monitoring of the Coordinated Plan.

AI Watch monitors the European Union's industrial, technological and research capacity in AI; AI-related policy initiatives in the Member States; uptake and technical developments of AI; and AI impact. AI Watch has a European focus within the global landscape. In the context of AI Watch, the Commission works in coordination with Member States. AI Watch results and analyses are published on the AI Watch Portal (https://ec.europa.eu/knowledge4policy/ai-watch_en).

From AI Watch's in-depth analyses, we will be able to better understand the European Union's areas of strength and the areas where investment is needed. AI Watch will provide an independent assessment of the impacts and benefits of AI on growth, jobs, education, and society.

AI Watch is developed by the Joint Research Centre (JRC) of the European Commission in collaboration with the Directorate-General for Communications Networks, Content and Technology (DG CONNECT).

This report addresses the following objective of AI Watch: to develop an AI index including the dimensions relevant for policy making. It does so by providing statistical evidence in the form of indicators that summarise the main results made available through AI Watch.

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Authors

Righi, Riccardo

Pineda, Camila

Cardona, Melisande

Soler Garrido, Josep

Papazoglou, Michail

Samoili, Sofia

Vázquez-Prada Baillet, Miguel

López Cobo, Montserrat (Editor)

De Prato, Giuditta (Editor)

Abstract

After very active years of technological development, both in hardware and software terms, the AI domain has spread, and its influence can be noticed everywhere in the economy and society, as more AI-supported tools and applications are used in working environments and in the personal sphere. As is the case with all innovative technologies, a thorough monitoring of the emerging AI field and its trends must be put in place in order to comprehend the reach of its impact. This exercise makes it possible to gain awareness about possible issues and situations requiring attention or intervention. In this respect, this publication provides an analysis of multiple indicators related to the development of AI from several perspectives. Although the geographical focus is on the EU27, when possible we provide a comparison with major worldwide AI powerhouses, i.e., the US and China, among others. Also, when available, an indicator is provided for the 27 EU Member States.

The analysis is structured in five dimensions: (i) global view on the AI landscape, (ii) industry, (iii) research and development (R&D), (iv) technology, and (v) societal aspects. The results show, as expected, that AI is in a phase of technological evolution and improvement. The US is in a leading position in the worldwide landscape in economic terms. China follows, notably due to a very prominent patenting activity in the field. The EU is third, but several elements support the thesis that the distance with the two leading countries is less than often suggested. The analysis reveals that the EU performs remarkably well in R&D — beyond the consideration of EC-funded projects. Also, the EU demonstrates specialisation in AI services and in autonomous robotics. Additionally, the EU shows very positive dynamics in trade in industrial robotics and in new robotics start-ups. Regarding investments in AI, we observe a positive signal for the potential development of the domain in the Union, as the level of private and public investments has increased in all of the 27 EU Member States in the last year.

Executive Summary

This report presents the AI Watch Index, a collection of indicators to better understand Europe's areas of strength and those deserving attention in the field of artificial intelligence (AI). The AI Watch Index provides a structured set of quantitative indicators on the performance and positioning of the EU[1] across various dimensions of AI relevant for policymaking. The geographical focus of the index is the EU, and Member States are covered at individual level where data are available. The comparative analysis of the EU with the US, China and other main actors in the AI domain is also possible thanks to the worldwide coverage of some of the indicators. The index is organised around five dimensions: (i) global view on the AI landscape, (ii) industry, (iii) research and development (R&D), (iv) technology, and (v) societal aspects. Table 1 presents the list of 22 indicators organised around 5 dimensions and 10 sub-dimensions.

Table 1. Summary of AI Watch Index indicators by dimension

AI Watch Index dimension	AI Watch Index sub-dimension	Indicator name
G – Global view on the AI landscape	AI activity	G1: AI economic players
		G2: AI player intensity
	AI areas of strength	G3: AI areas of specialisation: comparative advantage in AI thematic areas
		G4: AI thematic hotspots
		G5: EU's comparative advantage in industrial robotics trade
	AI investments	G6: AI investments in the EU
I – Industry	Industry	I1: AI firms' profile
		I2 Robotics start-ups in the EU
R – Research and development	R&D activity	R1: AI players in AI R&D
		R2: AI R&D activity score
	Network of collaborations	R3: AI R&D collaborating countries
		R4: Peer-to-peer collaborations
		R5: Strategic position in the network of collaborations
T – Technology	Performance of AI	T1: Performance of AI research
	Standardisation	T2: Standardisation activity engagement
S – Societal aspects	Diversity in research	S1: Gender diversity index
		S2: Geographic diversity index
		S3: Business diversity index
		S4: Conference diversity index
	Higher education	S5: AI in university programmes in the EU
		S6: University places with AI content in the EU
		S7: AI intensity in university places in the EU

Source: Adapted from AI Watch report "AI Watch Index. Policy relevant dimensions to assess Europe's performance in artificial intelligence", López Cobo et al. (2021).

The analysis shows the **US is global leader in AI**, in the global AI landscape, AI industry, and AI R&D dimensions, followed by China and the EU.

The most **important elements for the EU** lie, on the one hand, in its significant role in AI Services and Robotics (both autonomous and industrial robots), and on the other hand, on its strong position in terms of AI R&D activity. Regarding ***AI Services*** – which are activities related to the provision of AI services and applications,

1 Throughout the report the EU is referred to the EU27 (as of 31 January 2020 onwards), irrespective the time period for which the indicators are computed.

including infrastructure, software and platform services – the EU has a comparative advantage in the worldwide landscape, as its share of economic activities in this AI area is higher than the global average[2]. In fact, although the US holds a higher world share of AI services, the relative EU's share of AI services in the total number of the EU's AI activities is higher than for the US. Similarly, the EU also has a comparative advantage in ***Autonomous Robotics*** – robotic systems that are meant to operate in a relatively-complex environment involving interaction with other machines or humans. This is complemented by Europe's comparative advantage in the **industrial robotics trade** (considering both exports and imports), as well as its steadily increasing trend in the number of new **robotics start-ups**. This is especially relevant in light of the prominent role AI is expected to play in the domain of robotics as a key enabler for the next steps of its technological evolution. In fact, future generations of robots supported by AI are expected to be better able to interact with the physical reality, and especially with humans (e.g., robots for care of humans). The EU's dominant position in areas related to robotics indicate its future competitiveness in the field. At the same time, the technological domains considered here are extremely dynamic, requiring investments in industrial and technological development in order to maintain a competitive edge.

Second, **the EU is very dynamic in terms of AI R&D activities**, here represented by AI-related patents and frontier research publications at top AI conferences—. The research collaborations and partnerships that EU players[3] form enable them to have a position of influence worldwide, despite the clear impact of Brexit on the overall EU AI landscape. In other words, EU players establish networks of R&D collaborations that support their ability to exchange information and, in turn, build knowledge. These are key elements of innovation capacity. Considering patents and research publications independently, some relevant differences are observed: while the EU has a very important role in terms of frontier research publications, second only to the US, patenting activity in the EU remains more modest. There is a third type of R&D activity, EC-funded projects, which for the sake of international comparison are not always considered in our analysis. However, their contribution to the overall R&D ecosystem is fundamental. In addition, as discussed in previous AI Watch works (Righi et al., 2021), framework programmes' projects (such as FP7 and H2020) enable a multitude of economic players to get involved in the AI landscape. Thanks to them, the EU has almost doubled the number of economic players in this technological domain (when compared to the number of players without considering EU-funded projects). However, the ability of these players to remain active in the AI landscape without public support is a point that deserves further exploration.

As mentioned above, **the US is the global AI leader**: it is home to a very large number of active AI players; it has a comparative advantage in multiple AI areas (*AI Services*, *Audio & Natural Language Processing*, *Autonomous Robotics*, and *Connected and Automated Vehicles*); it has a good presence of firms with a core business in AI and simultaneously developing AI patents; and engages in a notable number of R&D activities (both patents and frontier research). Therefore the leading position of the US appears solid and without specific weaknesses.

The picture we get of **China's AI landscape is mainly supported by its very intense patenting activity**. However, lower standards of quality in patents and recent policies implemented by the Chinese government, which have resulted in an inflation of filings, support the thesis that the size of China in the AI landscape may be less significant than it appears at first sight. Despite this, China should be considered as a primary player in the field for two main reasons. Firstly, its significant involvement in the ICT manufacturing sector guarantees the basic hardware needs for the flourishing of any digital technology (including AI). For instance, in recent years China has experienced an annual increase in the ICT sector value added of 13.1 percentage points (Mas et al., 2021), while already starting from a dominant position (second in value added, behind only the US). Secondly, even considering the aforementioned caveats, the high number of AI-related patent applications filed in China cannot be dismissed, especially given the huge number of economic players that become involved in the AI landscape as a consequence (more than 9,000). Another aspect worth considering regarding China is massive access to data, the fuel of AI systems. This is due to, among other things, a large population that makes use of digital services and applications, and to fewer legal limitations on the access and use of personal data (Arenal et al., 2020).

Additional insights of this work concern the **technological evolution of the AI domain**. We observe an ongoing increase in the performance of AI technology across several tasks (e.g., image classification, face recognition, speech recognition, text summarisation). The fact that benchmarks improve on a yearly basis clearly

2 See definition of revealed comparative advantage in the description of the *G3* indicator, sub-section 3.1.2.1.

3 AI players are firms, universities, research centres and local governmental institutions that are involved in AI-related industrial, innovative or research activities.

confirms the technological phase of expansion that AI is currently experiencing. This conclusion is reinforced by the substantial levels of AI standardisation activity observed, an aspect where EU Member States are active players, in particular considering the development of standards in support of the European AI regulation proposal (the AI Act).

Two further strands of indicators of the AI Watch Index cover **societal aspects**: **diversity in AI research, and educational offerings of advanced AI skills at university level**. Importantly, preliminary results show a recent increase in the heterogeneity of the AI research community in terms of gender, affiliation location, and type of institution to which the researcher is affiliated, possibly reflecting the impact of inclusion and diversity policies in the research community. This is relevant for both the development of trustworthy AI and for social inclusion. In fact, heterogeneity in the origin, gender and affiliation of researchers is expected to reduce bias in algorithm development, promote selection of representative data sources for training sets, and mitigate other types of risks that could result from a limited perspective of the research community. This dimension also analyses university **academic offerings** related to AI, as this is bound to affect future workers' employability and the overall presence of advanced digital competencies in the economy. In this respect, noticeable differences among Member States are detected which may lead to future inequalities among the EU population. The results show that AI content is more frequently present in master's degree programmes than in bachelor's degree courses. This seems to indicate that AI is considered a specialised subject mostly covered in a late phase of the education path, after basic knowledge has already been imparted to students. A wider provision of AI-related contents at all levels, and not only advanced courses, would be advisable in order to promote the digital inclusion of the population and increase the economic benefits from the digital transition in Europe.

1 Introduction

Initially born back in the 1950s, the pace of development of artificial intelligence (AI) reached new heights in the last decade, and its expansion phase has not yet slowed down. From a technological point of view, AI is the result of the combination of new hardware components and new software developments. The former have made it possible to reach much larger computational capacity and enabled stronger interconnectivity among multiple devices. The latter, which are mainly based on machine-learning statistical methods, are partially revolutionising the way computers work. Indeed, for the first time in human history, self-adapting algorithms are being used in a multiplicity of contexts: industrial processes, data analyses, a large variety of daily activities (e.g., the functioning of latest-generation mobile phones and self-driving vehicles is based on AI), and many more.

From a socio-economic perspective, AI is boosting technological and industrial capacity, with consequently increased productivity, facilitating improvement of public services and improving individual living conditions, from work-related issues to daily habits. However, as is the case with all disruptive technologies, its future evolution and its impact on social and economic aspects need to be monitored and associated risks minimised. In addition, the fact that AI is neither purely a hardware tool nor a pure matter of software development makes examining it and regulating it even more challenging. For these reasons, a constant monitoring of pertinent indicators is fundamental to informing the action of policy makers. Indeed, this work provides an up-to-date view of a number of dimensions of AI on which to commence a knowledge-based discussion and to build forward-looking frameworks and policies.

In the context of the ongoing digital transformation of Europe, the European Commission (the EC) is promoting the development and uptake of AI as one of the main drivers to boost the EU's technological and industrial capacity. Since 2018 a number of strategies and initiatives have been put in place with the objective of identifying the political, economic and societal actions needed to reinforce the EU's global leadership in a human-centric trustworthy AI, while preserving our core values, protecting citizens' rights and promoting the well-being of people. These include, among others, the European Strategy on Artificial Intelligence and its Coordinated Plan, the Communication "Fostering a European approach to Artificial Intelligence", and the European AI regulation proposal, the AI Act. The 2018 Coordinated Plan and its 2021 review mentions the role of AI Watch to support implementation and monitoring of the Coordinated Plan. AI Watch monitors the European Union's industrial, technological and research capacity in AI; AI-related policy initiatives in the Member States; uptake and technical developments of AI; and AI impact. AI Watch has a European focus within the global landscape. In the context of AI Watch, the Commission works in coordination with Member States. AI Watch results and analyses are published on the AI Watch Portal[4].

In order to provide valuable information for the discussion, elaboration and monitoring of the objectives set by policies, the AI Watch Index collects, presents and discusses several indicators regarding different aspects related to the performance of the EU[5] in AI. Based on multiple data sources, most of which originate from AI Watch activities, the AI Watch Index organises the indicators around five analytical dimensions of policy relevance. These are: (i) global view on the AI landscape, (ii) industry, (iii) research and development, (iv) technology, and (v) societal aspects. A former AI Watch report[6] describes the composition of the index: from the identification and selection of suitable indicators that facilitate cross-country and temporal comparability, to their grouping into policy relevant dimensions. The report contains, for each indicator, a metadata fiche detailing aspects related to the indicator, such as its definition, data sources or geographical granularity. These aim to facilitate the understanding of the variables measured and the indicators' usefulness, and also support replicability in the case that all required data are available. Annex 1 of this report reproduces the metadata fiches for the indicators included, which have been updated where needed.

The focus of this report lies on the performance of the EU in AI, and on the involvement of the Member States whenever possible and meaningful. Additionally, to facilitate international comparisons and to position the EU in the global landscape, some indicators are also provided for the US, China, the UK, India, Canada, South Korea and Japan, while the rest of world countries are grouped according to their continent (e.g., Other Asian countries, Other American countries).

4 https://ec.europa.eu/knowledge4policy/ai-watch_en

5 Throughout the report the EU refers to the EU27 (as of 31 January 2020 onwards), irrespective the time period for which the indicators are computed.

6 "AI Watch Index: Policy relevant dimensions to assess Europe's performance in artificial intelligence" (López Cobo et al., 2021).

The rest of this report is structured as follows: Section 2 presents a discussion of the results for each individual dimension, presenting an integrated view of the most relevant facts resulting from the indicators in each dimension. Section 3 presents, for each indicator, its definition, the results portrayed in a plot and a concise analytical description of results. Section 4 presents some concluding remarks. Additionally, Annex 1 presents the metadata fiches of all indicators included in the AI Watch Index.

2 Integrated analysis by dimension

2.1 Global view on the AI landscape

This dimension of the AI index provides the basis for understanding the global landscape of AI and covers general aspects of its composition and geographical distribution, areas of AI specialisation, and AI investments in the EU. This dimension presents a picture of AI from the economic perspective, focusing on the EU and including international comparison across most indicators. It aims to provide an overview and to frame the other dimensions of the AI Watch Index. It includes indicators on: AI activities, reflecting the size of global AI economic activity, both in absolute terms and relative to the economic weight of countries; areas of specialisation in AI, showing the prevalence of AI thematic areas and country specialisation patterns; and AI investments in the EU, which provide information on public and private investments for AI development and implementation in the EU and the Member States. Sub-section 3.1 presents in detail the indicators covered by this dimension.[7]

The economic impact of AI has started to spread widely and accelerate over the last 10 years, although the first concepts were initially developed in the 1950s. The technological domain of AI has recently found many economic and social applications and is expected to have even stronger impacts on our daily lives in the future. This analysis and the indicators regarding the global AI landscape provide relevant information about a part of the economy that is not yet specifically addressed by official statistics.[8] Indeed, it is very difficult to collect and discuss statistics, especially with international coverage and comparability, as AI is a cross-cutting technology not adequately captured by existing classifications of products or economic activities. Using the results of an AI Watch report aimed at providing an operational definition of AI to detect and characterise AI-related activities (Samoili et al., 2020, 2021), AI Watch has been able to produce and gather a variety of analyses of AI. These cover multiple perspectives and dimensions of knowledge to deepen our understanding of this important disruptive technology and its impact on the European economy and society.

The EU plays an important role in the global AI landscape, although the absolute number of AI players (i.e., firms, universities, research centres and local governmental institutions that are involved in AI because of the activities that they perform) and its ratio to GDP are not as high as in the US or China. The positive signals regarding the EU AI landscape are: (i) the large number of research institutes active in the field, (ii) the EU's strong specialisation in the thematic area of *AI services*, (iii) the high level of competitiveness in robotics and related fields, and (iv) the increasing trend observed in public and private investment across the AI domain. The dynamism of the field of AI in the EU is also reflected in the increasing level of AI investment, as the total of public and private investment in AI increased from 2018 to 2019 in all EU Member States. This investment effort, mostly driven by private investment, leaves the EU in a promising path towards achieving its €20 billion AI investment target by 2025 (Dalla Benetta et al., 2021).

The large number of research institutes active in AI in the EU should allow the EU to maintain a high level of research and development in this area, which is necessary to achieve a leading position in the medium to long term. It is clear that research efforts need to find direct implementations and applications in order to lead to innovations that have a positive impact on society and the economy. In this respect, it should be noted that the EU appears to lag behind other major AI players in terms of patents.

We also see a large number of EU actors in *AI service* activities. This shows that AI already plays an important role in the EU's economy and that a variety of AI-based products and services are already marketed. Moreover, robotics is one of the areas of AI where the EU seems to be most competitive. Our analysis shows that this thematic area has strong roots in the EU, as evidenced by: (i) a prominent standing in *Autonomous Robotics*, one of the most important topics in AI scientific research; and (ii) a strong and highly consistent comparative advantage in the trade (aggregated imports and exports) in industrial robotics – the percentage of the EU's trade in robotics in all of the EU's trade is higher than the global average percentage of trade accounted for by robotics, demonstrating the strong competitiveness of the sector in the EU.

A key point for understanding the EU's positioning in the global AI landscape, and for the assessment of possible future political and economic initiatives, is related to the UK. Indeed, before Brexit, the UK alone accounted for

7 *G1 – AI economic players, G2 – AI player intensity, G3 – AI areas of specialisation: comparative advantage in AI thematic areas, G4 – AI thematic hotspots, G5 –EU's comparative advantage in industrial robotics trade,* and *G6 – AI investments in the EU.*

8 Only very recently has Eurostat started to address the topic, by covering AI uptake in the EU survey on ICT usage and eCommerce in enterprises.

more than half of the players in the EU28 AI landscape. The importance of the field of AI in the UK economy is well known, as demonstrated by the high share of AI players relative to GDP in the UK. Brexit has therefore led, at least in statistical terms, to a considerable downsizing of the EU AI landscape.

Globally, the three major economies that mainly control the AI economy are the US, the EU and China. The United States has become the world leader, with the largest number of AI players[9]. In addition, the US has a relatively high number of AI players per unit of GDP. This indicates that the number of AI players in the US is not only high compared with other geographical areas, but also high relative to the size of its economy.

Our analysis also shows that the US AI landscape is mainly specialised in the thematic areas of *AI Services*[10] , *Audio & Natural Language Processing* (*NLP*)[11], *Connected and Automated Vehicles* (CAVs*)* and *Autonomous Robotics*. These are the AI thematic areas where the US concentrates its AI activity compared with other regions.

China is also home to many AI players, including a relatively large percentage of research institutes. Unlike in the US (and in the EU), relatively few AI activities in China are related to the thematic area *of AI Services*, suggesting that the level of AI development has not significantly reached the stage of commercialisation of goods and services. Alternatively, the country could be participating at other tiers of the value chain, such as the development of algorithms and parts to be integrated into final products. However, the difficulty of collecting reliable information about economic activities in China may affect international comparability; therefore the deployment *of AI Services* in China is an issue that should be further investigated.

One of the essential features emerging from the analysis of the AI landscape in China is the strong focus that Chinese players put on patenting activity, as demonstrated by the very high percentage of AI companies that have filed AI-related patent applications. A large number of patents developed in AI by Chinese players concern thematic areas related to the technological development of AI components (such as *Automation,* the *Internet of Everything* (*IoE*), and *Machine Learning for Image Processing)*. This point is further discussed in the AI industry dimension.

2.2 Industry

This dimension of the AI index addresses AI-related industrial activity. It aims to reveal how AI is approached by private economic players worldwide and in the EU Member States, especially with respect of the development of core-businesses in AI, i.e., the creation of companies with a main activity in AI, and the involvement in the filing of AI-related patent applications. In this sense, the objective is to understand how many enterprises are already focusing their business on AI (e.g., trading AI-based services), and how many of them are developing AI as support for their non-AI main economic activity (e.g., in the automotive sector). In addition, a focus on robotics is proposed, as its connections with AI are very likely to be even tighter in the near future. Indeed, the combination of AI and robotics is starting to produce a new set of products and tools that are even more capable of interacting with the physical reality than the current generation of AI-based devices. Sub-section 3.2 presents in detail the indicators covered by this dimension.[12]

The US is home to the highest number of AI firms worldwide (more than 13,000), followed by China (almost 10,000), the EU (more than 5,500) and the UK (more than 3,000). Thus the EU appears to have a secondary role after the US and China. However, the size and productivity of the firms are aspects that are not considered in this analysis, and additional information in this regard may reveal a different picture. Here, again, the impact of Brexit can be noticed, with the UK accounting for approximately 40% of the AI firms previously part of the EU28 landscape.

When considering the top geographic areas (the US, China, the EU and the UK), it is possible to observe a very different profile for China compared with the others. Indeed, most of its firms are engaged in patenting activity (which is not the case for the US, the EU and the UK). This strong focus of Chinese industry in patenting is due

9 AI players are institutions of different kinds, such as companies, universities, research centres and government institutions, involved in AI-related economic activities.

10 Economic activities that market AI products and provide AI-based services and applications, including platform infrastructure, software and services.

11 Includes activities related to the perception, processing, understanding and synthesis of text and audio signals, including speech, by AI systems.

12 I1 – AI firms' profiles and I2 – Robotics start-ups in the EU.

to a different approach to this type of intellectual property. The reference is to lower standards of quality[13], which, on the one hand, ultimately induces more applicants to present a filing, and on the other hand, it also reveals the modest innovative potential of these patents.. In addition, in recent years, a series of governmental subsidies related to the development of patents has attracted a multitude of firms to patenting activity, and the number of filed patents has increased substantially. These elements therefore suggest that the observed patenting activity in China does not fully correspond to its true innovative capacity.

We identify three types of AI firms: those with a core business in AI that do not patent, those that only file AI-related patent applications, and those with a core business in AI and filing patent applications. The latter usually correspond to high-tech companies, and the largest number of those are located in the US and China (233 and 226, respectively, corresponding to 1.7% and 2.2% of AI firms in those countries). This insight confirms the leading position of these two countries in this domain. In this respect, the position of the EU is more modest, since just 43 firms (0.7% of all EU AI firms) have a core business in AI and file AI-related patent applications.

Important signals for the EU are found in the robotics sector. The analysis of the number of start-ups over time shows that in the EU this sector has been able to consistently attract entrepreneurs to found new firms. Since the late 1990s 4,000 new enterprises have been founded, with an upward trend of newly created start-ups until 2015, since when it remains relatively constant (at a level of around 300 new start-ups per year from 2016 to 2019).

2.3 Research and development

This dimension of the AI Watch Index investigates those activities that contribute to the development of the technological domain. From a socio-economic point of view these activities are crucial in order to make progress happen, and so to improve technology maturity, and to reach (or maintain) economic competitiveness. Research and development (R&D) activities considered in this work are of three types: frontier research activities (i.e., scientific publications in top international conferences), filing of patent applications, and participation in EC-funded projects (i.e., FP7[14] and H2020[15]). To avoid a biased vision of AI R&D, the latter are considered only when addressing the EU Member States. This dimension considers several network indicators, as information exchange and interactions between multiple actors are essential for the blooming of innovation. Sub-section 3.3 presents in detail the indicators covered by this dimension.[16]

At worldwide level, the AI Watch Index analysis of R&D relies on data sources about patent applications and publications in AI international conferences. The former are used to address innovation capacity, while the latter are used as a proxy for involvement in frontier research. When the analysis is done at the EU level, participation in EC-funded projects is also considered.

The indicators show that in terms of AI R&D, the three worldwide leading regions are the US, China and the EU. The US presents the most consolidated position, with a remarkable level of activity in terms of frontier publications, in which it leads in terms of the number of players involved, the number of publications and the strategic position of US players in the network of collaborations – a score that provides a metric of players' capacity to act as connecting bridges between other players. It is important to note that the role of scientific publications is more relevant for innovation in a domain such AI than it is in technologies developed during the third industrial revolution (e.g., semiconductor materials, automation, computers). Indeed, a large part of AI research is on physical supports enabling increasingly faster and more distributed computation. Additionally, AI is to a significant degree about algorithmic and software-related improvements, without forgetting interaction between humans and machines and its related ethical considerations. Since software innovations are typically not patentable, this makes scientific publications more appropriate than patents as a measure of the techno-scientific progress in the AI domain.

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13 Several studies analyse the issue from different perspectives and metrics and find overall lower performance for Chinese patents, e.g., large citation lag (which indicates lower value of the patent), large shares of domestic citations and of self-citations, alternate effects (depending on the sector) in terms of consequences on firms' productivity, less accurate or shorter description of the innovation, and few number of claims that Chinese patents on average contain (Fisch et al., 2017; Christodoulou et al., 2018; Boeing at al., 2019, Song, 2014).

14 The seventh framework programme funding research, technological development, and innovation of the European Community.

15 Horizon 2020 is the eighth framework programme funding research, technological development and innovation of the European Community.

16 R1 – AI players in AI R&D, R2 – AI R&D activity score, R3 – AI R&D collaborating countries, R4 – Peer-to-peer collaborations, and R5 – Strategic position in the network of collaborations.

The US also performs well in patents, where it ranks second by number of applications, just after China. What seems to be the common feature of US patenting activity and US frontier research is the outstanding involvement of firms in both. This insight suggests that the US private sector is very active in AI R&D, and thus it is building its future competitiveness in the domain. This may also reflect the shift from academia to industry that is increasingly observable in the AI domain, as shown by the diversity indices analysed in the societal aspects dimension (Sub-section 3.5). China also has a prominent role in R&D. Its competitiveness in this respect mainly comes from an extensive involvement in patenting activity. However, what observed with regard to scientific publications is modest.

The EU holds a significant position in R&D, although its patenting activity is quite limited when compared to China and the US. Nevertheless, patenting involves a network of collaborations that makes the EU the third geographic area in terms of strategic position in that network, above Japan and other Asian countries (among the others). Only China and the US have a better strategic position than the EU. With regard to AI frontier research, the EU has basically the same number of players as the US, and it is second in terms of overall number of activities developed. These two elements enable it to be the second geographic area in terms of strategic position in the network of frontier research collaborations. It is important to note that, especially in R&D activities, a favourable position in terms of collaborations is expected to result in a future advantage in competitiveness. Indeed, as innovations typically emerge from the accumulation of knowledge that follows interactions and exchange of information, it is of major importance to have and maintain a strong set of connections and collaborations.

EC-funded projects stimulate AI R&D in the EU. Thanks to them, the number of players involved in the AI domain has gone up considerably in every country of the Union, and it is thanks to these projects that EU Member States can establish connections across multiple countries. Although aimed at the development of research projects, it is important to note that EC-funded projects not only substantially stimulate the joint work of research centres of the EU, they also give an important push to collaborations between firms located in different Member States.

2.4 Technology

This dimension of the AI Watch Index addresses the evaluation of the technical progress in an illustrative set of AI tasks found in different subareas (including image classification, face recognition, speech recognition, text summarisation, etc.). The aim of this dimension is to provide information about the technological evolution that the domain is experiencing. In addition, the technological dimension is also investigated with regard to the standardisation work that is carried out by Standardisation Development Organisations supporting interoperability, promoting consistent application of best practices in the development of AI products and services, and ensuring proper consideration is given to their potential risks in terms of safety and fundamental rights. Sub-section 3.4 presents in detail the indicators covered by this dimension.[17] The results show an overall improvement in performance of all analysed AI tasks from 2016 to 2021, with higher growth rates for the tasks that start with lower levels (*Computer Vision – Video* and *Natural Language Processing – Language Reasoning Skills*). The best performing AI task is *Natural Language Processing – Speech*.

In the standardisation sphere, intense activity is observed both nationally and internationally. Indeed, many standardisation deliverables regarding AI (including standards, as well as technical specifications, technical reports and certification criteria) have been identified. Importantly for the EU, a substantial number of these are significant in the context of the requirements for AI systems laid down in the European AI Act. This is a promising sign for the harmonisation of further innovations in the field.

2.5 Societal aspects

The fifth dimension of this study addresses societal aspects of AI. In order to fully consider the digital transformation process, the discussion on economic aspects (i.e., industry, investments made in AI, and research and developments) must be completed along with societal considerations. Indeed, it is fundamental to have insights regarding the way the opportunities opened by AI are enjoyed by society, especially with respect to who develops AI and who will work with it in the near future. Thus the AI Watch Index includes seven indicators to target the level of diversity among active researchers in the field, and to investigate how the educational offer related to AI content is distributed among Member States. The consideration of diversity among the AI research community is relevant, as there are many concerns about the ethical issues related to AI, and therefore it is

17 T1 – Performance of AI research, and T2 – Standardisation activity engagement.

advisable that the research community should present heterogeneous characteristics in order to reduce bias-related risks. Indeed, the presence of diversity should encourage the consideration of multiple perspectives in the development process. And this, in turn, should make the technology fairer and more neutral. At the same time, diversity in research may be the result of inclusion policies which are worth monitoring. The second aspect considered to address the theme of AI and society, that is academic offerings about AI content, provides elements to proxy the supply of AI skills of future cohorts of workers, which will affect both the individual employment opportunities and the overall human capital present in the economic system to support the innovativeness of industry. In fact, it is likely that the future availability of skilled workforce will have positive consequences on the overall competitiveness of the economy. Also, as AI competences become increasingly desirable in the labour market, they will constitute an increasingly relevant part of a worker's skill-set, and having them will likely have consequences on families' incomes and individual well-being. Finally, this technology is so pervasive that having a basic knowledge of its elementary principles is going to be useful for several aspects of one's personal life (e.g., security, privacy). Sub-section 3.5 presents in detail the indicators covered by this dimension.[18]

Regarding the diversity of the active AI research community, the index considers four indicators of the diversity of participants in a set of international AI conferences. Even if all these indicators present upward trends, translated into an increase of gender, geographical and business-academia diversity, still their values are not close to 1 – meaning maximum diversity. In other words, although in general terms heterogeneity has improved among AI researchers, there is still room to improve diversity in AI teams.

The indicators related to education show that AI content intensity in official studies is heterogeneous across EU Member States, as drawn from a selection of AI programmes taught in English language. Some have a low proportion of university programmes with AI content, for example Slovenia, Luxembourg, Croatia and Bulgaria. They have very low numbers of AI programmes in the total offer of bachelor's degrees, and also small numbers of available places for students in programmes that contain any type of AI content. Germany is the country with the largest number of available university places with AI content in both master's and bachelor's degrees. Other Member States have much less availability of places, with a few positive exceptions, such as Poland and Romania, with regard to bachelor's degree-level courses, and France and Italy in the availability of places in AI-related master's degrees.

For most Member States, the presence of AI content in master programmes is higher than in bachelor programmes. The same pattern is detected for the AI intensity in university places – or proportion of university places including AI content – which shows larger percentages in master's degree-level programmes for almost all Member States. This seems to indicate that AI is considered to be specialised content proposed mostly in a phase of the education path at which basic knowledge has already been provided to students. Indeed, this reflects the characteristics of AI, an advanced technological domain. At the same time, its pervasiveness in the daily life and in many aspects of society and economy should also encourage a wider provision of related contents in less advanced courses (e.g., bachelor's degrees).

18 S1 – Gender diversity index, S2 – Geographic diversity index, S3 – Business diversity index, S4 – Conference diversity index, S5 – AI in university programmes in the EU, S6 – University places with AI content in the EU, and S7 – AI intensity in university places in the EU.

3 Detailed analysis by indicator

3.1 Dimension G – Global view on the AI landscape

3.1.1 AI Activity

3.1.1.1 G1 & G2: AI economic players and AI player intensity

Description of indicators

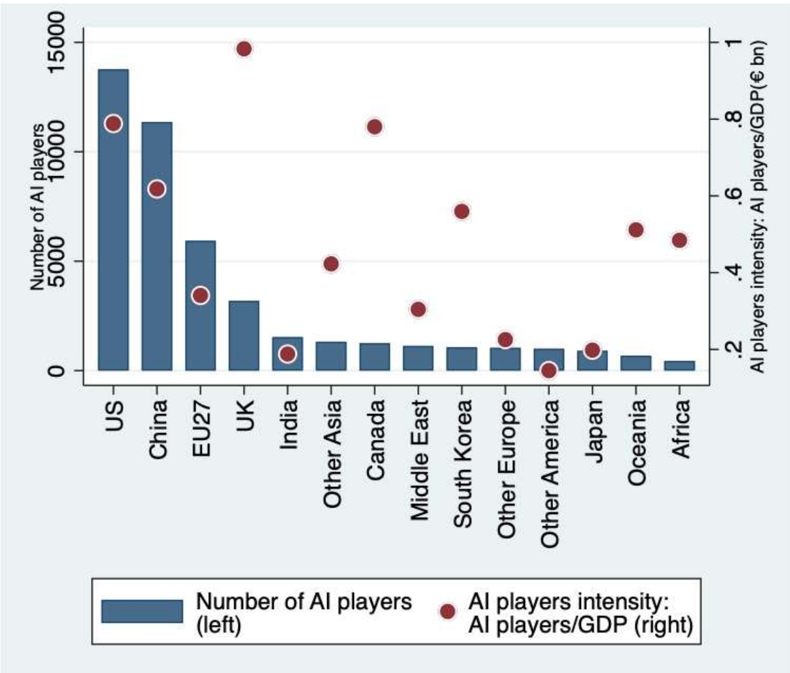
The *G1 – AI economic players* indicator measures the number of the three types of economic players included in the AI landscape analysis: research institutes (including universities), firms and governmental institutions. The breakdown of AI players by organisation type makes possible further analysis of the relationships between research, industry and government in different geographic areas and facilitates the assessment of different properties of the entire AI landscape and local areas. The types of AI activities tracked are: business activities (firms with a core business in AI), research activities (scientific articles in top AI and robotics international conferences), and innovative activities (AI-related filed priority patent applications). Additionally, a fourth group is considered: AI-related EC-funded projects. International comparability is given when the first three groups are used. EC-funded projects are only used for the in-depth analysis of the EU and its Member States.

The second indicator, *G2 – AI economic activity intensity*, expresses the presence of AI economic players in relation to the size of the economy. It is calculated as the ratio between the number of AI players and GDP in billions of euro. Hence the G2 indicator makes possible a comparison of the size of the AI landscape for each geographic area.

For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

World

Figure 1. AI economic players and AI player intensity. Worldwide, 2009–2020

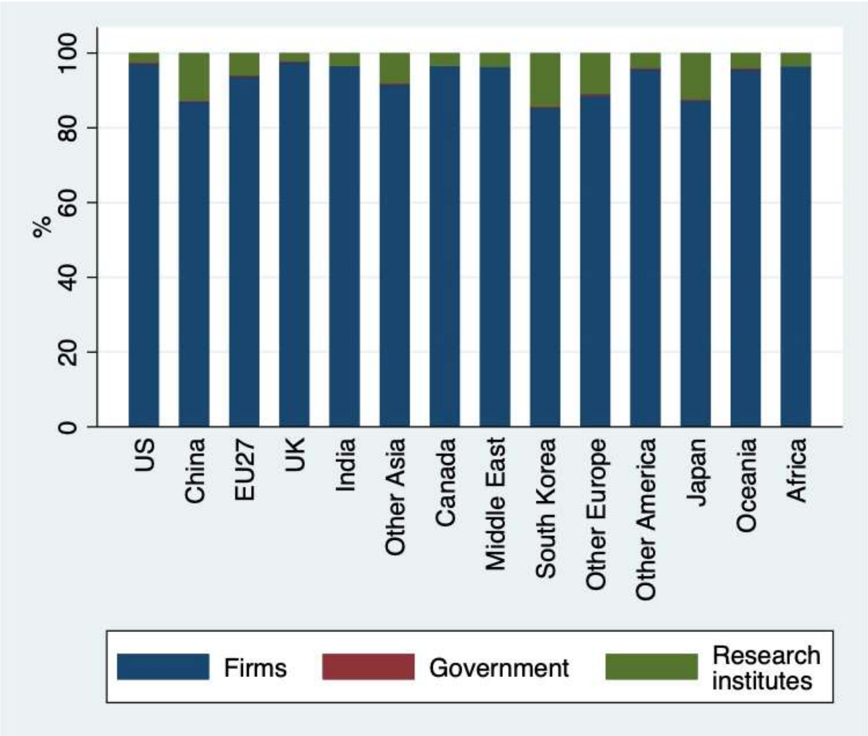


The US is home to the largest number of AI economic players, with 13,770 organisations. It is followed by China, which has 11,362 players, and in third place is the EU, with 5,933. These three dominate the worldwide AI landscape. However, we can see a clear distance between the US and the EU, since the former has more than twice as many players as the EU (Figure 1).

Nevertheless, the number of AI players has limitations as an indicator, as it does not consider the size of the country's economy, the size of the players themselves (e.g., a small start-up and a multi-national both each count as one player) or their intensity of AI engagement (e.g., number of AI publications or AI patents). The ratio of number of AI players to GDP provides a different perspective of the AI landscape, giving a relative measure that enables one to compare countries of different economic weight. The UK holds simultaneously a remarkable number of AI players and the highest ratio of players to GDP of all geographic areas considered. This highlights the consequent loss of strength of the EU AI landscape in the global perspective after the Brexit. While the UK has 0.98 AI players per billion euro of GDP, in the US the ratio is 0.79, in Canada 0.78, in China the ratio is 0.62 and in the EU 0.34. Therefore, even if the US and China have the highest number of AI players in the AI landscape, is the UK the country with the highest AI player intensity.

The majority of AI players are firms, followed by research institutions and government (Figure 2). While firms account for more than 85% of the total number of players for all the cases, for some Asian countries the participation of research institutes is higher than the global average (6.5%). This is the case in China, where 12.6% of the players are research institutes, Japan (12.4%) and South Korea (14.2%). Even if this information does not assess the quantity or the quality of the research that is carried out, the presence of research institutes in the AI landscape is very important, due to the obvious link between research and innovative outcomes. The position of the EU in this respect (6.0%, without considering the impact of EU-funded projects) is halfway between the very poor presence of research institutes in the US (2.6%) and the UK (2.1%), and the higher proportion of research institutes found in China, Japan and South Korea. Government institutions play a minor role in the AI landscape. No government participation is observed in Africa, Canada, India and the Middle East.

Figure 2. AI economic players by organisation type (%). Worldwide, 2009-2020



The European Union

Within the EU, Germany and France are the two countries with the highest number of AI players, with 1,136 and 1,055 players, respectively. They are followed by Spain, which has a much smaller number of players (614), while the rest of the Member States do not have more than 450 AI players. Estonia, with 66 AI players and a ratio of 1.57 AI players per billion euro of GDP, is the Member State with highest AI player intensity. The ratio in Malta is also remarkable, 1.02 AI players per billion euro of GDP. For the rest of the Member States this value is smaller than 1, indicating that there is less than one AI player per billion euro of GDP (Figure 3).

Figure 3. AI economic players and AI player intensity. EU Member States, 2009–2020

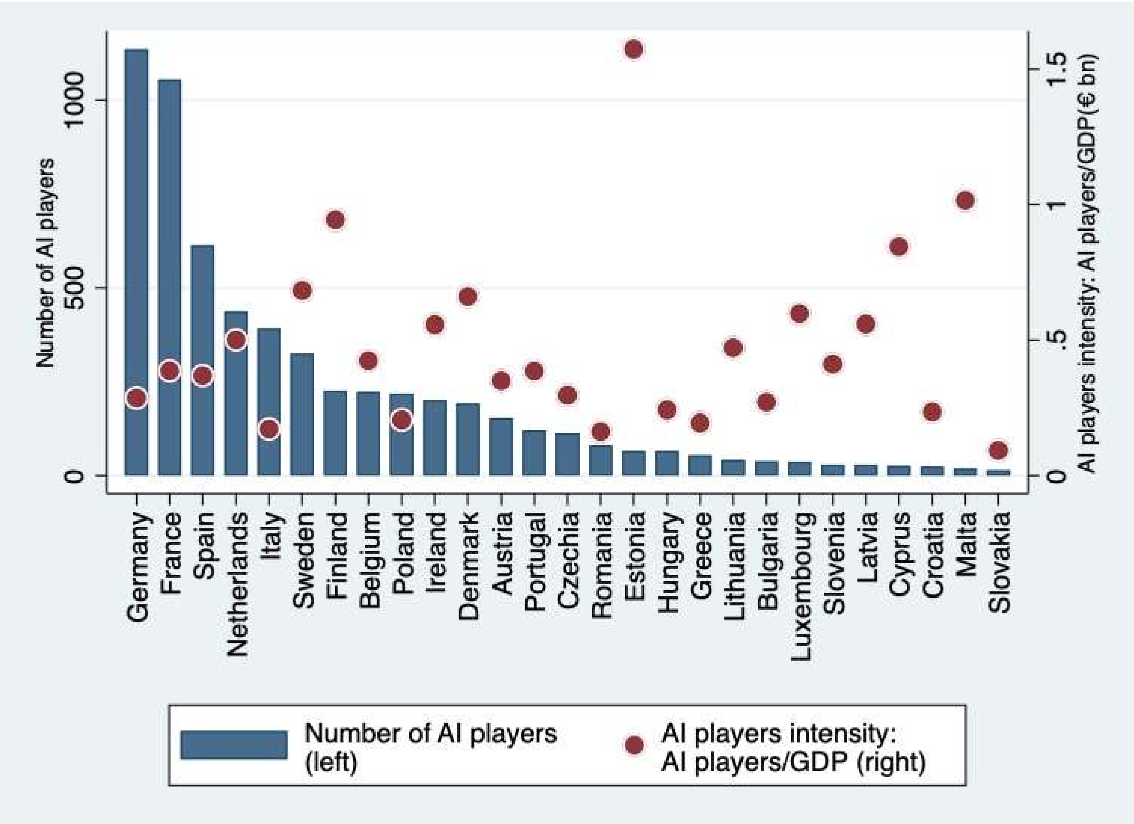


Figure 4. AI economic players by organisation type (%). EU Member States, 2009–2020

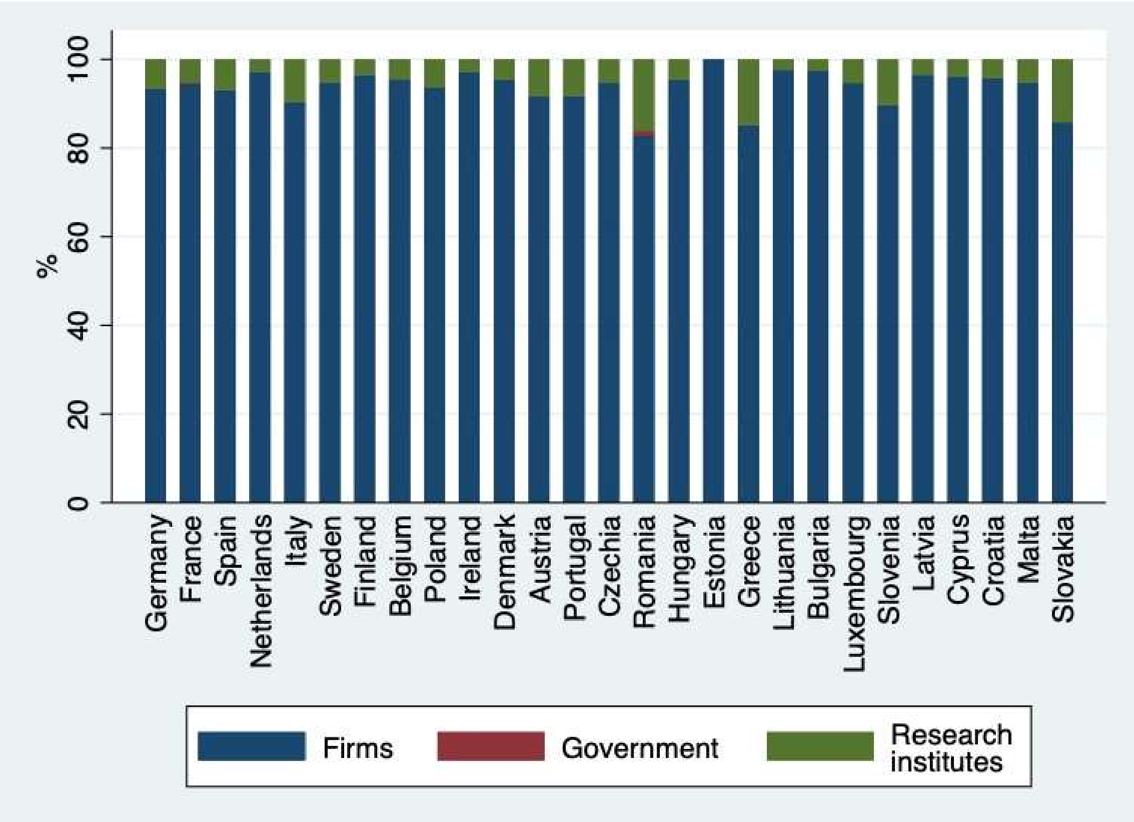


Figure 4 provides a view on the composition of AI players in the EU by type of organisation. Firms are the predominant type of AI player in all Member States, and governmental institutions account for only a small proportion. The presence of research institutes is significantly high in Romania (16.05%), Greece (14.82%), Slovakia (14.29%), Slovenia (10.34%) and Italy (9.67%).

3.1.2 AI areas of strength

3.1.2.1 G3: AI areas of specialisation: comparative advantage in AI thematic areas

Description of indicator

The *G3 – AI areas of specialisation: comparative advantages in AI thematic areas* indicator explores the specialisation of geographical areas in the AI field by means of their revealed comparative advantage (RCA). It measures a country's specialisation in a thematic area in comparison with the global average specialisation for that area. The RCA is a ratio calculated as share 1 / share 2: share 1 is the share of activities of a geographical area in a thematic area (or technological subdomain) in the total amount of activities in that geographical area; share 2 is the share of activities in that thematic area worldwide in the total amount of activities worldwide. For the calculation activities are assigned to the thematic area that best represents the activity's content (resulting from a topic-modelling analysis). Since a RCA value of 1 represents the global average specialisation, this is taken as the benchmark (it is represented as a red dashed line in the graph). When the RCA is greater than 1 for a geographical area in an AI thematic area, that geographical area has a comparative advantage in that AI thematic area.

Let A_{C_i,k_z} be the number of activities of country C_i in topic k_z, defined as the sum for all the country's players, j, of AI-related industrial, innovative or research activities in said topic: $A_{C_i,k_z} = \sum_j A_j^{C_i,k_z}$; then the RCA for country C_i and topic k_z is defined as:

$$G3_{c_i,k_z} = RCA_{C_i,k_z} = \frac{\frac{A_{C_i,k_z}}{\sum_z A_{C_i,k_z}}}{\frac{\sum_C A_{C_i,k_z}}{\sum_{C,Z} A_{C_i,k_z}}} = \frac{\frac{sum\ of\ activities\ of\ country\ C_i\ in\ topic\ k_z}{sum\ of\ activities\ of\ country\ C_i\ in\ all\ topics}}{\frac{sum\ of\ worlwide\ activities\ in\ topic\ k_z}{sum\ of\ worlwide\ activities\ in\ all\ topics}}$$

The types of AI activities tracked are: business activities (firms with a core business in AI), research activities (scientific articles in top AI and Robotics international conferences), and innovative activities (AI-related filed priority patent applications). Additionally, a fourth group is considered: the AI-related EC-funded projects. International comparability is granted when the first three groups are used. EC-funded projects are only used for the in-depth analysis of the EU and its Member States.

We use the textual information contained in the activities of the collected microdata to infer their technological content. Through a topic model we identify the following thematic areas or technological subdomains of AI.

— **Audio and Natural Language Processing (NLP)**: Audio Processing AI systems facilitate the perception or generation (synthesis) of audio signals, including speech, and also other sound material (e.g., environmental sounds, music). Natural Language Processing is a machine's ability to identify, process, understand and/or generate information in written and spoken human communications.

— **Computer Vision applications** are activities that identify human faces and objects in digital images, as part of object-class detection.

— **Machine Learning (ML) Fundamentals** are the ability of systems to automatically learn, decide, predict, adapt and react to changes, improving from experience, without being explicitly programmed.

— **ML for Image Processing** are machine learning methods used for image processing activities.

— **The Internet of Everything (IoE)**: this refers to the interconnectivity of various technologies, processes and people. The human interaction in this context allows people to monitor or configure devices and processes through interfaces.

— **Automation** refers to activities related to the production or use of physical machines, computer software and other technologies to perform repetitive tasks, for which they are specifically designed and programmed. They can have several degrees of freedom, e.g., in terms of movement, and they may include intelligent control modules to interact with the environment in a controlled setting, e.g., using a temperature sensor. However, they are limited to a set of actions for which they are designed to operate, and have to be re-programmed for new or additional operations. The use of AI in automated machines is mainly related to the adaptation of the defined set of operations as a reaction to external parameters.

— **Autonomous Robotics**: activities related to the development or use of robotic systems that are meant to operate in a relatively complex environment involving interaction with other machines or humans. Autonomous robots perform multiple operations without any prior exact set of instructions, nor programmed sequence of actions. AI enables autonomous robots to have this higher degree of autonomy compared with automated machines.

— **Connected and Automated Vehicles (CAVs)** involve technologies for autonomous vehicles, connected vehicles and driver assistance systems, considering all automation levels and all communication technologies (V2X)**.**

— **AI Services** are activities related to the provision of (online) AI services and applications, including infrastructure, software and platform services (e.g., cognitive computing, ML frameworks, bots and virtual assistants, etc.).

For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

World

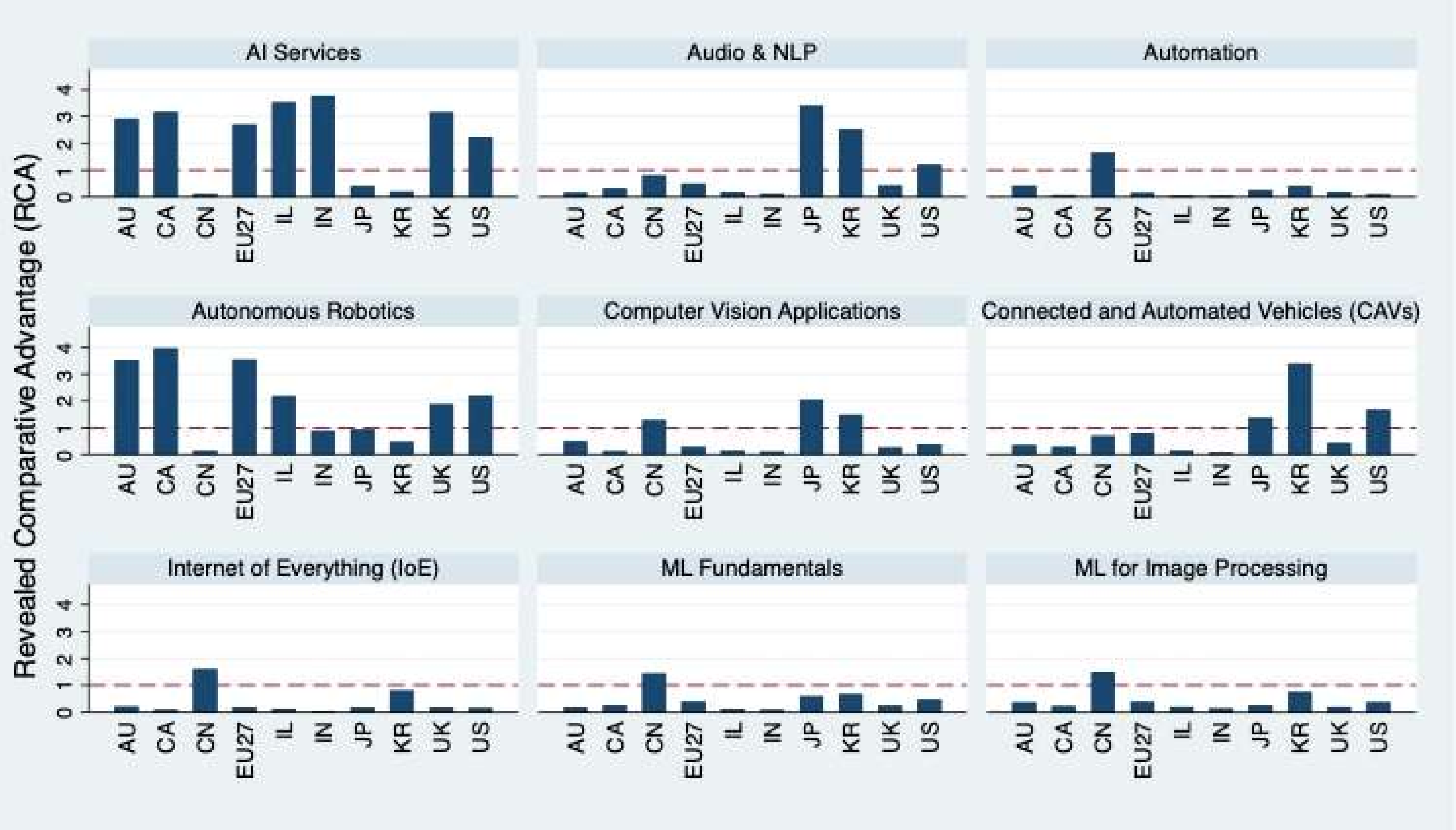
This indicator presents large values in the thematic area of *AI Services*, which refers to the provision of AI services and applications, including infrastructure, software and platform services. All major countries except Japan, South Korea and China have a value larger than 2 (Figure 5). On the one hand, this indicates a clear orientation of western areas economies towards the development of businesses based on AI services. On the other, it also reflects the different involvement of China, Japan and South Korea in the AI landscape, which are more oriented towards the development of patents.

The advantage of the EU is especially evident in two thematic areas. The first is *AI Services*, highlighting the salient role of the EU AI players in the provision of services between firms (B2B) or to the end-consumers (B2C). The second is *Autonomous Robotics*, which is expected to positively affect the EU's competitiveness and sustainability in industry and services, and is increasingly impacting many sectors, such as health, logistics or manufacturing, among others.

The European Union

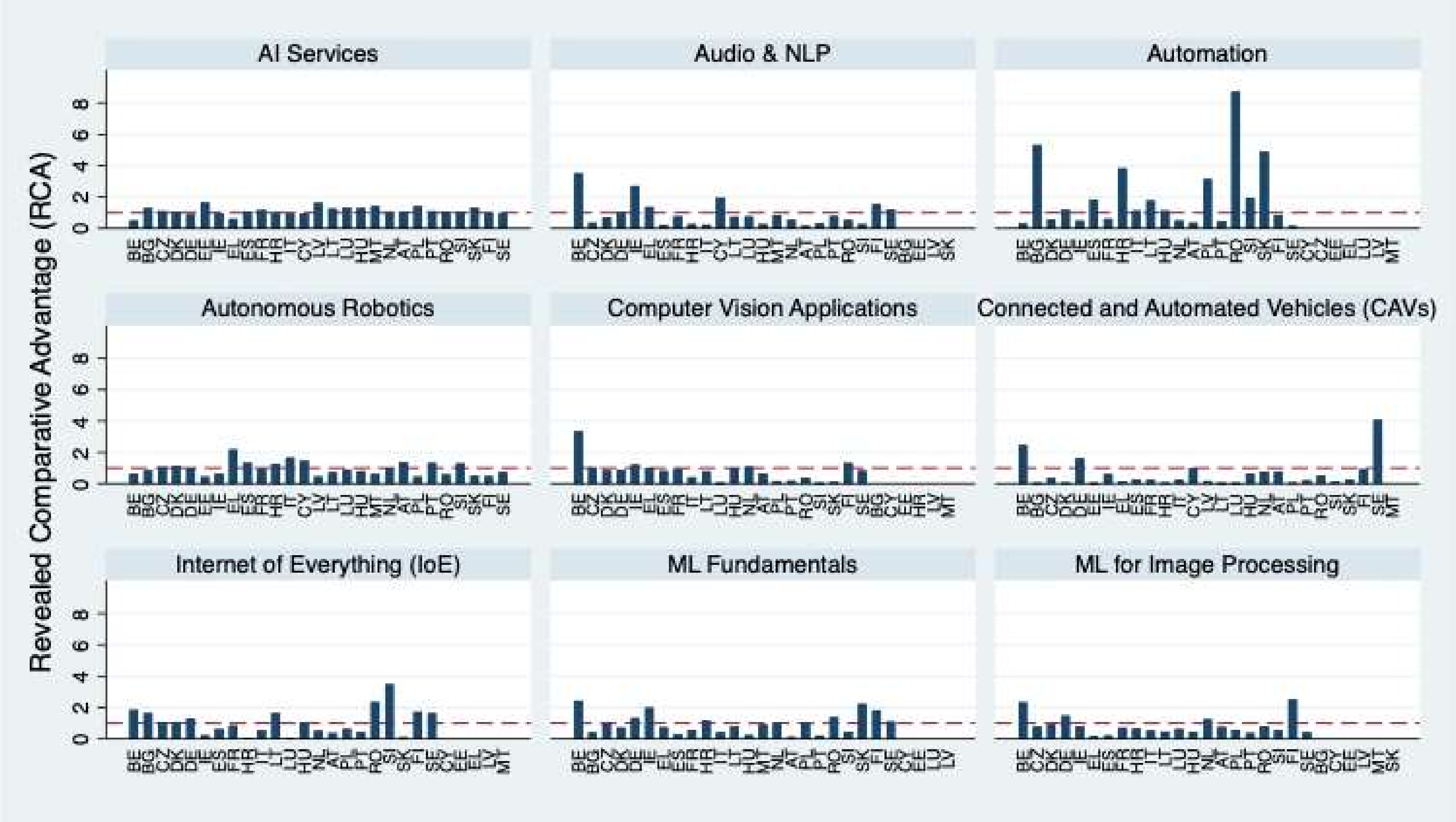
Regarding EU Member States, some Eastern European countries, such as Romania, Bulgaria, Slovakia, Poland and Croatia, show high RCA values in the thematic area of *Automation*. However, these countries are not involved in many AI activities, and in some cases this high RCA is the result of a relatively higher concentration in this AI thematic area, even if the number of related activities is small. We note strong specialisations in Belgium and Ireland for *Audio & NLP*, in Spain for *Automation*, in Sweden for *Connected and Automated Vehicles (CAVs)*, in Belgium for *Computer Vision Applications*, in Belgium and Ireland for *Machine Learning Fundamentals*, in Belgium and Finland for *Machine Learning for Image Processing*, and in Greece and Italy for *Autonomous Robotics* (Figure 6).

Figure 5. AI areas of specialisation: comparative advantage in AI thematic areas. Top worldwide countries and the EU, 2009–2020



Note: AU: Australia, CA: Canada, CN: China, EU27: European Union as of 2020, IL: Israel, IN: India, JP: Japan, KR: South Korea, UK: United Kingdom, US: United States.

Figure 6. AI areas of specialisation: comparative advantage in AI thematic areas. EU Member States, 2009–2020



3.1.2.2 G4. AI thematic hotspots

Description of indicator

The *G4 – AI thematic hotspots* indicator presents the geographical distribution of activities of each AI thematic area. It offers a view of the global performance and geographical hotspots of activity within each AI thematic area. Let A_{C_i,k_z} be the number of activities of country C_i in topic k_z, defined as the sum for all the country's players, *j*, of AI-related industrial, innovative or research activities in said topic: $A_{C_i,k_z} = \sum_j A_j^{C_i,k_z}$; then the *AI thematic hotspot* indicator for country C_i and topic k_z is defined as:

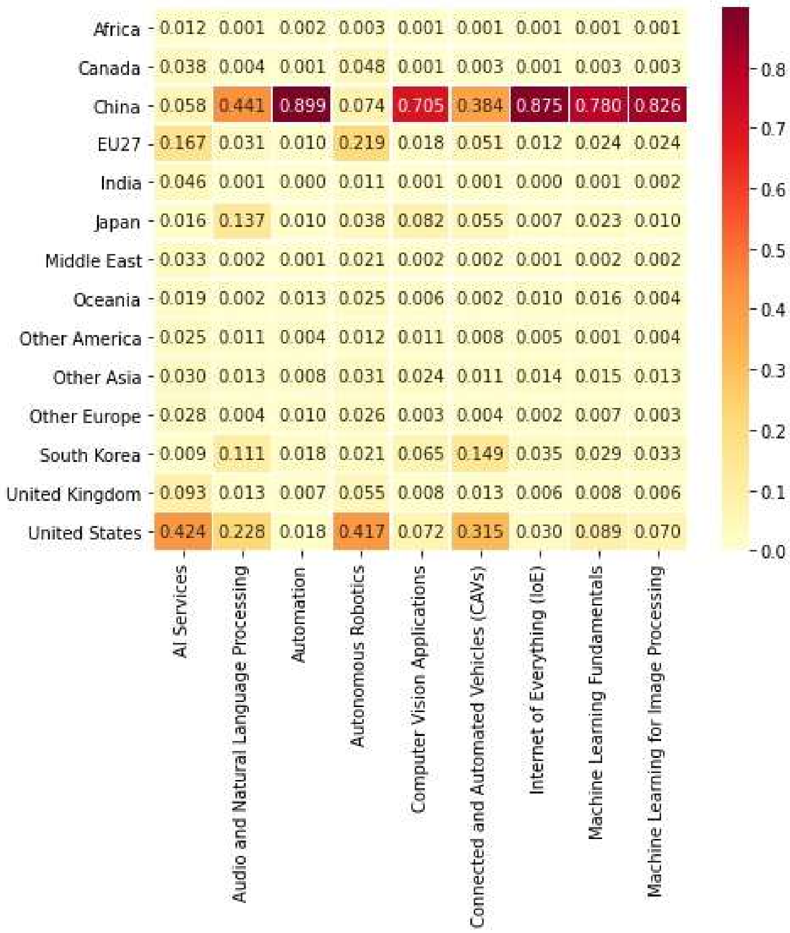
$$G4_{C_i,k_z} = \frac{A_{C_i,k_z}}{\sum_i A_{C_i,k_z}} = \frac{sum\ of\ activities\ of\ country\ C_i\ in\ topic\ k_z}{sum\ of\ activities\ of\ countries\ worldwide\ in\ topic\ k_z} x100$$

The types of AI activities tracked are: business activities (firms with a core business in AI), research activities (scientific articles in top AI and Robotics international conferences), and innovative activities (AI-related filed priority patent applications). Additionally, a fourth group is considered: the AI-related EC-funded projects. International comparability is granted when the first three groups are used. EC-funded projects are only used for the in-depth analysis of the EU and its Member States.

For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

World

Figure 7. AI thematic hotspots: geographic distribution of AI activities per thematic area (share). Worldwide, 2009–2020

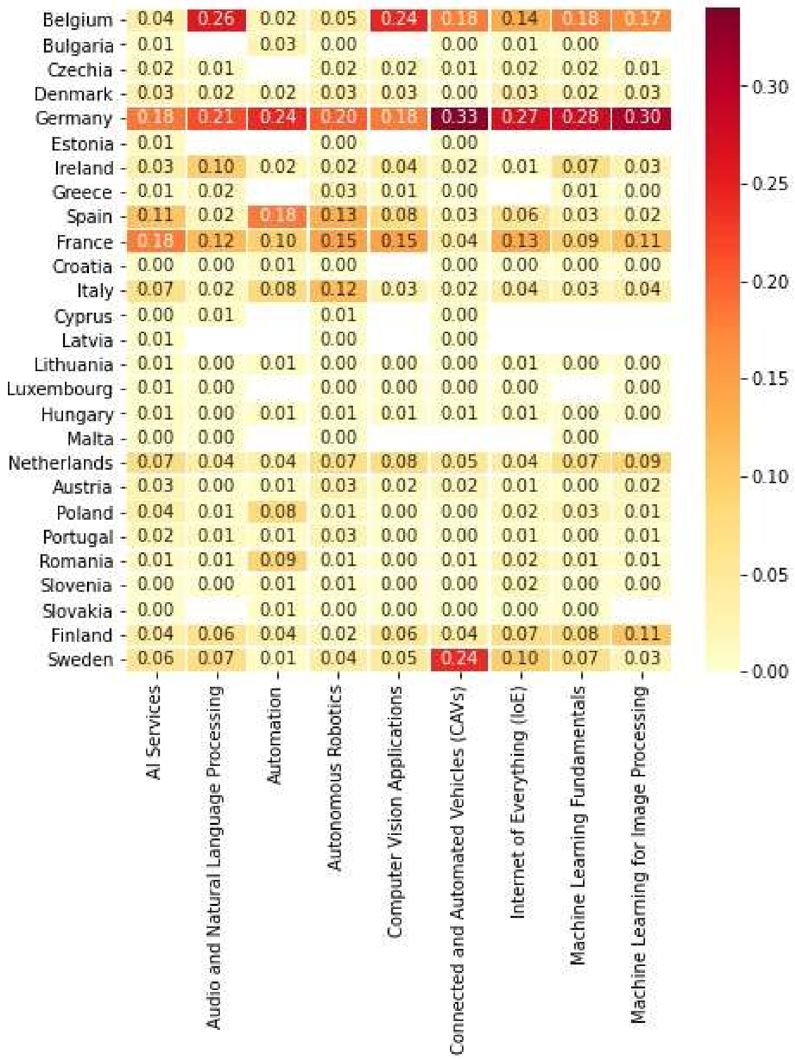


Note: The share of a country in a thematic area is calculated based on the total number of activities of all countries in that thematic area.

Figure 7 presents for each thematic area the percentage of activities by geographical area. We note a concentration of *AI services* in Western countries, especially in the US (42.4% of worldwide *AI Services* are concentrated in this country), the EU (16.7%), and the UK (almost 10%). Along with this, we also detect a noteworthy concentration of activities related to *Audio & NLP*, *Connected and Automated Vehicles (CAVs)* and *Autonomous Robotics* in the US (22.8%, 31.5% and 41.7%, respectively), as well as activities related to *Autonomous Robotics* in the EU (21.9% of worldwide activities related to this thematic area). China concentrates the vast majority of worldwide activities in five of the nine AI thematic areas: *Automation* (89.9%), *Internet of Everything* (87.5%), *Machine Learning for Image processing* (82.6%), *Machine Learning Fundamentals* (78.0%) and *Computer Vision Applications* (70.5%). China also has high proportions of worldwide activity in *Audio and NLP* (44.1%) and in *CAVs* (38.4%). It is important to note that China is the geographical area that files the highest number of AI patent applications, supported by a series of governmental incentives and policies to boost AI patenting activity. Therefore China is especially concentrated in the AI thematic areas more closely connected to the development of AI-related technological components and algorithms, rather than in the provision of AI services. In South Korea and Japan the most important AI thematic areas are *Audio & NLP*, *CAVs* and *Computer Vision Applications*.

The European Union

Figure 8. AI thematic hotspots: geographic distribution of AI activities per thematic area (share). EU Member States, 2009–2020



Note: The share of a country in a thematic area is calculated based on the total number of activities of all countries in that thematic area.

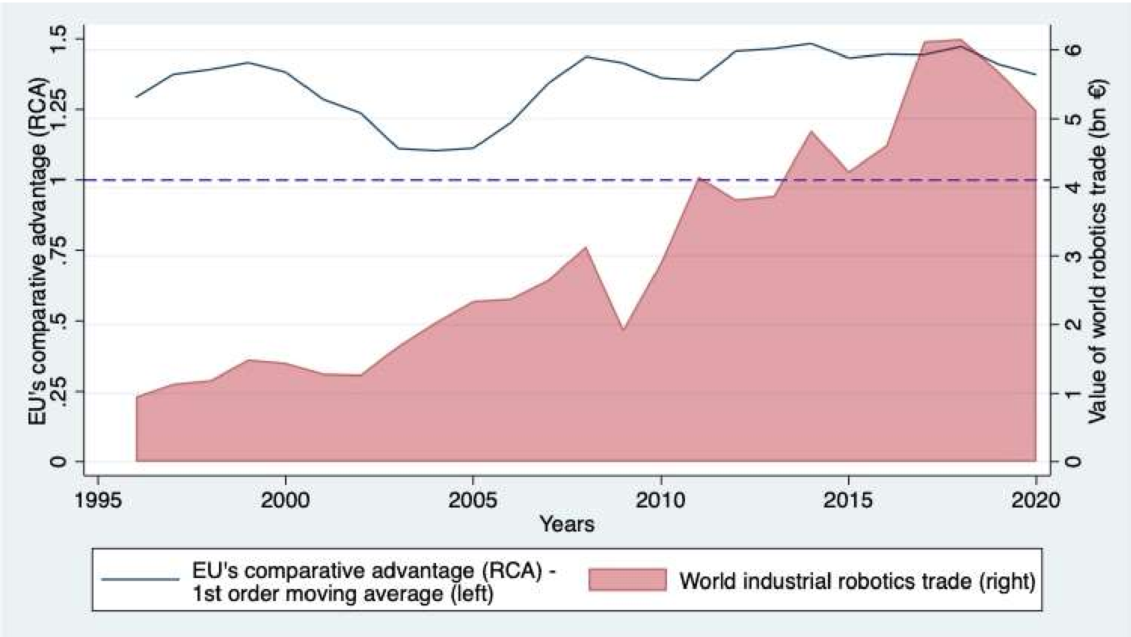
Figure 8 shows the *G4* indicator for EU Member States and highlights the concentration of AI activities in very few countries. Germany is the Member State that develops the highest number of AI activities in seven of the nine AI thematic areas, being top ranked in *AI Services*, *Automation*, *CAVs*, *IoE*, *ML for Image Processing*, *ML Fundamentals* and *Autonomous Robotics*. Overall, Germany is responsible for one fifth of all the EU's activities in AI. Only in the domains of *Audio & NLP* and *Computer Vision Applications* is Germany is surpassed (for both by Belgium). France, Spain and Belgium are the other three most active Member States in AI. Those four countries carry out more than 50% of activities in any AI thematic area in the EU (and 53% overall), highlighting how much AI activity in the EU is concentrated in a few countries. The only other EU Member States that account for more than 10% within some AI thematic area are: Finland, in *ML for Image Processing* (10.6%); Italy, in *Autonomous Robotics* (11.7%); and Sweden, in *CAVs* (24.1%).

3.1.2.3 G5. EU's comparative advantage in industrial robotics trade

Description of indicator
The *G5 – Comparative advantage in robotics trade* indicator applies the Revealed Comparative Advantage (RCA) indicators to the industrial robotics trade. It is calculated as the share of industrial robotics trade value (imports and exports) of the EU countries divided by the share of industrial robotics trade value worldwide.
For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

The European Union

Figure 9. The EU's comparative advantage (RCA) and worldwide trade in industrial robots, 1996–2020



Note: The blue line depicts the revealed comparative advantage (RCA) of the EU's value of trade of industrial robots with respect to the worldwide value. In order to remove noise produced by random fluctuations, and hence to better show the trend, the series is smoothed with a simple moving average transformation (or first-order moving average). The red area represents the value of the worldwide industrial robotics trade, and provides the overall trend in this market to contextualise the RCA indicator. In addition, the horizontal blue dashed line represents the benchmark for comparison. When the EU RCA (the blue line) is above the dotted line (i.e., greater than 1), this indicates that EU's trade is more concentrated in robotics than the global average, so the EU has a relative comparative advantage or specialisation in the industrial robotics trade.

In Figure 9, the RCA of the EU presents values greater than 1 for the entire period assessed (1995–2020), hence always showing a comparative advantage. However, it is possible to see some alternating fluctuations in the pattern of the RCA series. In particular, there is an important downturn from 2001 to 2004, reaching the lowest level in 2004. This fall may be due to a fall in demand in all major markets, which led to a drop of 12% in the worldwide sales of robots and a fall of 16% for the EU in 2002 (UNECE, 2003). The decrease of the RCA values for this period indicates that robot sales in the EU suffered more intensively the contraction in the world sales. After being relatively close to the global average, from 2005 the series shows an upward trend and the EU starts to recover. Since then, and with the exception of only 2010 and 2011 (when small decreases were seen), the indicator has maintained remarkable values. This continuity confirms that the EU's industrial robotics sector has reached a considerable solidity and competitiveness worldwide.

It is also possible to note that the RCA decreases in 2020. It is likely that the COVID-19 pandemic produced a fall in the demand (as usually occurs with durable goods, the purchase of which is delayed when a crisis occurs), and this seems to have resulted in a stronger fall in the EU industrial robotics competitiveness. Nonetheless, it is important to note that the EU has maintained its advantage from 1996 onwards. Moreover, the EU has managed to preserve its relative specialisation in a period (i.e., the last two decades) during which the industrial robotics trade has expanded worldwide. As the series of global industrial robotics trade in Figure 7 indicates (red area, right axis), the trade of industrial robots has grown rapidly since 2002, when it globally accounted for €1.27 billion, until reaching €5.7 billion in 2019. During this period the EU not only always presents an RCA greater than 1, but the value of the indicator has increased progressively.

3.1.3 AI investments

3.1.3.1 G6: AI investments in the EU

Description of indicator

The *G6 –AI investments in the EU* indicator provides an estimate of AI investments by public and private sectors in the EU. To estimate the AI investments in the EU and the Member States, a top-down approach based on national statistics has been used. This methodology is the one utilised for the 2020 EU AI investments report (Dalla Benetta et al., 2021). The approach used considers the following two categories of AI investments: (i) expenditures on labour and skills, and (ii) tangible and intangible capital assets incurred by public and private organisations to develop and implement AI to (re-)design business processes aimed at creating new or improving existing products or services.

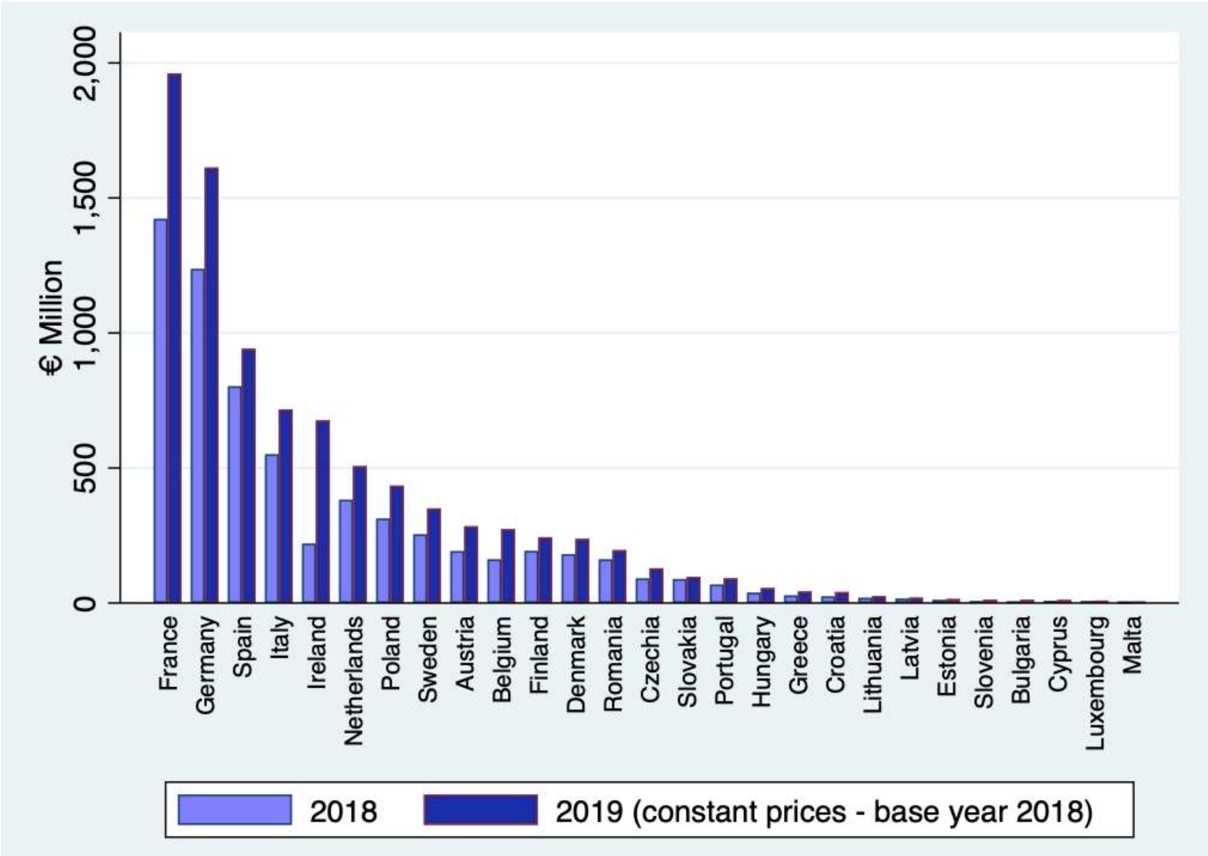
For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

The European Union

The EU invested between €7.9 billion and €9 billion in AI in 2019.[19] This is an estimated increase of 39% compared with 2018. If a similar trend is maintained, the EU will exceed its annual AI investment target of €22 billion by 2030. This would imply that the annual investment target of €20 billion (which was set in the 2018 Communication Artificial Intelligence for Europe (European Commission, 2018)) will be reached ahead of schedule. Figure 10 represents the estimated maximum investment scenario. All EU Member States increased their level of AI investments from 2018 to 2019. Among the countries that invested more than €50 million in 2019, we find that Ireland, Belgium and Austria had the largest annual increases. Among countries with lower investment levels (i.e., less than €50 million), we see Bulgaria, Slovenia and Croatia presenting the highest yearly increases (+96%, +75%, and +67%, respectively). In absolute terms, France and Germany lead, as in 2019 they accounted for 22% and 18% of all EU AI investments, respectively. If along with them we include Spain, 50% of EU investments in AI during 2019 were made by only three countries. Nevertheless, in 2018 the same three countries accounted for 53% of EU investments in AI. Thus, even if just one year is not sufficient to establish a trend, the fact that the concentration of investments decreases may suggest a progressively larger investment effort by a larger number of countries. The increase in the volume of AI investments in 2019 was driven to a large extent by the private sector, which accounted for 66% of all investments, while the public sector also increased its AI investments from 2018 to 2019 and accounted for 34% of the investments in 2019.

19 The methodology provides a range of values considering a minimum and a maximum scenario. For more details, see the original report "AI Watch: 2020 EU AI investments" (Dalla Benetta et al., 2021).

Figure 10. Public and private AI investments. EU Member States, 2018–2019



3.2 Dimension I – Industry

3.2.1 Industry

3.2.1.1 I1: AI firms' profiles

Description of indicator

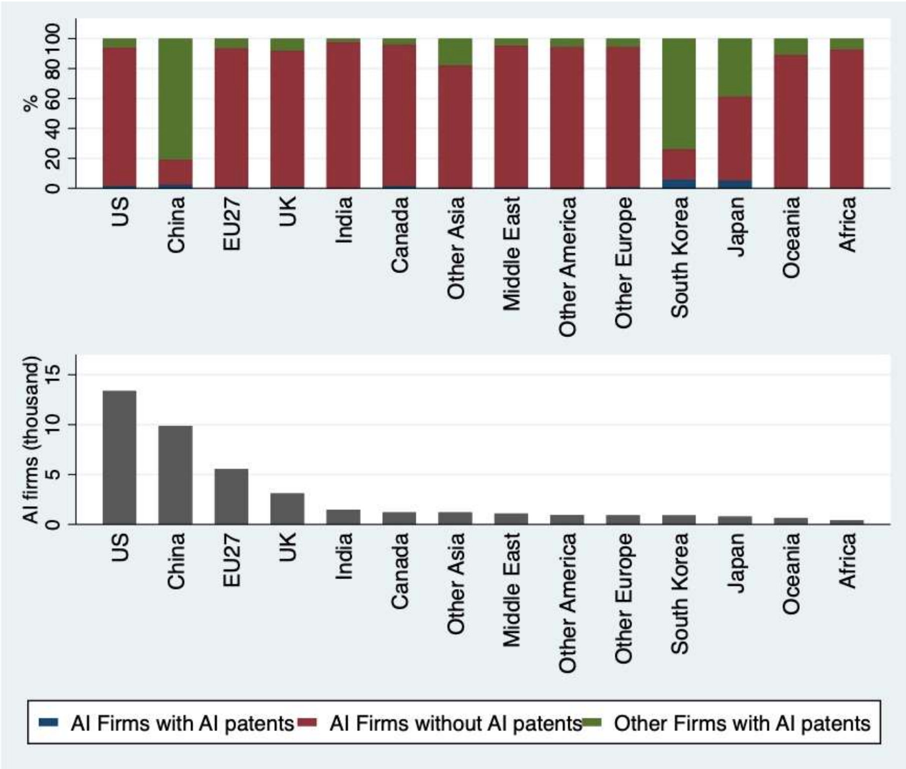
The *I1 – AI firms' profiles* indicator characterises the AI industry in a geographical area by means of the distribution of AI firms according to their business type. The AI business type is defined based on the core business activity of the firm (i.e., the core business either is or is not related to AI) and its innovative activity (i.e., the firm files or does not file AI patent applications). The combination of these two elements of analysis allows us to differentiate three types of AI firms: AI firms with AI patents, AI firms without AI patents, and Other firms with AI patents. This is useful for uncovering the presence of different kinds of involvement in the AI landscape. The I1 indicator is presented in combination with the total number of AI firms, for a better contextualisation.

For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

World

The largest number of AI firms is found in the US, followed by China, the EU and the UK. In all these countries except China, most firms have a core AI business but they do not file patent applications in the field. Therefore while for the US, the EU and the UK most firms sell goods and services based on AI, just a small portion of them are actively involved in the development of the technology. It should be noted that the number of AI firms in the UK alone is almost half the number of AI firms in the entire EU (Figure 11).

Figure 11. AI firms' profiles (%) and number of AI firms. Worldwide, 2009–2020



In China, a very large proportion of firms (more than 80%) are involved in AI patenting activity. This situation is influenced by two important factors. First, the approach followed in China for the development of patents leads to lower standards of quality for the same[20]. Second, in recent years a series of governmental subsidies and proactive support for the development of AI patents has attracted a multitude of firms, and the number of AI-related patent applications filed has increased substantially, without necessarily reflecting true innovative capacity.[21] More recently, the Chinese government has introduced changes in the guidelines for patent examination with a view to keep protecting and facilitating the generation of AI intellectual property (Jianchen and Ming, 2021).

South Korea and, to a lesser extent, Japan also have a high number of firms with AI-related patent activity. Additionally, these two countries present the largest percentages of AI firms with AI patents. These firms, which typically can be identified as the big-tech companies, can have a very relevant role in leading the expansion of their national AI landscape, as they have a core business centred on AI while at the same time contributing to the technological advancements of the field by filing patent applications (e.g., Samsung, Softbank Robotics).

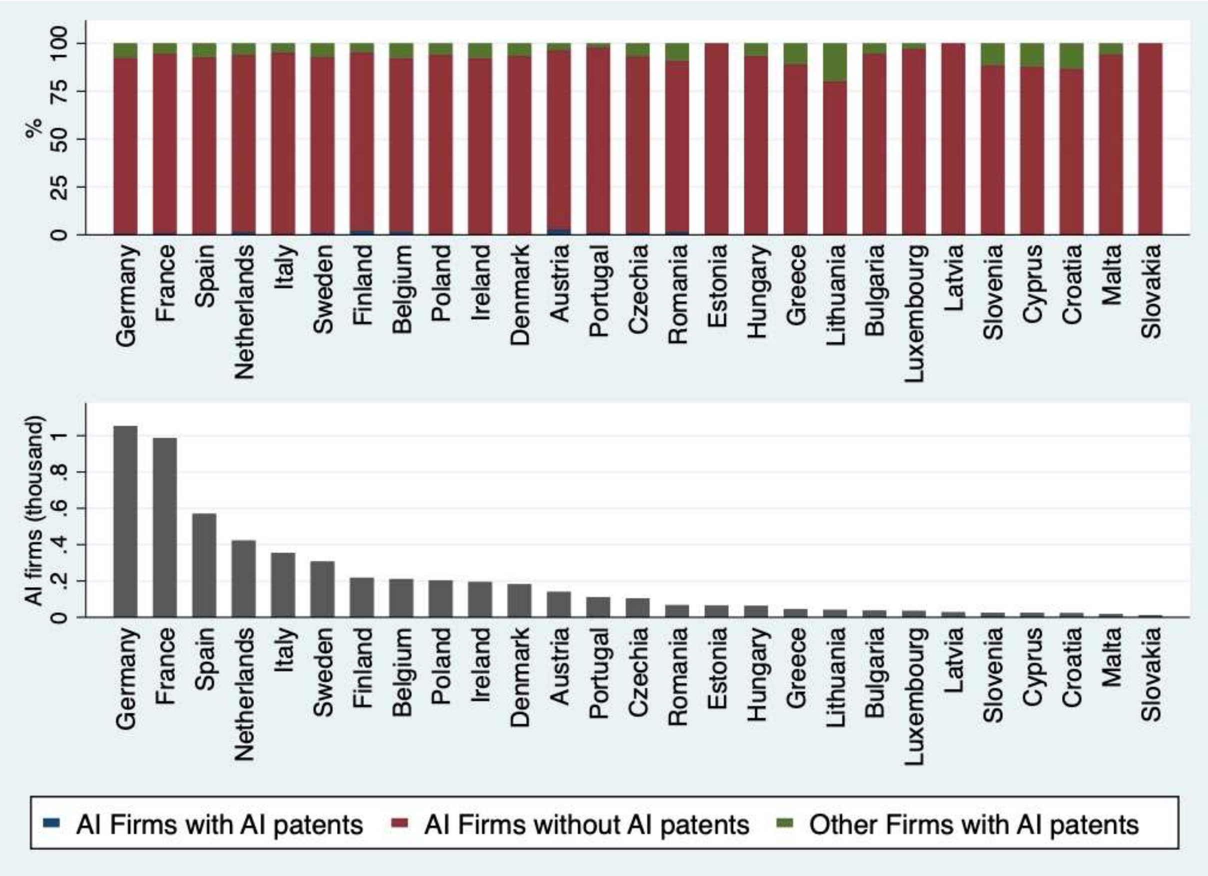
Although in percentage terms this is not easily observable, the largest number of AI firms with AI patents are found in the US and China (233 and 226, respectively, corresponding to 1.7% and 2.2% of all AI firms). This insight underlines the leading position of these two countries in the AI domain. In this respect, the position of the EU is more modest, as just 43 firms (0.7%) are found to have a core business in AI and to file AI-related patents.

20 Several studies analyse the issue from different perspectives and metrics and find overall lower performance for Chinese patents, e.g., large citation lag (which indicates lower value of the patent), large shares of domestic citations and of self-citations, alternate effects (depending on the sector) in terms of consequences on firms' productivity, less accurate or shorter description of the innovation, and few number of claims that Chinese patents on average contain (Fisch et al., 2017; Christodoulou et al., 2018; Boeing at al., 2019, Song, 2014).

21 China has experienced an unprecedented increase in the number of AI patent applications in the last years. In fact, we detect many of China's players through their patenting activity. This is influenced by the Chinese government's support in local AI patenting since 2015, which may come to an end in 2021, as announced by the Chinese government.

The European Union

Figure 12. AI firms' profiles (%) and number of AI firms. EU Member States, 2009–2020



The distribution by type of firm in EU Member States is quite uniform, as in all countries at least 75% of the firms have a core business in AI but no AI-related patents, and in most cases this percentage is close to 90% (Figure 12). This indicates that only a few firms are actively involved in the technological development of AI, which may cause some future loss of economic competitiveness and technological advantage. Nevertheless, a technology such as AI, which has a very strong and relevant algorithmic component, challenges patent eligibility criteria (Hashiguchi, 2017). This is leading to the amendment of examination guidelines in most countries, which are being solved with different approaches to protect intellectual property in the field.[22] This is a new aspect brought by the Fourth Industrial Revolution. Indeed, in the second half of the 20th century the disruptive technologies brought by the Third Industrial Revolution were mostly tangible inventions related to the use of semiconductors.

In absolute terms, Germany and France lead by number of firms, followed by Spain, the Netherlands, Italy and Sweden, all having more than 300 AI firms. Then comes a second set of countries, namely Finland, Belgium, Poland, Ireland and Denmark, which have around 200 firms each.

22 Depending on the criteria of the specific patent office, patents on abstract AI concepts may not be found eligible, and, similarly to other computer-implemented inventions, patentability may depend on other factors such as the degree to which the inventions solve a concrete technical problem in a specific field of technology.

3.2.1.2 I2: Robotics start-ups in the EU

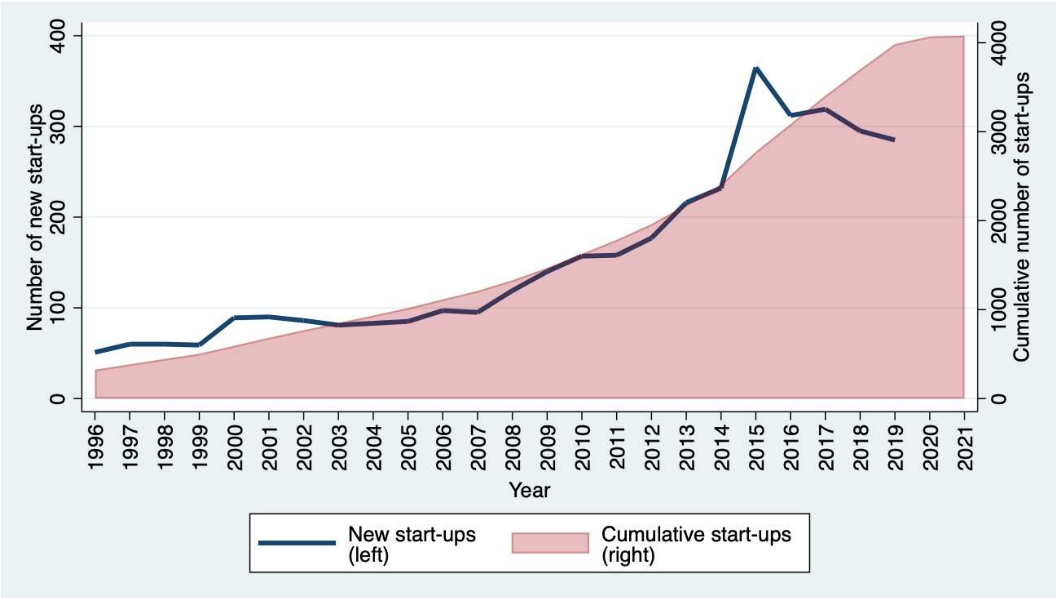
Description of indicator

The *I2 – Robotics start-ups in the EU* indicator presents the number of new robotics businesses founded each year (the blue line in the graph). This indicator provides insights about the vitality of this sector, in which the EU stands out as shown by indicator G5. In order to complement the information, the indicator is plotted together with the cumulative number of robotics start-ups, which is calculated as an aggregation of start-ups in a year but does not remove firms that do not survive. Therefore this cumulative number is expected to overestimate the total number of active start-ups.

For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

The European Union

Figure 13. Robotics start-ups (new and cumulative number). EU, 1996–2021



The growth of new businesses in the EU in the field of robotics has been consistent over time (The European Union

Figure 13). Starting from a level of slightly more than 300 start-ups in 1996 (the red area), every year saw a considerable amount of them being founded, starting with slightly more than50 new start-ups in the late 1990s, and reaching a peak of +365 in 2015 (the blue line). For most of the period, we see an acceleration in the pace of creation of new robotics start-ups (the blue line), leading to an annual increase of around 10% of the cumulative number of start-ups from 2003 to 2015 (the red area).[23] This constant creation of new businesses indicates that the sector is solidly rooted in the EU and that it is able to attract and stimulate new entrepreneurial activities, which is a key point for maintaining competitiveness over time. In the last years of the period assessed, from 2016 to 2019, the number of new robotics start-ups seems to find stability, with 300 new start-ups per year, which leads to a positive but flatter growth of the cumulative number of robotics start-ups (red surface). However, this could also reflect delays in the data collection, due to the difficulty of capturing recently created firms. Thus the trend observed in the most recent years could change as data sources are updated.

23 Although the cumulative number of start-ups includes all start-ups.

3.3 Dimension R – Research and development

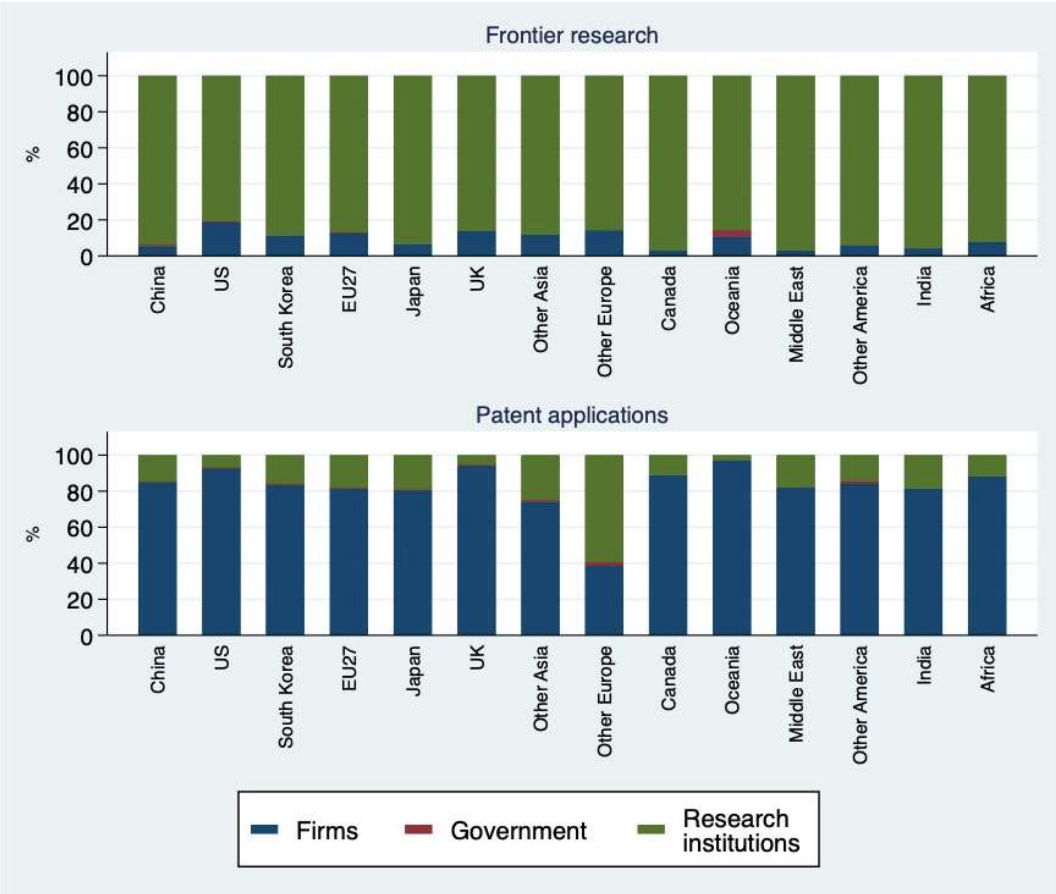
3.3.1 R&D activity

3.3.1.1 R1: AI players in AI R&D

Description of indicator
The *R1 – AI players in AI R&D* indicator shows the presence of players active in AI R&D activities, to assess how distinct geographical areas are involved in the technical development of AI. The indicator further distinguishes between the type of organisations involved: firms, research institutes (including universities) and governmental institutions.
For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

World

Figure 14. AI economic players in AI R&D by R&D activity type and organisation type (%). Worldwide, 2009–2020

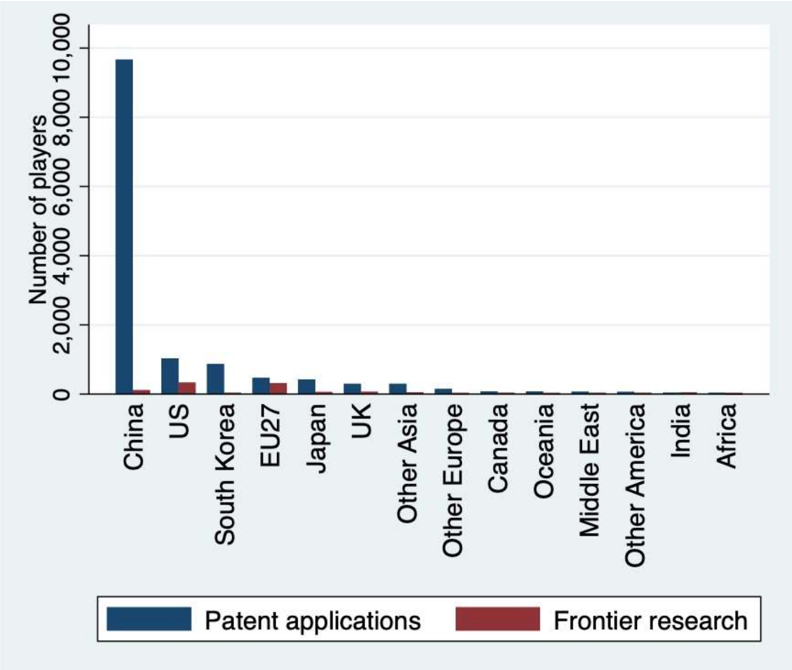


This indicator offers insights about the players taking part in AI-related R&D activities. As expected, the presence of research institutes is more concentrated in frontier research (proxied by participation in international AI conferences), while firms opt mainly for the development of patents (Figure 14). Nonetheless, some elements deserve to be discussed.

Firstly, the US leads in terms of percentage of firms involved in frontier research. Considering also the overall size and role of the US in AI (Figure 15), this element may suggest that the competitiveness of this country will last, as the private sector is remarkably involved in the scientific domain of AI. Indeed, a considerable presence of firms in frontier research activity should guarantee easier flows of knowledge to be transferred from the early phase of scientific research to the final phase, in which the patented innovations are incorporated in industrial processes. This could explain why the US is the geographic area that has not only the highest percentage of firms developing frontier research, but also one of the highest percentages of firms that file patent applications.

Secondly, other two geographical areas show considerably higher percentages of research institutes active in patents: other Asian countries (which include, for example, Taiwan, Malaysia and Singapore) and, in particular, other European countries (which include, for example, Russia, Switzerland and Norway). These substantially higher values suggest that in these areas the activity of research institutes is more directed towards the development of applied innovations.

Figure 15. AI economic players in AI R&D by R&D activity type. Worldwide, 2009–2020



The European Union

The *R1 – AI players in AI R&D* indicator at the EU Member States level (Figure 16) also includes the R&D activities carried out in the context of EC-funded projects. We can see a very different composition of AI R&D players by organisation type based on the different types of R&D activities considered.

Firstly, when looking at frontier research activities (the first graph in Figure 16), most players in all Member States are research institutes. For some Member States, such as Spain, Slovenia, Portugal and Poland, research institutes are even the only type of players involved in this kind of R&D activity. Governmental institutions have no representation in any of the countries except for France. Belgium and Czechia stand out as the two Member States with the highest participation of firms in frontier research.

The second graph in Figure 16 shows the composition by organisation type of players filing patent applications. As expected, firms constitute the main type for all countries, only Luxembourg and Slovakia have a stronger participation of research institutes than firms in patenting activities.

Finally, in the third graph of Figure 16 we find that the composition by type of player participating in EC-funded projects is again dominated by firms in all Member States. The distinctive feature seems to be the higher participation of governmental institutions, whose participation in the previous two types of R&D activities is anecdotal. Nevertheless, governmental institutions remain in a third place by order of importance when compared with firms and research institutes, including in EC-funded projects.

Figure 16. AI economic players in AI R&D by R&D activity type and organisation type (%). EU Member States, 2009–2020

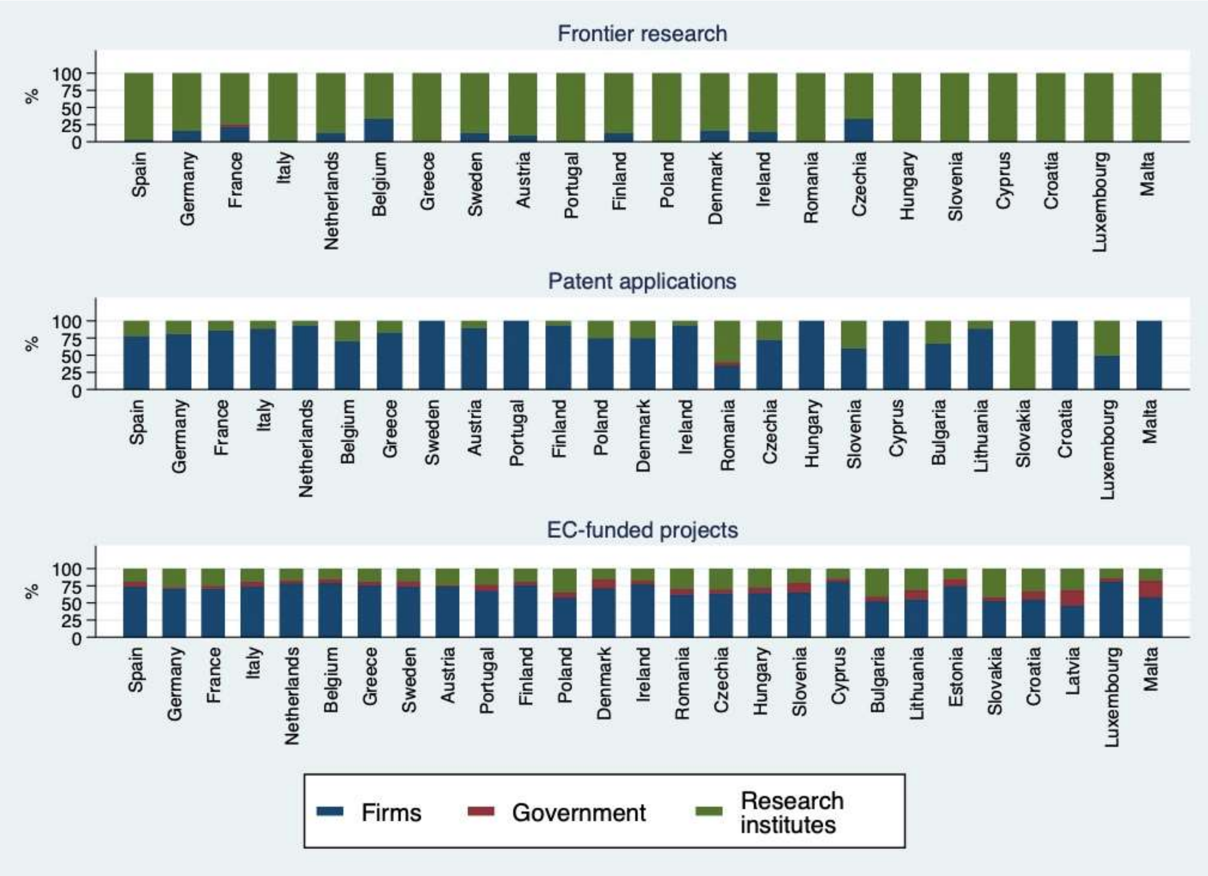
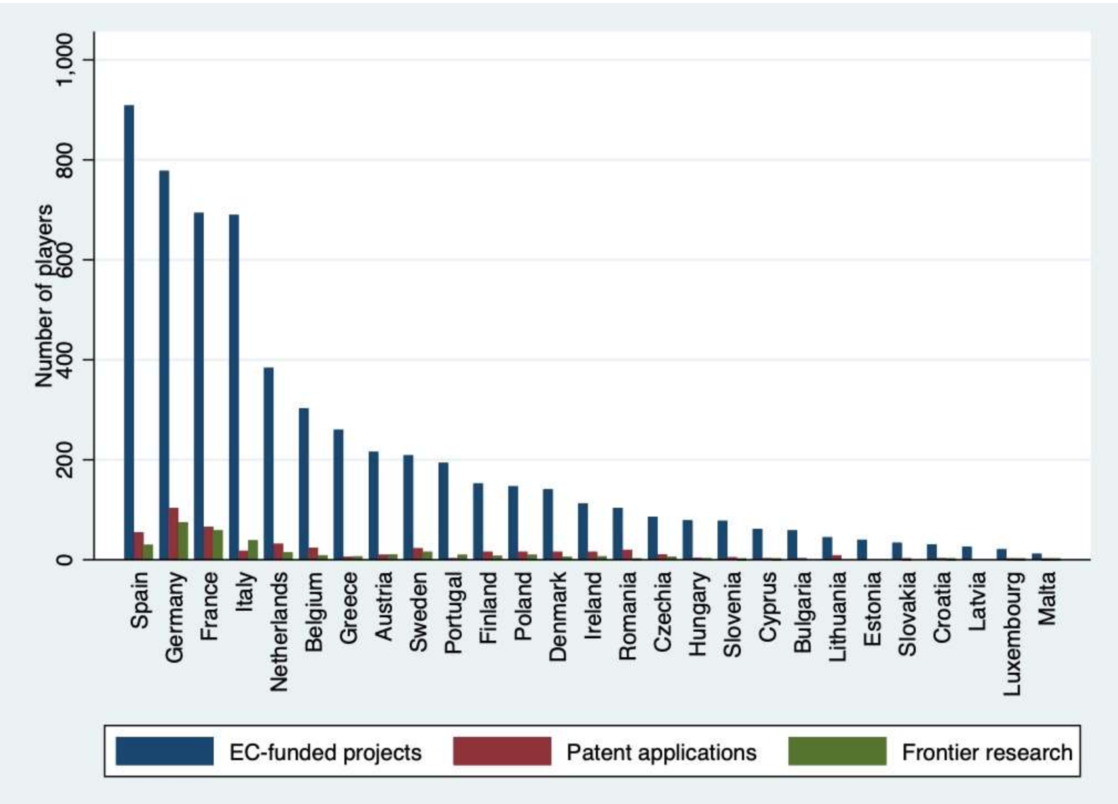


Figure 17. AI economic players in AI R&D by R&D activity type. EU Member States, 2009–2020



Complementary to the analysis by organisation type of AI R&D players, Figure 17 shows the absolute number of AI R&D players by type of R&D activity. It is noteworthy that for activities related to EC-funded projects the number of players is considerably higher than the number of players involved in patents or scientific publications. Therefore public funds significantly support the AI domain in the EU. This may, on the one hand, lead to further growth of the AI sector, but, on the other hand, may be interpreted a signal that the EU AI landscape relies excessively on public support. In fact, a deeper analysis of AI players participating in EC-funded projects reveals that for many of them this activity is the only AI-related activity they carry out, as they do not have a core business in AI nor any other AI-relevant activity, such as patent applications or frontier research (Righi et al., 2021).

3.3.1.2 R2: AI R&D activity score

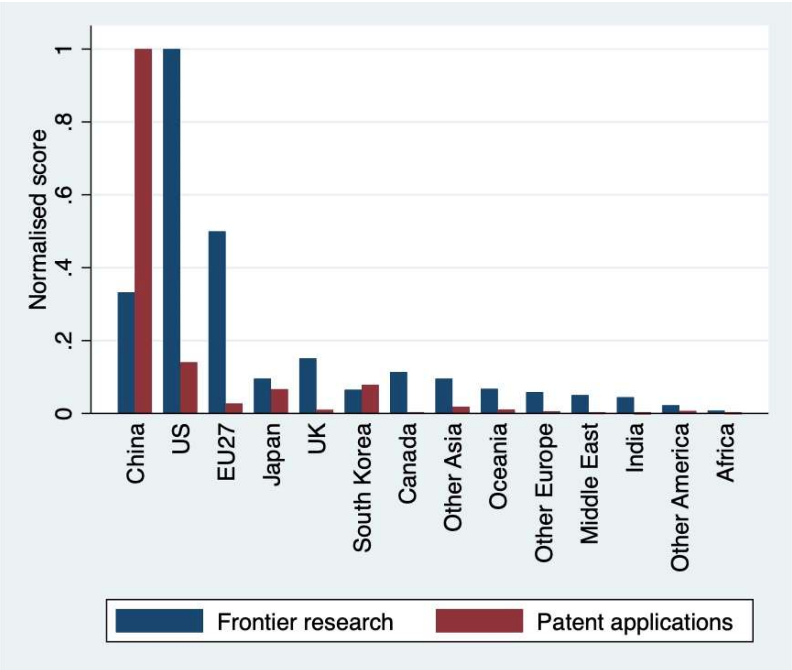
Description of indicator

The *R2 – AI R&D score* indicator assesses the level of involvement of different geographical areas in AI R&D activities, by considering the weight of the activities developed by AI economic players and therefore taking into account the relative importance of players. To avoid double counting, the indicator considers co-participation (e.g., a patent filed by two players is counted half for each of them). Therefore *R2* is calculated as the sum of the fractional count of the activities that the players located in each geographical area develop. As the AI landscape involves different types of AI activities, the indicator is first calculated separately for each of them and normalised in the interval [0,1]. This enables us to overcome the limitations concerning the aggregation of types of activities of different natures and economic implications.

For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

World

Figure 18. AI R&D Activity score. Worldwide, 2009–2020



The R2 indicator facilitates a finer analysis of the importance that different geographic areas have in the different types of R&D activities assessed, i.e., scientific publications in frontier research (the blue bars in Figure 18) and patent applications (the red bars).

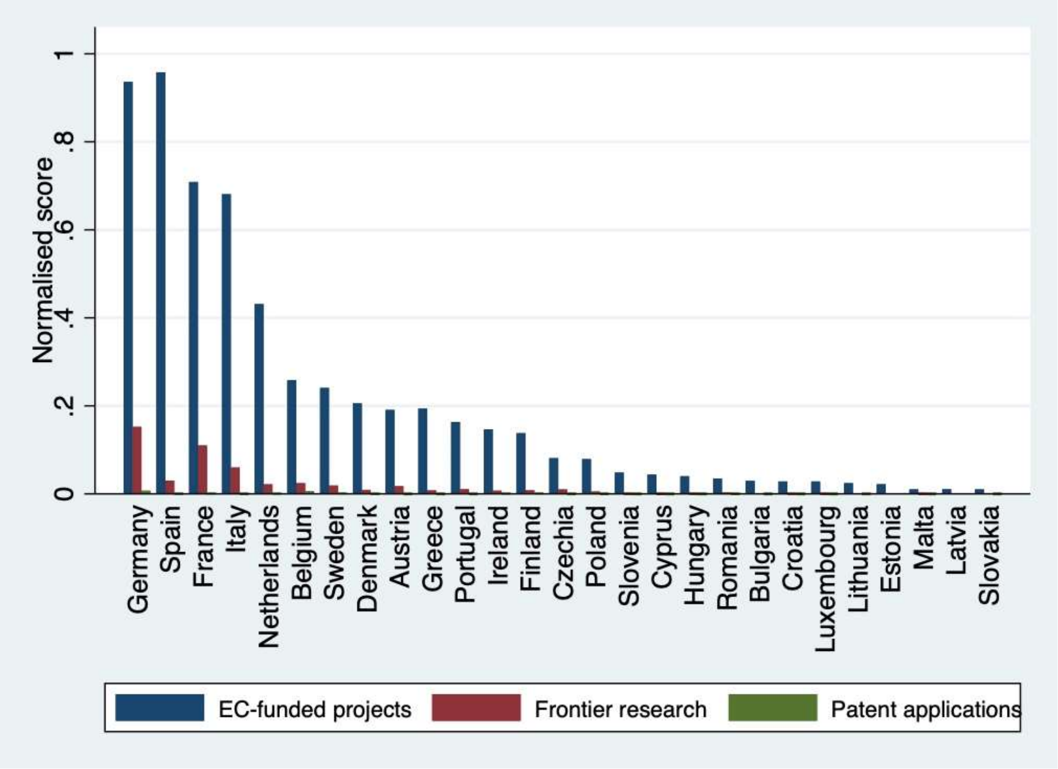
It is possible to observe that the level of patent applications filed by players is highly concentrated in China, which dominates the landscape in this respect. However, this evidence should be considered in light of the subsidies that the Chinese government has provided for the developments of AI patents since 2015. In 2021, the Chinese government announced that, in order to boost the country's high-quality intellectual property services, this policy should be reconsidered by the end of the year. Therefore in following years this could lead to a decrease in the number of patents Chinese players are filing on a yearly basis, but also an increase of their overall quality. On the contrary, we could also expect an increase in the number of AI patent applications, as the revision of patent examination guidelines in China are meant to protect and support AI intellectual property generation in the country. After China, the countries with highest AI patenting activity scores are the US, South Korea and Japan. The EU comes fifth, which highlights its modest performance in terms of development of applied innovations in AI.

In frontier research the US is the global leader, with activity that is twice as intense as that of the EU. Although the gap is considerable, the EU holds the second position, showing remarkable involvement in terms of scientific research in the domain. Given that AI has a strong component related to the improvement of algorithms and software, scientific publications have a more relevant role in applied AI innovation compared with other domains. China and the UK follow the EU, and then the remaining geographical areas present relatively similar values.

Overall, the US appears to have a key role in AI R&D, as its level of activity is outstanding in terms of both patents and frontier research. The EU presents a low level of patenting activity (including if considered in comparison with the US), but the position in frontier research is indeed relevant and appears to be a crucial point for future innovativeness and competitiveness in this domain. Nonetheless, the low level of patenting activity observed should be considered.

The European Union

Figure 19. AI R&D Activity score. EU Member States, 2009–2020



We find several insights regarding AI R&D at the Member State level. Firstly, the EU Member States are mostly involved in AI-related EC-funded projects. However, it is important to note that the Member State that gets the highest score, i.e., Spain, is not the country which has the largest involvement of EC-funded projects, as its score is not equal to 1. Indeed, the country leading the ranking (of all countries worldwide) is the UK. This is important, as it highlights the role that the UK has had so far in the EU AI landscape. Indeed, after Brexit the involvement of the UK in EC-funded projects will rapidly decrease, probably causing further modifications in the amount and distribution of research funds among Member States. Secondly, the gap between involvement in EC-funded projects and other R&D activities is considerable. In terms of scientific publications, some Member States show considerable activity scores (such as Germany and France) and this enables the EU (when all Member States are considered jointly) to have a relevant overall role in this type of R&D activity (Figure 19). By contrast, in terms of patents no Member State shows some any substantial involvement at all.

3.3.2 Network of collaborations

3.3.2.1 R3: AI R&D collaborating countries

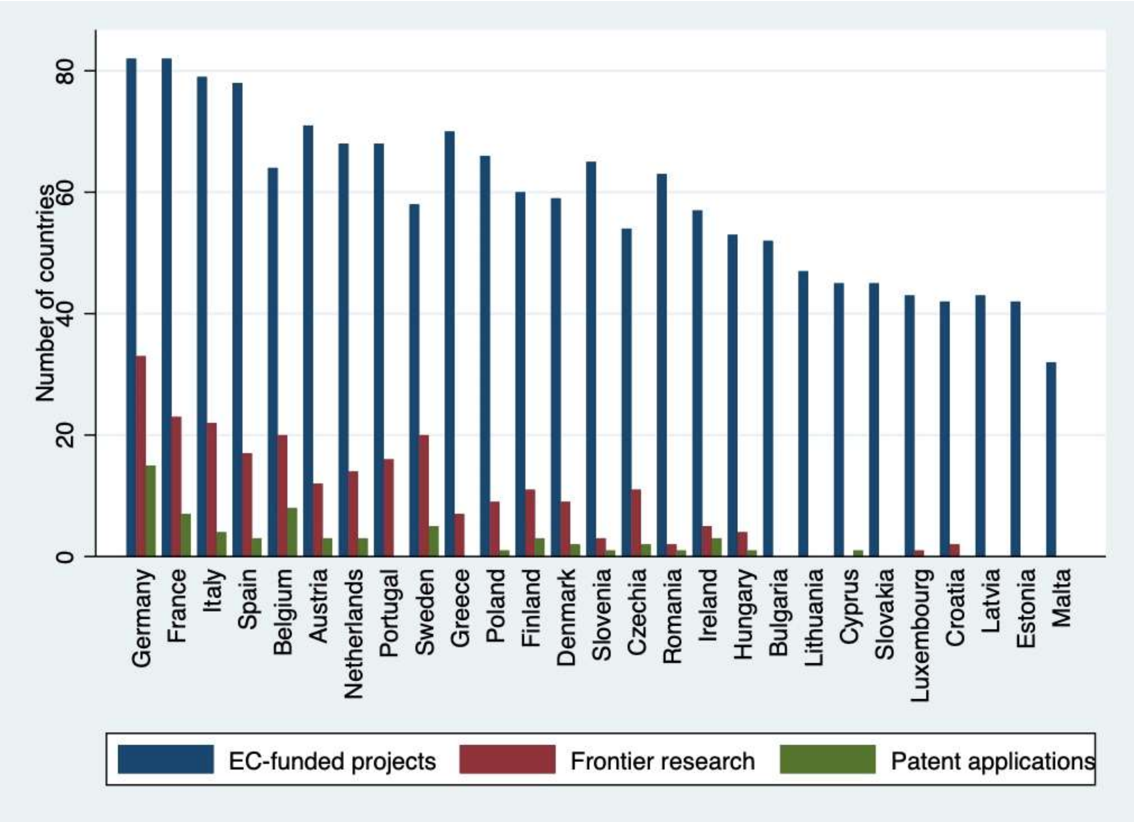
Description of indicator

With the *R3 – AI R&D collaborating countries* indicator we investigate the EU 27 Member States' propensity to structure collaborations with many different countries. More specifically, the R3 indicator reflects the number of countries with which the Member States have at least one AI-related collaboration, by type of AI R&D activity. In order to have had an active collaboration, players must have filed a patent together or be co-authors in a publication or be part of a same partnership for an EC-funded project.

For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

The European Union

Figure 20. AI R&D collaborating countries. EU Member States, 2009–2020



As expected, the densest network of collaboration is related to EC-funded projects. Therefore it is in this context that Member States structure most of their contacts with other countries. Interestingly, the effects of EC-funded projects in terms of collaborations with different areas go much further than the borders of the EU. Indeed, all Member States (except Malta) have at least one collaboration with more than 40 different countries. By means of EC-funded projects, Germany, France, Italy and Spain reach almost 80 different countries.

The two networks developed in the context of frontier research activities (the red bars) and in patents (the green bars) show a series of countries that barely structure any collaboration with other countries. These are the countries in the right tail of Figure 20. For most of them the only connections they have with other countries come through EC-funded projects. Among the EU Member States that are more able to connect with other countries, both in patenting and in frontier research, are Germany, France and Belgium. Italy, Spain and Sweden also deserve consideration, but mainly for what shown in their networks of scientific publications. For every EU Member State except Cyprus the network of frontier research collaboration is always more extended than that for patents.

Member States can reach a large number of collaborating countries by means of EC-funded projects. However, the gap that is observed with respect to the other two R&D networks is considerable. On the one hand, the connectivity promoted by EC-funded projects is significant and appears to be fundamental. On the other hand, in a R&D context interactions and knowledge exchange are crucial and therefore international collaborations are important. However, the number of collaborating countries is larger than 10 in only one case for patents (Germany) and for just 11 Member States in scientific publications.

3.3.2.2 R4: Peer-to-peer collaborations

Description of indicator

The *R4 – Peer-to-peer collaborations,* indicator measures how many collaborations are developed by AI players from each geographical area (or Member State) by type of R&D activity: patent applications, frontier research publications and, when analysing the EU, EC-funded projects. The indicator further distinguishes between collaborations according to the profile of the players involved. The collaborating players are therefore classified according to their organisation type (firms, governmental institutions and research institutes) and according to their location (local or abroad). This enables us to distinguish between the following types of most relevant collaborations:

— *B2B abroad*, which shows business players (i.e., firms) located in the assessed geographical area and collaborating with other business players located abroad (i.e., not in the same geographical area);

— *B2B local*, which indicates that business players located in a specific geographical area collaborate with business players located in the same geographical area;

— *B2R local*, which indicates that business players located in a specific geographical area collaborate with research institutes that are located in the same geographical area;

— *G2B local*, which indicates that the governmental institutions of that geographical area are collaborate with business players in the same geographical area;

— *R2R abroad*, which indicates that research institutes located in that geographical area collaborate with research institutes located abroad; and

— *R2R local*, which indicates that research institutes located in that geographical area collaborate with research institutes located in the same geographical area.

— The remaining forms of possible collaborations are summarised in the category *Other*.

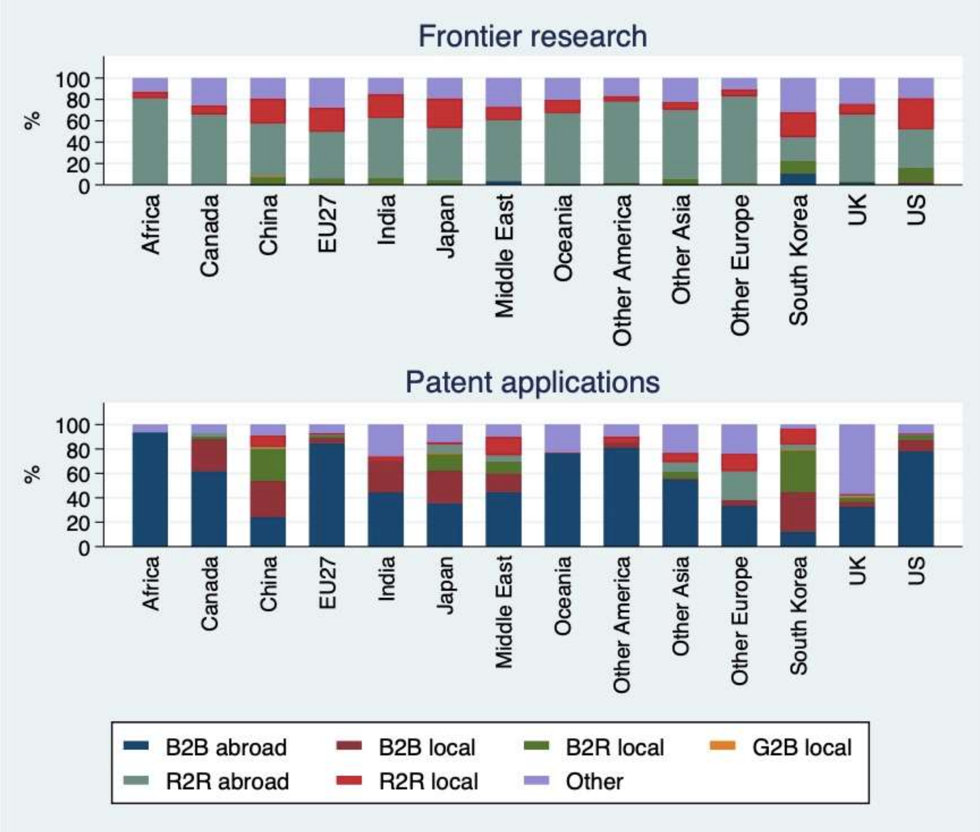
For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

World

In Figure 21, the composition of peer-to-peer collaborations is presented by geographical area. As expected, for scientific publications, the predominant AI players are research institutes (*R2R abroad* and *R2R local*, in the plot on top). For all the geographical areas except South Korea the main type of collaboration in the scientific publication context is *R2R abroad*. This is highly relevant, as a higher number of interactions in research implies a higher degree of information exchange. South Korea is the only country to show a modest share of *B2B abroad* collaborations. In addition, South Korea and the US are the only areas with a considerable share of *B2R local*. This is a key type of interaction, as it demonstrates local connections between the actors in research (i.e., research institutes) and the private sector (i.e., firms) and is an important channel of knowledge transfer between research and industry

When looking at collaborations in patenting activities, the most important type of player are businesses, given that patenting activity is usually led by firms. Indeed, in most geographical areas the largest percentage of collaborations is detected between local firms and firms located abroad (*B2B abroad*). In second position are the collaborations involving local firms (*B2B local*), in particular in Asian economies such as China, Japan, South Korea and India, but also in Canada. Nonetheless, it is interesting to observe that a substantial number of patents filed by more than one party (and that therefore imply some collaboration) are developed outside the borders of the corresponding geographical area. This is especially the case for the US, Oceania, the EU and Canada, while China and South Korea appear to be more oriented towards developing patents among local partners.

Figure 21. Peer-to-peer collaborations by R&D activity type and collaboration type (%). Worldwide, 2009–2020



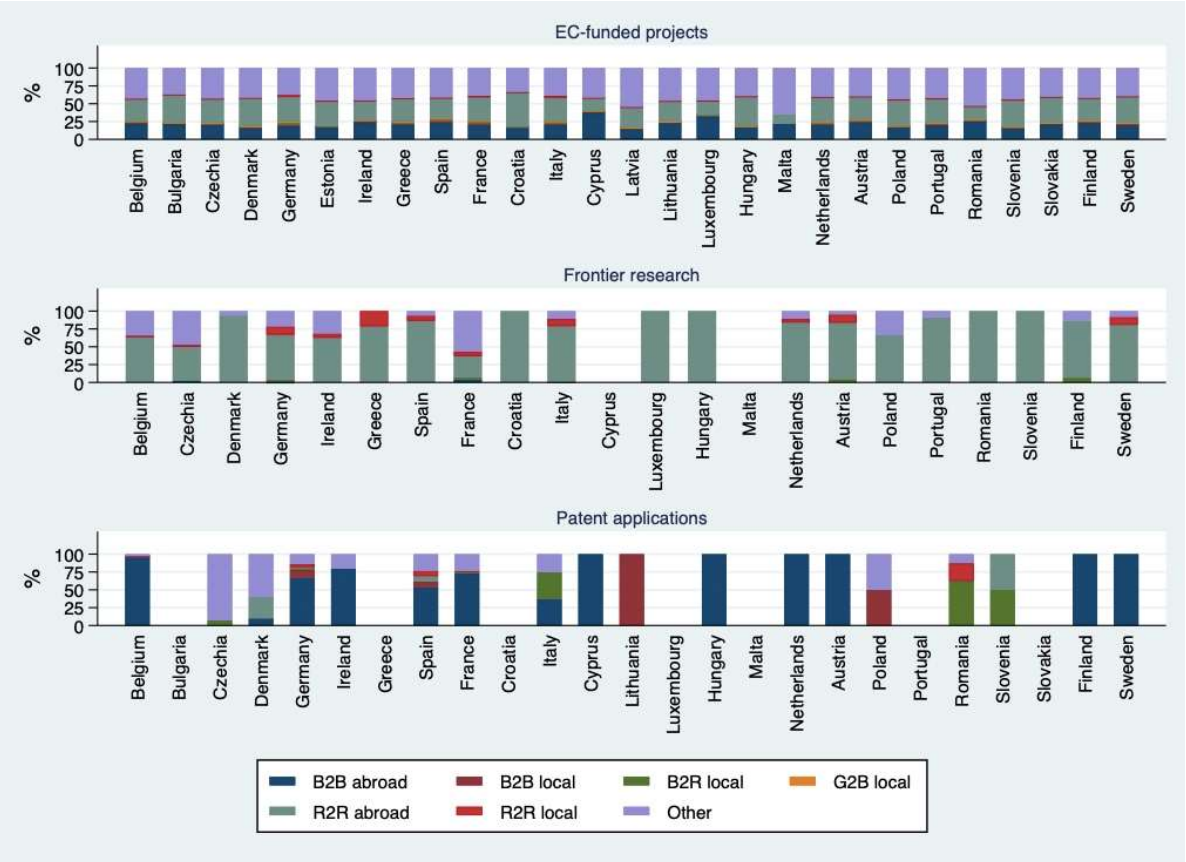
The European Union

In Figure 19, the indicator R5 is analysed for EU Member States. For EC-funded projects (Figure 22 – above), the most important types of interaction are *R2R abroad* and *B2B abroad*. Therefore, as expected, EC-funded projects substantially promote cooperation between players in different Member States, and they support in a very balanced way both interactions between firms from different countries and between research institutes from different countries.

If we focus on scientific publications (Figure 22 – middle), it is possible to note that research institutes collaborating with research institutes from another country (*R2R abroad*) is the main type of collaboration established. In some cases, a considerable percentage of collaborations take place between research institutes in the same country (*R2R local*). This is the case for Greece, Germany, Sweden, Italy and Austria, and, to a lesser extent, Spain, the Netherlands, Ireland and France.

The last graph (Figure 22 – bottom) shows that patent applications are filed mainly by firms in collaboration with other firms (*B2B abroad* and *B2B local*). The exceptions are Denmark and Czechia, where the largest percentage of collaborations are developed by combinations of players which are different from those already considered and so are included under the *Other* category. Countries for which there are bars are those in which no cooperation is taking place in patent activities, which is the case for Slovakia, Portugal, Malta, Luxembourg, Greece, Croatia and Bulgaria. It is important to note that the number of collaborations is lower than for the previous types of R&D activities, because most patent applications are filed by a single player.

Figure 22. Peer-to-peer collaborations by R&D activity type and collaboration type (%). EU Member States, 2009–2020



3.3.2.3 *R5: Strategic position in the network of collaborations*

Description of indicator

The *R5 – Strategic position in the network of collaborations* indicator provides a metric for players' capacity to act as connecting bridges between other players, aggregated at the geographical level, to assess the influence that a geographical area can exert on other areas thanks to the structure of collaborations in which they are involved. The statistic used is the Weighted Betweenness Centrality (WBC) normalised in the interval from 0 to 1. The statistic is calculated on geo-based networks, i.e., networks in which nodes refer to geographical areas and each of which include all the corresponding players (i.e., the players located in that area). The connections between nodes are given by collaborations of players in R&D activities. Each collaboration has a weight equal to 1 divided by the total number of players involved in that activity (e.g., co-patenting). WBC counts how many times each node (geographical area) is included in the shortest path between every possible couple of nodes. The larger the value, the more likely the node has a relevant role in terms of communication exchange.

For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

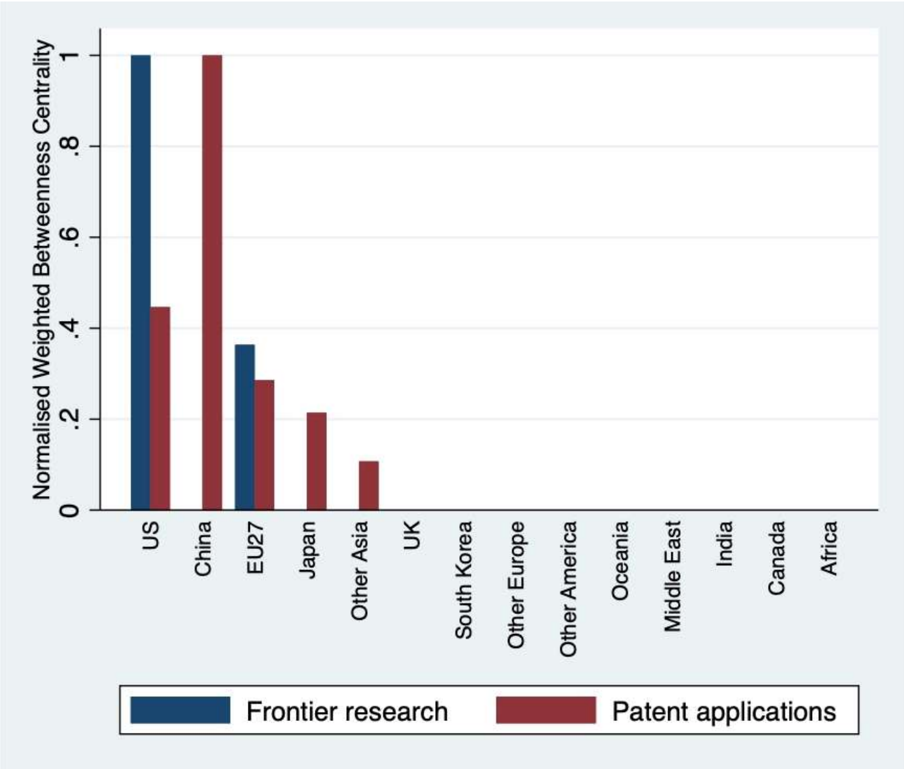
World

From Figure 23 it is possible to highlight that the two rankings about strategic position, i.e., one for scientific publications (in blue) and one for patenting (in red), differ substantially. For scientific publications, only the US and the EU have positive values, which indicates that these two areas are the ones with influential capacity within these type of activities at the global level.

With regard to patent activities, the clear leader is China, with a normalised WBC score of 1.0, which is more than double the score of the US (0.45) and is more than three times the score of the EU (0.29). Japan and other Asian countries have scores below 0.22, underlining the influential capacity role of China in patenting activities.

In general, the US appears to be best positioned in terms of R&D collaborations, as in both of the networks assessed its score is remarkable. The EU, although not leading in any of the networks, is the only other area whose role is notable both in terms of scientific publications and in patenting. In this sense, its position in terms of collaborations is relevant and strategic.

Figure 23. Strategic position in the network of collaborations by R&D activity type. Worldwide, 2009–2020



The European Union

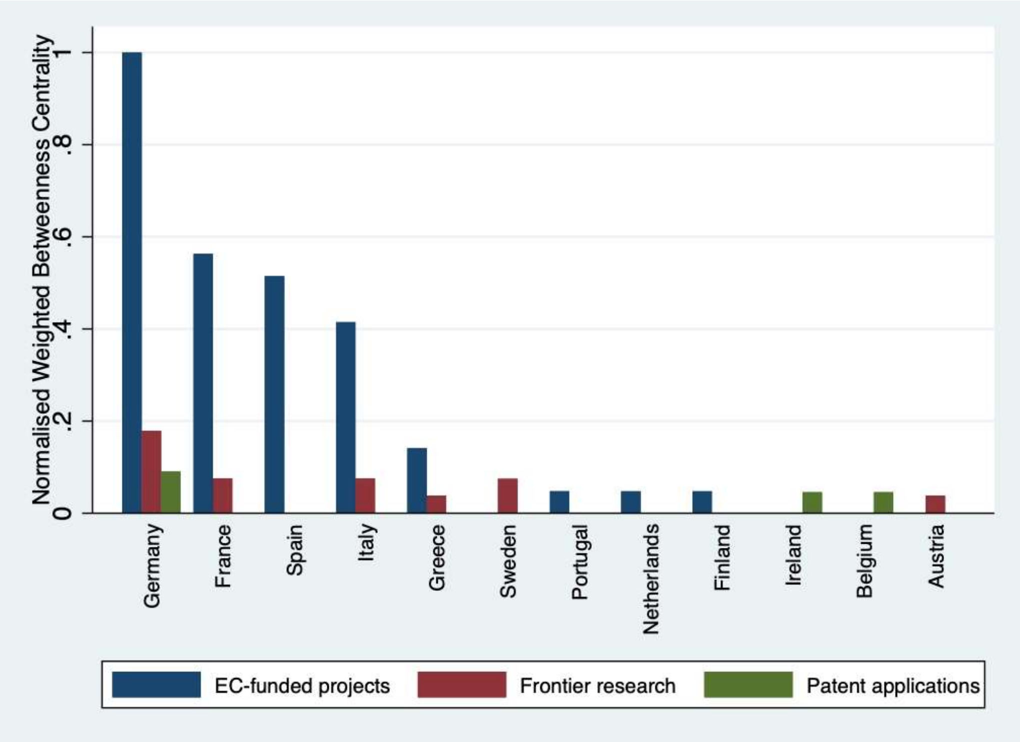
With regard to the EU Member States, Figure 24 shows that they do not hold very central positions in the worldwide networks of scientific publications and patents. Nevertheless, it is possible to observe some notable values for Germany in the network of scientific publications (the red bars), as well as France, Italy and Sweden (although they all have lower levels than Germany). Even if the performance of individual Member States does not appear to be very high, when considered all together they position the EU prominently in this R&D network (Figure 23).

The situation with regard to patents underlines the central role of Germany in the EU. In the same network, only Ireland and Belgium show positive values that indicate some influential capacity.

Finally, as expected, in the network of the EC-funded projects the largest values for centrality are detected for EU Member States.[24] In particular, Germany is shown to have the most central position in the network, followed by France, Spain and Italy. In addition, Greece, Portugal, the Netherlands and Finland also deserve attention, as they show some relevance here. Indeed, the positive values seen show the ability of the players in these countries to structure networks of collaborations in which they hold a central position. This should guarantee them an active role in terms of circulation of information.

24 The UK, not shown in the graph because it is not a Member State, takes the second position regarding centrality for EC-funded projects (WBC equal to 0.65).

Figure 24. Strategic position in the network of collaborations by R&D activity type. EU Member States, 2009–2020



3.4 Dimension T – Technology

3.4.1 Performance of AI

3.4.1.1 T1: Performance of AI research

Description of indicator

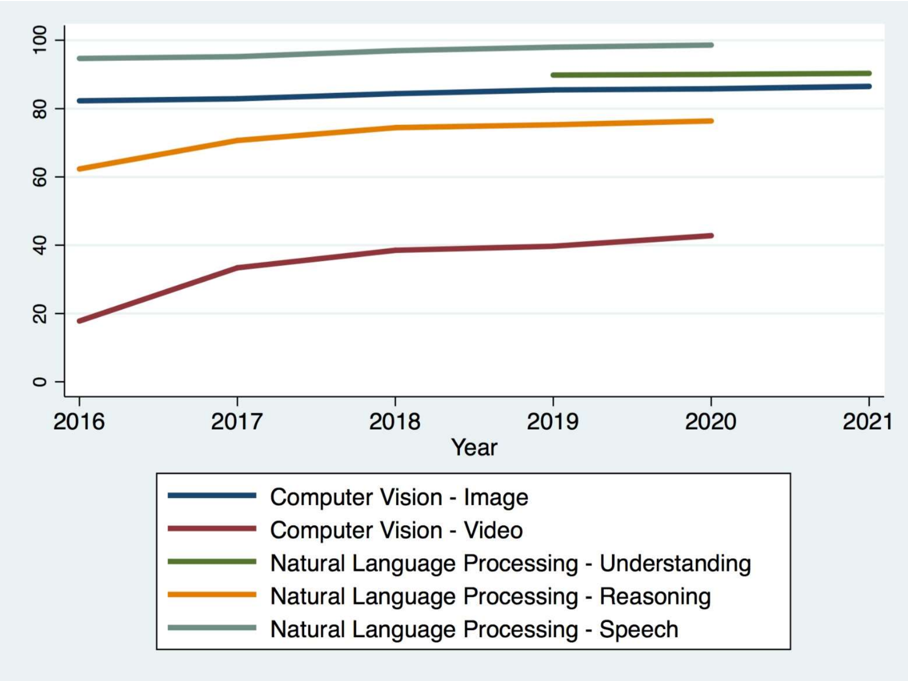
The *T1- Performance of AI research* indicator addresses evaluation of technical progress in an illustrative set of AI tasks belonging to different subareas (including image classification, face recognition, speech recognition, text summarisation, etc.), using a combination of quantitative measurements, such as in popular AI benchmarks and prize challenges. The indicator presents the performance of AI measured by means of different evaluation metrics (e.g., (mean) accuracy, score, error-rate, BLEU score, etc.) depending on the task at hand. The performance provides a value between 0 and 100. The *Natural Language Processing – Speech* task, originally measured through an error rate (where 0 is the highest performance and 100 is the lowest), is transformed as *1- error rate* to obtain a comparable measure of performance between 0 (lowest) and 100 (highest).

The datasets and metrics used to measure performance for each benchmark are: for *Computer vision – Image*, dataset: ImageNet, metric: top1 accuracy; for *Computer vision – Video*, dataset: ActivityNet, metric: mean average precision, for *Natural Language Processing – Language Understanding*, dataset: SuperGLUE, metric: score; for *Natural Language Processing – Language Reasoning*, dataset: VQA, metric: accuracy; for *Natural Language Processing – Speech*, dataset: LibriSpeech, metric: WER.

For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

World

Figure 25. Performance of AI research by AI task. Worldwide, 2016-2021



Recently, research activities carried out by the global AI community on the technical progress of various AI tasks (including computer vision, language modelling and processing, speech, machine translation, videogames, etc.) have used a combination of quantitative measurements such as in popular AI benchmarks[25] and prize challenges.

AI measurement is any activity that estimates the attributes (measures, metrics) of an AI system or some of its components, abstractly or in particular contexts of operation. These attributes, if well estimated, can be used to explain and predict the behaviour of the system. This can stem from an engineering perspective, trying to understand whether a particular AI system meets the specifications or the intention of its designers, known respectively as "verification" and "validation". However, in AI there is an extremely complex adaptive behaviour, and in many cases, a lack of a written specification. What the system is expected to do depends on feedback from the user or the environment (in the form of rewards) or is specified by example (from which the system has to learn a model).

The tradition in AI measurement has set the goal on task-oriented evaluation. For instance, given a scheduling problem, a board game or a classification problem, systems are evaluated according to some metric of task performance. Performance metrics are thus defined as figures and data representative of an AI system's actions, abilities and overall quality. There are many different forms of performance metrics depending on the task to address, and their values depend on how they are calculated[26].

Analysis of research reveals different levels of performance with regard to specific AI tasks that are assessed. It is important to note that the performance reached in a specific task cannot be directly compared with that for other tasks, as they tend to have a very different nature. Nevertheless, these metrics provide, independently for each task, a performance value from 0 to 100 and we study the evolution of this performance.

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25 An AI benchmark is a point of reference for measuring the performance of any new AI system, algorithm or method. Benchmarking initiatives have been replacing (since 2015) the traditional methods of evaluating scientific outputs (peer-review, etc.), becoming one of the major indicators of the quality of many new research papers.

26 For example, regression metrics such as mean absolute error or mean squared error have continuous outputs, classification accuracy goes between 0 and 1, etc. In general, these metrics are usually reported in research papers and compared to the metric values for previous systems. To standardise the comparisons, there are datasets and benchmarks that are used for evaluating these systems, so that evaluation data is not cherry-picked by the AI designers.

In Figure 25 it can be seen that the best results are obtained in *Natural Language Processing – Speech*, which shows very high performance throughout the assessed period. *Natural Language Processing – Language Understanding* also shows good performance. We can also note that *Computer Vision – Image* follows a trend that is relatively flat, but with an overall performance above 80 over the entire period. The progress in *Natural Language Processing – Language Reasoning* shows a clear improvement over time, especially between 2016 and 2018. Finally, *Computer Vision – Video*, with a level of performance well below that of other AI tasks, has recently experienced the largest improvement, more than doubling its performance in only four years.

Detailed analysis of the previous graph and the approaches used to address each task indicate that deep neural-based approaches have performed at the top of most competition leader boards in AI (mostly with regard to machine learning), even surpassing human-level performance on several specific tasks involving image classification or natural language understanding. However, it should be emphasised that the previous graph only explores the evolution of the top-performing systems and the raw improvement in accuracy (and other performance measures) over time. To obtain a more global evaluation of AI performance, it is useful to consider other factors as well, such as energy consumption trends, or advances in terms of algorithms and infrastructures, which have enabled researchers and practitioners to increase the efficiency of their training and inference phases. Although these considerations are outside the scope of this collection of indicators, they are covered in several works in the literature (Amodei and Hernandez, 2018; Canziani et al., 2017, Desislavov et al., 2021, Gholami et al., 2021). These sources state that, in general terms, the progress of some AI paradigms (such as state-of-the-art deep-learning approaches used in most AI tasks) stems from an exponential growth in algorithm complexity (e.g., the number of parameters in neural networks), which typically results in a higher energy consumption.

3.4.2 Standardisation

3.4.2.1 T2: Standardisation activity engagement

Description of indicator

The *T2 – Standardisation activity engagement* indicator provides an overview of the AI standardisation landscape across multiple international and European standards development organisations (SDOs). The indicator is composed of the total count of AI standardisation deliverables identified over the course of an extensive study, together with the subset of those that have been classified by AI Watch experts as significant in the context of the European AI regulation. The criteria for classification as significant favoured first-level standards dealing with AI-related risks in a horizontal manner and covering implementation aspects, as opposed to foundational and basic standards.

The indicator is complemented by a measure of participation by EU27 Member State national standardisation bodies in a key ISO/IEC technical subcommittee expected to be an important source of future harmonised standards supporting the European AI market.

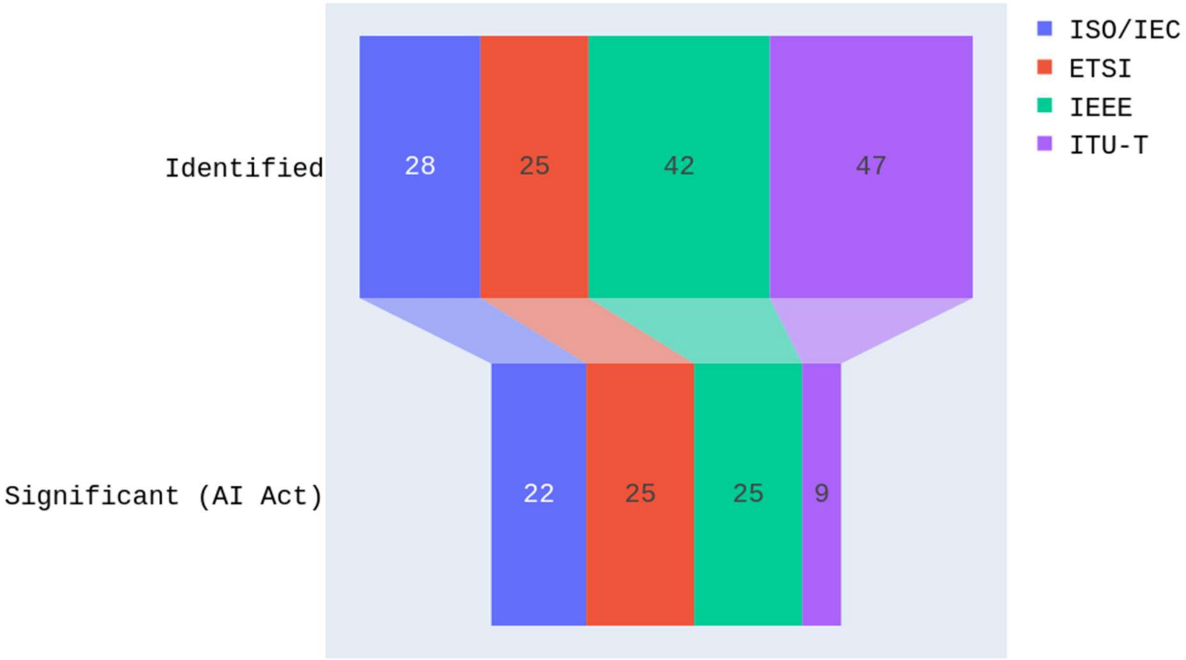
For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

World

An initial, broad analysis of the AI standardisation landscape resulted in approximately 140 standards and standardisation deliverables identified (Figure 26, top half) (Nativi and De Nigris, 2021). The analysis drew on multiple specialist sources, including publicly available surveys on AI standardisation and scientific publications, as well as direct interaction with experts from international and European Standardisation Development Organisations (SDOs), e.g., in the context of events and activities oriented towards the creation of standardisation roadmaps. The overall landscape includes AI standardisation deliverables from four of the major international and European SDOs, namely ISO/IEC, ETSI, IEEE and ITU-T.

In a second step, a subset of significant standards was selected for further analysis from the perspective of the requirements laid down by the proposed European regulation on AI (Figure 26, bottom half). More than half (57%) of the initially identified standards and related deliverables (such as technical specifications or reports) were deemed significant in that sense, already hinting at a substantial degree of a priori alignment between the activities of SDOs and European regulatory needs in the field of AI.

Figure 26. AI standards and standardisation deliverables of four major international and European Standard Development Organisations, 2021



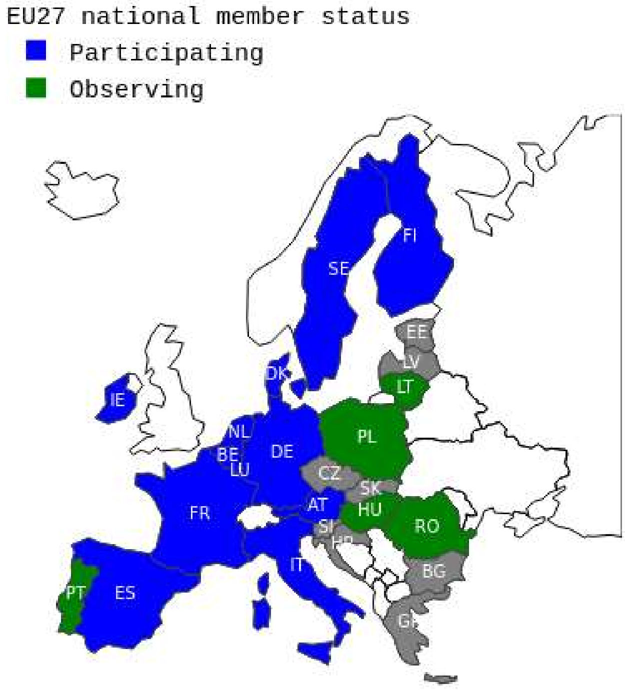
A final analytical step assessed the level of maturity of the sub-population of significant standards in terms of their degree of coverage of the different requirements of AI regulation, including data governance, technical documentation, record keeping, transparency, human oversight, accuracy, robustness, cybersecurity, risk management and quality management. Multiple attributes were analysed and quantified for each standard, notably the degree to which they operationalise the high-level requirements of the legal text, but also including a range of suitability aspects, such as typology, domain generality, maturity and compliance management,.

A detailed operationalisation and suitability analysis is not reflected in the current indicator, due to its ongoing nature, as standards from only two of the aforementioned SDOs have been assessed to date. Despite this, a significant number of standards from ISO/IEC have already been identified as offering high operationalisation and/or suitability values. This implies that future standardisation activities aiming to produce European and harmonised standards for the upcoming AI regulation should be able to leverage and build on existing work at the international stage.

A final observation supporting the above conclusion is the high level of European participation in international AI standardisation activities. With regard to ISO/IEC, the largest standard development body composed of representatives from national standards organisations, EU Member States participation on Subcommittee 42 (Artificial Intelligence) of the Joint Technical Committee 1 on Information Technology is substantial. Indeed, there are 18 EU national standardisation bodies among its participating or observing members, being 13 of those actively participating, of the current 33 participating members[27] (Figure 27). The significance of European participation in international standardisation activity on AI is further reinforced by the technical cooperation between European SDOs (CEN/CENELEC and ETSI) and ISO/IEC through the Vienna and Frankfurt agreements.

27 Data on participation in ISO/IEC JTC 1 /SC 42 retrieved on 5 January 2022[, available at: https://www.iso.org/committee/6794475.html?view=participation

Figure 27. Participation of EU Member States' standardisation bodies in ISO/IEC's AI standardisation activities, 2021



3.5 Dimension S – Societal aspects

3.5.1 Diversity in research

3.5.1.1 S1–S4: Diversity in research: Gender diversity index, Geographic diversity index, Business diversity index, Conference diversity index

Description of indicators

The *Societal Aspects* dimension includes four indicators addressing *Diversity in Research*. They measure different aspects related to diversity among participants[28] (i.e., keynote speakers, conference organisers and authors of papers) at a set of international AI conferences. All the indicators are presented in Freire et al. (2020) and are derived from Shannon and Pielou indexes. Maximum heterogeneity or diversity corresponds to an index value of 1, which means equal distribution of the r population categories – assessed (gender, geography, business types). For each year, diversity indicators are calculated for each conference. We present here an average of the indicators in a set of selected AI conferences: AAAI, NeurIPS, IJCAI, ICML, RecSys and ECAI.

The *S1 – Gender Diversity Index* (GDI) measures the average representation of researchers from different genders (male, female, other) at AI conferences, thus possibly revealing the impact of gender equality policies on AI research, and is useful for raising awareness about the need for more diverse research communities (Freire et al., 2020), such as the Affective Computing community addressed in Hupont at al., 2021.

The *S2 – Geographic Diversity Index* (GeoDI) tracks the average representation at AI conferences of participants from different geographical locations, representing the location of the institution to which they are affiliated.

The *S3 – Business Diversity Index* (BDI) assesses the participation of researchers from academia, research centres and industry in the AI research field.

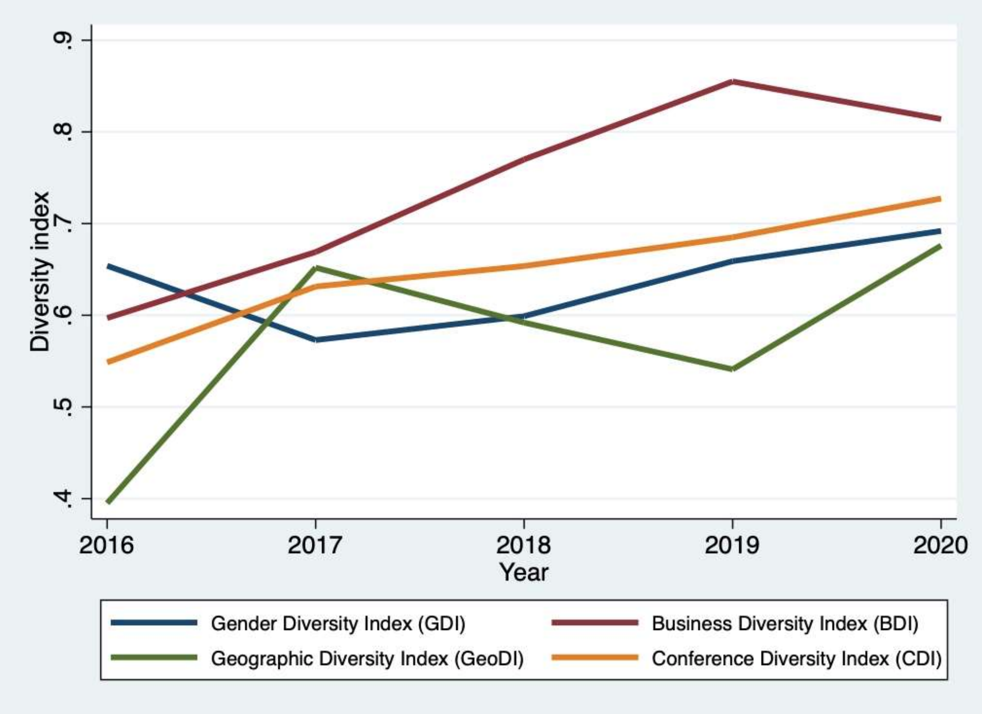
28 Depending on the indicator, conference attendees are grouped based on their gender (female/male), their country of origin, and the type of institution they work for (academia/industry/research centre).

The *S4 – Conference Diversity Index* (CDI), is an average of the previous three indices (Freire et al., 2020) and provides a single and overall indication on the different observed trends regarding diversity in the AI research field.

For more detailed information about the indicators and references, see the metadata fiches in Annex 1.

The European Union

Figure 28. Diversity in research. Worldwide, 2016–2020



We can see in Figure 28 that all indicators have a tendency to increase over time. This shows how the AI research community has recently tried to incorporate a diversity of profiles. This might drive towards a potential reduction of bias in research which would be derived from a very homogeneous composition of researchers.

The indicator with the smallest increase is the one on gender (S1 – GDI), which shifts from 0.65 in 2016 to 0.69 in 2020. After a sharp decrease in 2017, the series follows an upward trend, as gender heterogeneity increases almost 4 points per year.

The Geographic diversity index (S2 – GeoDI) is the one showing the most considerable improvement (plus 0.28 points from 2016 to 2020, or an increase of 70%). However, at the same time it is also the one presenting the most alternating dynamic. Indeed, after an increase of 0.26 points from 2016 to 2017, for two years in a row (2018 and 2019) the observed diversity falls, and then it significantly increases again in 2020 (by 0.13 points). These fluctuations might reflect changes in the geographical location of conferences and researchers' affiliation. Likewise, but only with regard to 2020, this could be due to increases in attendance in online mode due to the COVID-19 pandemic, which would have facilitated participation in conferences from a greater variety of countries.

The Business diversity index (S3 – BDI) shows the largest value of all four diversity indices in 2020, with a peak in 2019 (0.85). This might be explained by the greater presence of industry researchers at scientific conferences, which confirms that AI research raises considerable interest from the private sector too. The fact that the trend is overall positive but slightly decreases in 2020 could also reflect a shift in the dynamics between academy and industry in the AI field (from academia to industry).

Given that the conference diversity index (S4 – CDI) is the result of the simultaneous consideration of all the examined aspects, it is relevant to observe that diversity in conferences seems to have overall increased consistently over time since 2016. This enables one to have an optimistic view of possible advancements in diversity and inclusion for attendees of major AI conferences in the future. Nevertheless, the studied period is still too short to draw firm conclusions, it being too soon to assess the long-term impact of current diversity initiatives being carried out in the AI field (such as mentoring programs, visibility efforts, travel grants, committee diversity chairs and special workshops).

3.5.2 Higher education

3.5.2.1 S5: AI in university programmes in the EU

Description of indicator

The *S5 – AI in university programmes in the EU* indicator evaluates the intensity with which AI is considered in official curricula, as a proxy of AI skills acquired by current students (and therefore, future workers). For this purpose S5 considers the proportion of programmes with AI content in the total number of programmes in the 2020–21 academic year. The indicator is calculated for bachelor's and master's degree programmes to analyse how Member States are coping with the different stages in the training of AI-skilled students.

The methodology followed to calculate the indicator is based on a text mining approach that helps identify AI-related courses from a dataset of programmes that are fully or partially taught in English language, as detailed in Righi et al. (2022). This was considered as a potentially limiting factor for the validity of the study, and it had been therefore scrutinised in a previous report, together with other characteristics of the data source used (López Cobo et al. (2019) pp. 14–16). The impact of the teaching language was found not to be negligible, but limited and not substantially affecting the validity of the results, especially when these are presented to characterise the education offering and not as an absolute quantification of the programmes offered (López Cobo et al. (2019), Righi et al. (2021, 2022).

For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

The European Union

Figure 29. AI in university programmes by level of studies (%). EU Member States, 2020–21 academic year

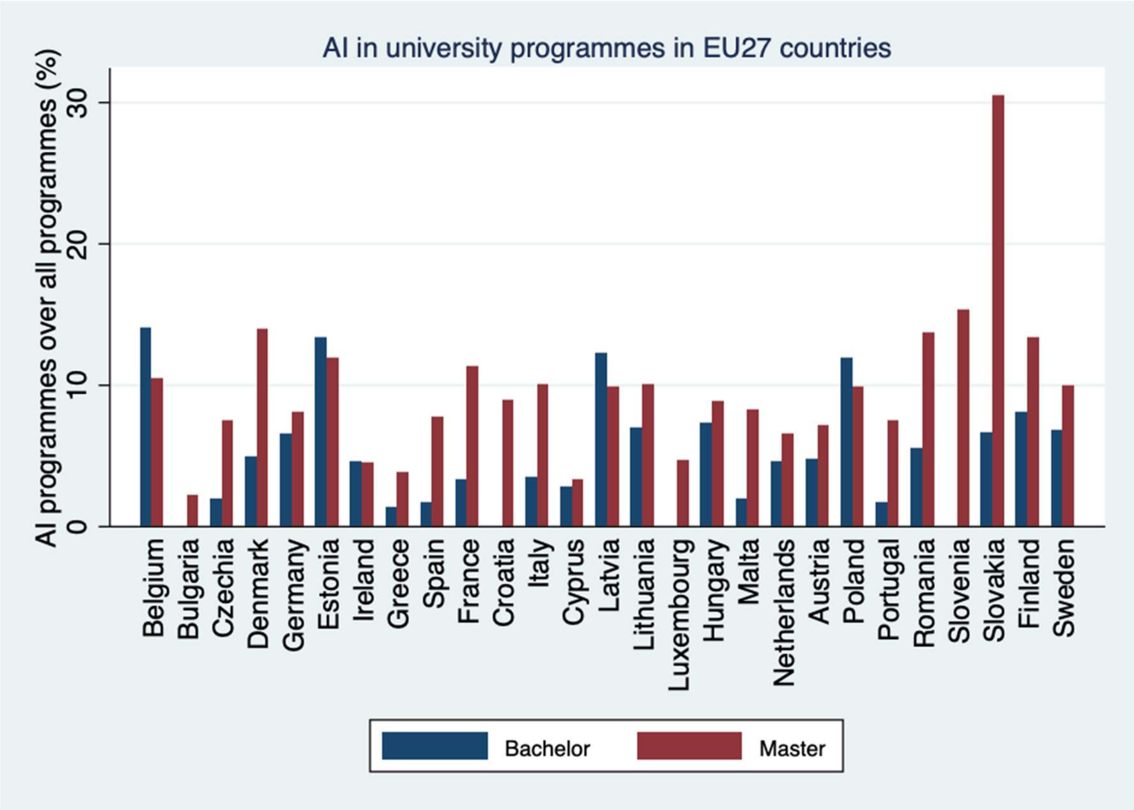


Figure 29 shows that the presence of AI content in master's degree programmes is higher than for bachelor's degree programmes in most Member States. The exceptions are the four countries with the highest proportion of AI content in their bachelor's curricula: Belgium, Estonia, Latvia and Poland. For the remaining countries, not only is master's degree AI intensity higher in percentage than bachelor's degree AI intensity, but their patterns are remarkably different. For instance, in Slovenia, where there is no AI content in bachelor's degree programmes, the AI intensity in the master's degree curricula is the second highest in the EU (15.3%). Other countries with 0% AI intensity in the bachelor's degree programmes are Luxembourg, Croatia and Bulgaria, which have an AI intensity in master's programmes of 4.6%, 8.9% and 2.2%, respectively. France and Italy (and to a smaller extent, Spain too), which are countries with a considerable weight in the AI landscape, also display the same kind of discrepancy, with their master's degree programmes being more able to include AI content than their bachelor's degree programmes. However, one needs to remember that this analysis is based on English-taught programmes, which leaves out a variable proportion of programmes taught in national languages. The last feature to remark upon is the high intensity of AI content shown by Slovakia in the master's degree programme, with a value of 30.4%, the highest in the EU. This is due to the limited overall academic offer (i.e., number of all master programmes) detected in the country.

3.5.2.2 S6: University places with AI content in the EU

Description of indicator

The *S6 – University places* indicator *with AI content* measures the number of available places in university programmes with AI content for each Member State. Therefore it provides a view of the potential labour force trained in formal education with AI skills within the EU. The S6 indicator only considers AI capabilities gained from formal tertiary education. The methodology followed to calculate the indicator (Gómez Losada et al., 2020) combines three types of data: the number of students enrolled by education level and education field; the proportion of applicants *accepted and studying*, *accepted and not studying*, and *rejected* in first-degree tertiary education; and the percentage of AI programmes over all programmes. The latter is based, as in S5, on programmes fully or partially taught in the English language. This was considered as a potentially limiting factor for the validity of the study, and it was therefore scrutinised in a previous report, together with other characteristics of the data source used (López Cobo et al. (2019) pp. 14–16). The impact of the teaching language was found not to be negligible, but limited and not substantially affecting the validity of the results (López Cobo et al. (2019), Righi et al. (2021, 2022)).

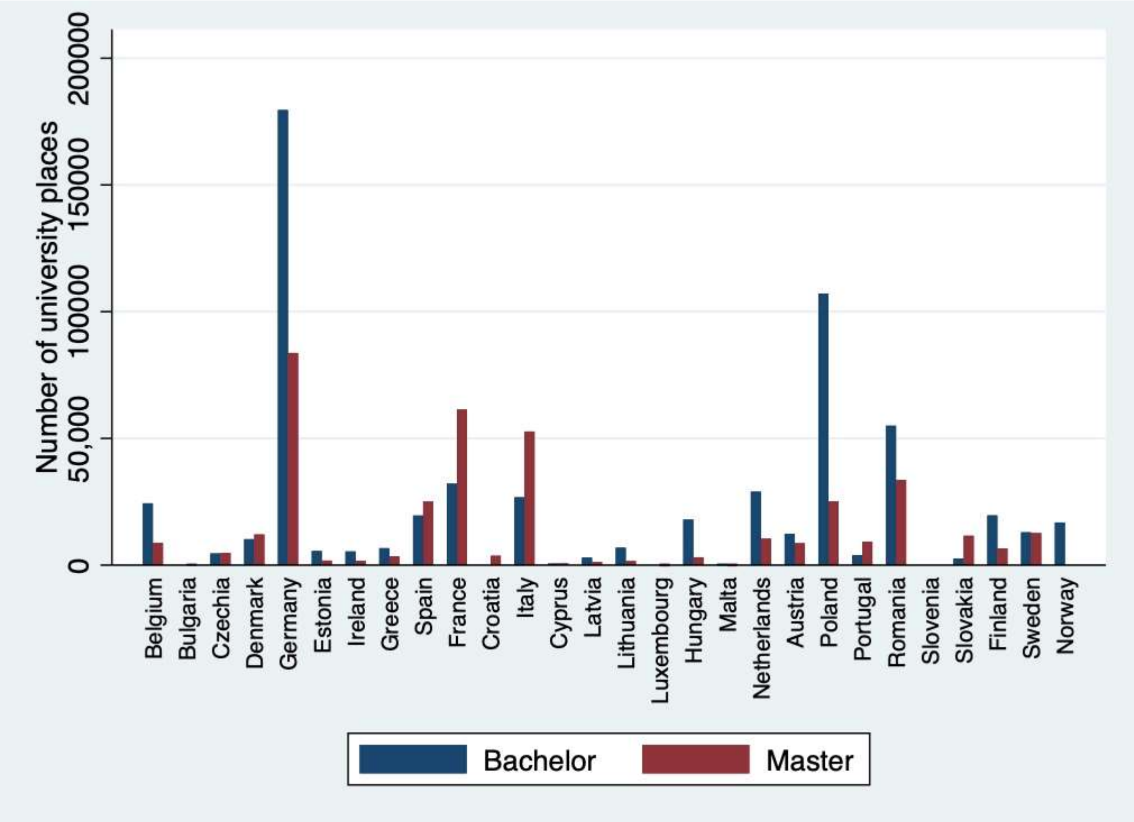
For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

The European Union

Figure 30 shows the number of places in university programmes with AI content in the EU. The country with largest number of places in these programmes, in both bachelor's and master's degree curricula, is Germany (179,600 places for bachelor's degree programmes). Every Member State apart from Poland (which accounts for 107,100 places in bachelor's degree programmes) has one third (or less) of the number of bachelor's degree programme places in Germany. Slovenia, Bulgaria, Croatia and Luxembourg have no available places at all in bachelor's studies with AI content in the curricula. Therefore, in terms of bachelor's degree programmes, Germany is the Member State training largest number of students with AI skills in the EU. In this sense, it is the Member State that is contributing the highest numbers to ensure the presence of skilled workforce in the future. After Germany, Poland and Romania offer the next highest number of bachelor's degree places with AI content, followed by France, Netherlands, Italy and Belgium.

Regarding master's degree programmes with AI content, the countries presenting the largest supply are Germany (with 83,700 available places), France (with 61,400), Italy (with 52,700) and Romania (with 33,600). Thus, among the countries capable to provide the largest number of available places in AI master's degree programmes, the differences are much more limited than what observed for bachelor's degree programmes. For the rest of the Member States, the S6 indicator for master's degree programmes presents values below 26,000.

Figure 30. University places with AI content by level of studies. EU Member States, 2020–21 academic year



3.5.2.3 S7: AI intensity in university places in the EU

Description of the indicator

The *S7 – AI intensity in university places* indicator measures the proportion of available places in university programmes with AI content in total number of places in university programmes by Member State. The S7 indicator only considers AI capabilities gained from formal tertiary education. The methodology followed to calculate the indicator (Gómez Losada et al., 2020) combines three types of data: the number of students enrolled by education level and education field; the proportion of applicants *accepted and studying*, *accepted and not studying*, and *rejected* in first-degree tertiary education; and the percentage of AI programmes over all programmes. The latter is based, as in S5 and S6, on programmes fully or partially taught in the English language. This was considered as a potentially limiting factor for the validity of the study, and it was therefore scrutinised in a previous report, together with other characteristics of the data source used (López Cobo et al. (2019) pp. 14–16). The impact of the teaching language was found not to be negligible, but limited and not substantially affecting the validity of the results (López Cobo et al. (2019), Righi et al. (2021, 2022)).

For more detailed information about the indicator and references, see the metadata fiche in Annex 1.

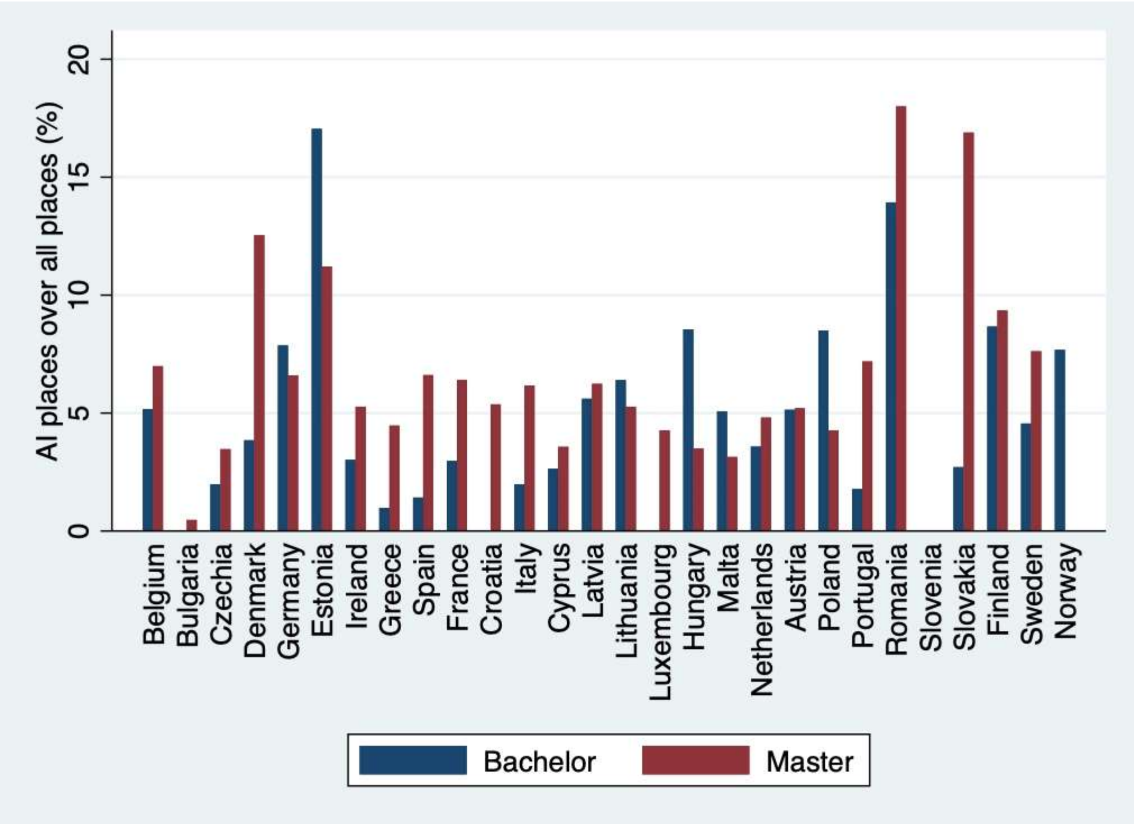
The European Union

In Figure 31 we see that Estonia and Romania are the two Member States with the highest percentage of AI programmes in tertiary education. They have the highest proportion of available places in university programmes with AI content in both bachelor's and master's studies. Concerning master's degree programmes, Slovakia and Denmark also have noticeable percentages of available AI-places, 16.9% and 12.5%, respectively. However, the intensity of AI in bachelor's degree places in these two countries is relatively low, less than 5% in both cases. All other Member States have an AI intensity in bachelor's degree and master's degree places below 10%.

As observed with indicator S5, for bachelor's degree studies there are no available places in university programmes with AI content in Slovenia, Luxembourg, Croatia and Bulgaria. However, Luxembourg and Croatia at least present modest percentages regarding master's degree courses. It needs to be remembered that this analysis is based on English-taught programmes, which leaves out a variable proportion of programmes taught in national language.

Finally, for several countries the AI intensity is higher for master's degree courses than for bachelor's degree programmes. This gap is more substantial for Greece, Spain, Portugal, Italy, Slovakia, France, Denmark and Sweden.

Figure 31. AI intensity in university places by level of studies (%). EU Member States, 2020–21 academic year



4 Conclusions

This report presents 22 indicators that offer a view of the development of AI in the EU and beyond. This provides a framework that facilitates the assessment of international and European comparisons for the AI field. The indicators have been grouped in five dimensions in order to analyse and highlight specific aspects of the standing of the EU in the AI domain.

The first dimension, **Global view on the AI landscape**, shows the leadership of the US in the worldwide landscape, followed by China and the EU. This result should be interpreted in the context of the indicators presented. Firstly, although the data available includes the number of AI players it does not provide an indication of their economic relevance (for instance in terms of number of employees or market size); having this additional information would allow a more accurate analysis of the landscape. Secondly, the detection of players in China mainly relies on their patenting activity. In recent years, China has experienced an explosion in the filing of patents (included those related to AI), yet the same is not reflected in other indicators (such as frontier research activity), indicating that its AI ecosystem may be less dense than it appears based on patenting activity alone. In spite of this, China certainly plays a substantial role, especially given its very strong involvement in the ICT manufacturing sector (whose products constitute the basis of all digital technologies). Another comment worth noting is the very relevant position of the UK, fourth worldwide after the EU, highlighting the impact of Brexit on the EU AI landscape.

The EU displays a comparative advantage in *AI Services* and *Autonomous Robotics*, meaning activity is more concentrated in these AI thematic areas in the EU than in other regions of the world. The EU's specialisation in *Autonomous Robotics* is complemented by a longstanding comparative advantage in trade in industrial robots, as well as with a consistent increase in the number of newly formed robotics start-ups. These findings confirm the good overall position of the EU in the sector worldwide, and makes it an interesting sector to be further developed. The EU Member States with the highest numbers of AI players are Germany, France and Spain, while Estonia, Malta and Finland have the highest relative economic activity intensity when considering the number of AI players per unit of GDP. Another positive insight revealed from our analysis at the EU level is the increasing effort in terms of AI investments made by all Member States from 2018 to 2019.

The second dimension, **Industry**, considers AI firms and their profiles at global level. For most geographic areas and for all Member States, the main type of AI firm is *AI firm without AI patents*. These are enterprises with a core business in AI but that do not contribute to the technological development of the field in the form of patents. In fact, most of them are firms providing AI services to other firms or to end-consumers. In China we see that the main type of firms involved in AI are firms that do not have AI as their core business (i.e. firms operating in other sectors such as energy, automotive) that do file AI-related patent applications. The number of EU firms that develop patents is very limited compared with other regions. It is important to note that the role of patents in a technology such as AI, which has a very strong and relevant algorithmic and software-related component, is arguably less relevant than it has been for innovations with an important hardware component, such as, for instance, semiconductors. This is because software innovations are typically not patentable. Nonetheless, as the future competitiveness of a region also depends on the innovation capacity of its players, the EU might benefit from additional support to innovation. Also, as the innovative capacity of a region depends on the intensity of exchanges and interactions between the players therein, collaborations between players from different Member States should continue to be encouraged.

A focus on robotics start-ups shows that the EU is strong in this domain, as we observe an upward trend in the annual creation of new robotics start-ups from 1996 to 2015, and a constant increase in their cumulative number up to 2021. It is likely that, in a near future, the integration between AI and Robotics will intensify. In light of this, AI is expected to be a catalyst for future improvements in robotics skills across different sectors (e.g., health & human-care, agriculture and environmental protection).

The **Research and Development (R&D)** dimension provides an analysis by type of R&D activity developed. As expected, frontier research activities (i.e., scientific publications) are mostly carried out by research institutions, and patent applications are mainly filed by firms. The involvement of the US and the EU in frontier research activities is significant, as shown by the AI R&D activity score; and the EU appears to be utterly central in the network of collaborations. This means that, to date, the EU has been able to establish meaningful interactions with relevant actors. This is key for two reasons. Firstly, it enables the EU to have strategic relevance in the worldwide R&D landscape, since it is in a good position to influence other regions. Secondly, to be involved in multiple interactions facilitates information exchange and, in turn, the blooming of innovation.

The fourth dimension covered addresses the **Technological evolution of AI**. In this respect, it is confirmed that AI is expanding, not only in terms of an increasing number of activities and players involved in the landscape, but also qualitatively, from a technological point of view. Indeed, all the types of AI tasks assessed, i.e., speech, language understanding, language reasoning skills, and computer vision (image and video), show improved performance over time, in some cases with a huge performance shift in very few years.

Standardisation is a key step in the technological process. AI standards are bound to promote interoperability, consistent application of best practices in the development of AI products and services, and appropriate management of potential AI-related risks in terms of safety and/or fundamental rights. In this regard, EU Member States plays a very active role at the international stage. Furthermore, analysis of the AI standardisation landscape shows that a substantial number of AI standards produced by four major international and European Standardisation Development Organisations – ISO/IEC, ETSI, IEEE and ITU-T – are significant from the perspective of the proposed European AI Regulation, the AI Act.

The last dimension considered, **Societal Aspects**, considers diversity in AI research and university-level offerings in AI, as two aspects related to advanced AI skills. The results show a progressive increase of gender, geographic and business diversity in the AI research community from 2016 to 2020, possibly due to a positive effect of inclusion policies put in place. The results also show, on the one hand, an uneven education offering of advanced AI skills across EU Member States, with the proportion of master's degree programmes including AI ranging from 2% in Bulgaria to 30% in Slovakia. On the other hand, we note an overall higher offering of AI skills in master's degrees when compared with bachelor's degrees. This may initially seem expected, as advanced AI skills are mostly covered in later education stages. However, this observation should lead to a reflection on the need for more AI-related education early in the curriculum. After all, AI-related skills are bound to have an increasing impact in terms of individual employability, as well as on the rate of economic growth. The lack of an adequately trained workforce in certain countries might affect their economic competitiveness and, in turn, their social well-being. Therefore it is important to reduce the inequalities observed across the EU population.

Overall, an analysis of the AI Watch Index results through its five dimensions shows a relatively strong position of the EU in the worldwide landscape, but still far from the US and China. The EU has prominent positions in AI R&D and the robotics sector – both industrial robots and autonomous robotics – and AI investments from the public and private sector show encouraging results that should be sustained in the future.

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Annexes

Annex 1. Metadata fiches

G – Global view on the AI Landscape

Dimension	***Global view on the AI landscape***
Sub-dimension	***AI activity***
Indicator name	***G1: AI economic players***
Rationale	This measures the size of the AI landscape. It measures the level of involvement of a geographical area (country, region…) in the global AI landscape. Useful for cross-country comparison. The breakdown by organisation type makes possible further analysis of the relationships between research and industry, research and government, and industry and government in different geographic areas, and facilitates the assessment of different properties of the entire ecosystem and local areas.
Definition	Number of economic players in the AI ecosystem. Players may be research institutes, universities, firms, laboratories, or governmental institutions, grouped into 3 types: research institutes, firms and governmental institutions. Further details: The "governmental institutions" category includes the institutions owned by the state, or with public administrative functions, which do not have an explicit research portfolio (i.e., excludes universities and research institutions, which fall under "research institutes"). The category "research institutes" encompasses all players mainly devoted to research activity, i.e., private research centres, public research centres, universities, university/academic spin-offs and industrial research centres exclusively dedicated to research activities. Departments of a single university are not considered to be separate players.
Unit of measurement	Number of players (integer, percentage)
Geographical coverage	World
Geographical granularity	Macro areas (top countries plus world regions), EU27 Member States
Breakdown	Organisation type: research institute, firm or governmental institution.
Data source(s)	JRC AI TES Dataset 2020, available at https://data.jrc.ec.europa.eu/collection/id-0126 This is a multi-source microdata dataset built by considering the main AI-related industrial, innovation and research activities, and all the economic players that are involved in them (i.e., firms, research institutes, governmental institutions). The TES approach takes into account information about location, technological aspects and interactions, in order to build a holistic and interconnected view of the worldwide AI ecosystem from 2009 to 2020.
Reference date	2009–2020 (one value for the entire period)
Known limitations	Does not address the relative importance of players, but their presence in the landscape. This limitation is overcome by the introduction of indicators addressing the level of involvement (number of AI R&D activities). This indicator does not consider the size of the economy of the geographic area. This is overcome by the consideration of the indicator relative to GDP.
References and Comments	The economic player is expected to have an active role in the techno-economic segment, with the capability to influence its economic development and future evolution. In this sense, the focus is set on the organisations, and not on individuals, namely the applicant organisation owning the invention in the case of patents, authors´ affiliation in conference proceedings, companies, governmental entities, etc. To establish a comprehensive landscape, we target both industrial and R&D activities. This helps to capture economic players that participate in the landscape with a variety of foci, interests and impact capacity. Therefore players' economic activities of interest for the analysis of the TES ecosystem include R&D processes (research and innovative developments), general economic processes (industrial

Dimension	***Global view on the AI landscape***
Sub-dimension	***AI activity***
Indicator name	***G1: AI economic players***
	production, trade, marketing and other services), and firms' funding (venture capital funds or other types of investment). Reference: Samoili S., Righi R., Cardona M., López Cobo M., Vázquez-Prada Baillet M., and De Prato G., TES analysis of AI Worldwide Ecosystem in 2009–2018, EUR 30109 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-16661-0, doi:10.2760/85212, JRC120106. https://publications.jrc.ec.europa.eu/repository/handle/JRC120106

Dimension	***Global view on the AI landscape***
Sub-dimension	***AI activity***
Indicator name	***G2: AI player intensity***
Rationale	This measures the presence of AI economic players with regard to the size of the economy. The ratio against national GDP allows for a comparison of countries irrespective their economic size.
Definition	Number of economic players compared with GDP
Unit of measurement	Number of players / GDP in billion € (ratio)
Geographical coverage	World
Geographical granularity	Macro areas (top countries plus world regions), EU27 Member States
Breakdown	-
Data source(s)	For number of players: JRC AI TES Dataset 2020, available at https://data.jrc.ec.europa.eu/collection/id-0126. See description of the dataset in indicator G1 For GDP: OECD.
Reference date	2009–2020 (one value for the entire period)
Known limitations	GDP at regional level is not available for all regions worldwide. It is available for EU regions (NUTS2).
References and Comments	Reference: Samoili S., Righi R., Cardona M., López Cobo M., Vázquez-Prada Baillet M., and De Prato G., TES analysis of AI Worldwide Ecosystem in 2009–2018, EUR 30109 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-16661-0, doi:10.2760/85212, JRC120106. https://publications.jrc.ec.europa.eu/repository/handle/JRC120106

Dimension	***Global view on the AI landscape***
Sub-dimension	***AI areas of strength***
Indicator name	***G3: AI areas of specialisation – comparative advantages in AI thematic areas***
Rationale	This explores the specialisation of geographical areas in the AI field. It measures a country's specialisation in a thematic area (or AI subdomain) within the AI domain in comparison with the global average specialisation in that area.
Definition	The Revealed Comparative Advantage (RCA) is a ratio calculated as the share of activities of a geographical area in a thematic area in the share of activities in that thematic area worldwide. For the calculation activities are assigned to the thematic area that best represents the activity's content.
Unit of measurement	Ratio
Geographical coverage	World
Geographical granularity	Macro areas (top countries plus world regions), EU27 Member States
Breakdown	Thematic areas: Machine learning, Computer vision, AI services…
Data source(s)	JRC AI TES Dataset 2020, available at https://data.jrc.ec.europa.eu/collection/id-0126 See description of the dataset in indicator G1.
Reference date	2009–2020 (one value for the entire period)
Known limitations	The collected activities must contain text to be considered in this indicator.
References and Comments	The RCA value = 1 represents the global average or average specialisation in the thematic area when all countries are considered. It is the benchmark towards which all countries are compared. When a country has an RCA >1 in a thematic area, that country is relatively specialised in that area and has a revealed comparative advantage. Reference: Samoili S., Righi R., Cardona M., López Cobo M., Vázquez-Prada Baillet M., and De Prato G., TES analysis of AI Worldwide Ecosystem in 2009–2018, EUR 30109 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-16661-0, doi:10.2760/85212, JRC120106. https://publications.jrc.ec.europa.eu/repository/handle/JRC120106

Dimension	***Global view on the AI landscape***
Sub-dimension	***AI areas of strength***
Indicator name	***G4: AI thematic hotspots***
Rationale	This measures national or regional performance globally in each AI thematic area or subdomain, in terms of number of R&D and industrial AI activities. This indicator shows the intensity of a country's or a region's participation in a thematic area compared with all countries or regions globally.
Definition	Distribution of activities in a thematic area by geographic area: the number of activities in a geographic area in a thematic area, divided by the number of worldwide (or EU) activities in that thematic area.
Unit of measurement	Number of activities (percentage)
Geographical coverage	World
Geographical granularity	Macro areas (top countries plus world regions), EU27 Member States
Breakdown	Thematic areas (i.e., AI Services, Audio & Natural Language Processing (NLP), Automation, Autonomous Robotics, Computer Vision Applications, Connected and Automated Vehicles (CAVs), Internet of Everything (IoE), Machine Learning (ML) for Image Processing, and Machine Learning (ML) Fundamentals)
Data source(s)	JRC AI TES Dataset 2020, available at https://data.jrc.ec.europa.eu/collection/id-0126 See description of the dataset in indicator G1.
Reference date	2009–2020 (one value for the entire period)
Known limitations	The collected activities must contain text to be considered in this indicator.
References and Comments	Reference: Samoili S., Righi R., Cardona M., López Cobo M., Vázquez-Prada Baillet M., and De Prato G., TES analysis of AI Worldwide Ecosystem in 2009–2018, EUR 30109 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-16661-0, doi:10.2760/85212, JRC120106. https://publications.jrc.ec.europa.eu/repository/handle/JRC120106

Dimension	***Global view on the AI landscape***
Sub-dimension	***AI areas of strength***
Indicator name	***G5: EU's comparative advantage in industrial robotics trade***
Rationale	This is an indicator traditionally used to identify strengths in global comparisons, applied in this case to trade activity.
Definition	The Revealed comparative Advantage (RCA) is a ratio calculated as the share of trade activity of a geographic area in the share of trade activity worldwide.
Unit of measurement	Imports and exports (volume and value)
Geographical coverage	World
Geographical granularity	EU27 (as a single aggregated area)
Breakdown	
Data source(s)	UN Comtrade This is a publicly available repository of official international trade statistics and relevant analytical tables.
Reference date	1996–2020
Known limitations	At a very disaggregated level, trade data may present a high percentage of missing information. If imputations are needed, this may generate concerns, depending on the methodology used.
References and Comments	

Dimension	***Global view on the AI landscape***
Sub-dimension	***AI investments***
Indicator name	***G6: AI investments in the EU***
Rationale	A sufficient and continued level of investments is crucial for supporting the development and uptake of AI throughout Europe. This indicator provides an estimation of AI investments by public and private organisations at country level.
Definition	In absence of reliable data on the level of AI investments by the private and public sector, AI Watch has developed a comprehensive methodology to estimate AI investments for the EU and the Member States. In this framework, AI investments include: expenditures on labour and skills, as well as tangible and intangible capital assets incurred by public and private organisations to develop and implement AI to (re-)design business processes in order to create new or improve existing products or services.
Unit of measurement	Real values (Euro)
Geographical coverage	EU27 Member States
Geographical granularity	Country
Breakdown	Type of expenditure: AI-related expenditures on education programmes, compensation of AI ICT specialists, AI-related corporate training, R&D, product design, brand, organisational capital ICT software and hardware, telecommunications equipment, and data. Public and private sector.
Data source(s)	JRC estimates for AI Watch based on multiple sources
Reference date	2018, 2019
Known limitations	
References and Comments	Reference: Nepelski, D., and Sobolewski, M., Estimating investments in General Purpose Technologies. The case of AI Investments in Europe, EUR 30072 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-10233-5, doi:10.2760/506947, JRC118953. https://ec.europa.eu/jrc/en/publication/estimating-investments-general-purpose-technologies-case-ai-investments-europe

I – Industry

Dimension	***Industry***
Sub-dimension	***Industry***
Indicator name	***I1: AI firms' profiles***
Rationale	This measures the level of industrial involvement of a geographical area in the global AI landscape and compares the different firm demographic profiles of AI firms.
Definition	Number of firms in the ecosystem. Distribution of firms categorised by age, size, industry sector and AI-business type.
Unit of measurement	Number of firms (integer), percentage for breakdowns
Geographical coverage	World
Geographical granularity	Macro areas (top countries plus world regions), EU27 Member States
Breakdown	Firm demographics: Industrial sector, Size class, Age group; and core-business type
Data source(s)	JRC AI TES Dataset 2020, available at https://data.jrc.ec.europa.eu/collection/id-0126 See description of the dataset in indicator G1.
Reference date	2009–2020 (one value for the entire period)
Known limitations	Breakdown by firm demographics is limited to the subset of firms for which there is available data in the sources. Coverage varies depending on the macro area, with Asian countries more poorly covered. Population data is inferred based on this subset.
References and Comments	Reference: Samoili S., Righi R., Cardona M., López Cobo M., Vázquez-Prada Baillet M., and De Prato G., TES analysis of AI Worldwide Ecosystem in 2009–2018, EUR 30109 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-16661-0, doi:10.2760/85212, JRC120106. https://publications.jrc.ec.europa.eu/repository/handle/JRC120106

Dimension	***Industry***
Sub-dimension	***Industry***
Indicator name	***I2: Robotics start-ups in the EU***
Rationale	This indicator provides insights about the vitality of this sector, in which Europe has an outstanding position. It also provide clues regarding potential shifts in worldwide leadership and competition landscape.
Definition	Number of new robotic start-ups by year
Unit of measurement	Number of companies
Geographical coverage	EU27
Geographical granularity	EU27 (as a single aggregated area)
Breakdown	Firms' categories
Data source(s)	Dealroom, a private provider of data on start-ups, growth companies and tech ecosystems in Europe and worldwide.
Reference date	1996–2021
Known limitations	The database does not have full coverage of worldwide start-ups, so it may provide an incomplete picture.
References and Comments	

R – Research and Development

Dimension	***Research and development***
Sub-dimension	***R&D Activity***
Indicator name	***R1: AI players in AI R&D***
Rationale	This shows the presence of economic players involved in the development of AI. The distinction by organisation type facilitates analysis of the institutional profiles of the key players in the technological advances and innovative activities in the domain, and assessment of the overall propensity of firms and research institutions to engage in AI R&D activities.
Definition	Distribution of economic players involved in AI-related R&D activities. The R&D activities considered are: (i) patent applications, (ii) frontier research publications (i.e., publication in top AI journals and conferences) and (iii) EU-funded projects (only when analysing the EU focus, to avoid an EU-centric biased view).
Unit of measurement	Number of players (integer)
Geographical coverage	World
Geographical granularity	Macro areas (top countries plus world regions), EU27 Member States
Breakdown	Organisation type: research institute, firm or governmental institution. Type of R&D activity: patent applications, frontier research publications, EU-funded projects FP7-H2020 (where relevant)
Data source(s)	JRC AI TES Dataset 2020, available at https://data.jrc.ec.europa.eu/collection/id-0126 See description of the dataset in indicator G1.
Reference date	2009–2020 (one value for the entire period)
Known limitations	
References and Comments	Reference: Samoili S., Righi R., Cardona M., López Cobo M., Vázquez-Prada Baillet M., and De Prato G., TES analysis of AI Worldwide Ecosystem in 2009–2018, EUR 30109 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-16661-0, doi:10.2760/85212, JRC120106. https://publications.jrc.ec.europa.eu/repository/handle/JRC120106

Dimension	***Research and development***
Sub-dimension	***R&D activity***
Indicator name	***R2: AI R&D activity score***
Rationale	This assesses the level of involvement in AI-related R&D, by weighting the presence of AI economic players in a geographical area with the amount of AI activity they develop.
Definition	Number of R&D activities developed by players, calculated as the sum of the fractional count for all the economic players included in a geographical area. The R&D activities considered are: (i) patent applications, (ii) frontier research publications (i.e., publication in top AI journals and conferences), and (iii) EU-funded projects (only when analysing the EU focus, to avoid an EU-centric biased view). To account for collaboration in the same activity by several economic players, the fractional count of the activity corresponding to one economic player is calculated as 1 divided by the number of participating players in that activity, so that the sum of all fractions adds up to 1.
Unit of measurement	Real positive number
Geographical coverage	World
Geographical granularity	Macro areas (top countries plus world regions), EU27 Member States
Breakdown	Type of R&D activity: patent applications, frontier research publications, and EU-funded projects FP7-H2020 (where relevant)
Data source(s)	JRC AI TES Dataset 2020, available at https://data.jrc.ec.europa.eu/collection/id-0126 See description of the dataset in indicator G1.
Reference date	2009–2020 (one value for the entire period)
Known limitations	
References and Comments	Reference: Samoili S., Righi R., Cardona M., López Cobo M., Vázquez-Prada Baillet M., and De Prato G., TES analysis of AI Worldwide Ecosystem in 2009–2018, EUR 30109 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-16661-0, doi:10.2760/85212, JRC120106. https://publications.jrc.ec.europa.eu/repository/handle/JRC120106

Dimension	***Research and development***
Sub-dimension	***Network of collaborations***
Indicator name	***R3: AI R&D collaborating countries***
Rationale	This measures the extent to which a region is able to develop a network of collaborations with other regions (within the same country or outside it). The creation of a network of interaction is fundamental in terms of information exchange and knowledge accumulation. In addition, with specific reference to innovation capacity, this is linked to the capacity of actors to interact between themselves. When multiple perspectives and different notions are brought together and converge towards a common objective, they are very likely to favour the generation of innovations (Lane & Maxfield, 2005).
Definition	Number of countries with which the considered areas have established AI-related R&D collaborations. The R&D activities considered are: (i) patent applications, (ii) frontier research publications (i.e., publication in top AI journals and conferences), and (iii) EU-funded projects (only when analysing the EU focus, to avoid an EU-centric biased view).
Unit of measurement	Number of countries (integer)
Geographical coverage	World
Geographical granularity	EU27 Member States
Breakdown	Type of R&D activity: patent applications, frontier research publications, and EU-funded projects FP7-H2020 (where relevant)
Data source(s)	JRC AI TES Dataset 2020, available at https://data.jrc.ec.europa.eu/collection/id-0126 See description of the dataset in indicator G1.
Reference date	2009–2020 (one value for the entire period)
Known limitations	
References and Comments	Reference: Samoili S., Righi R., Cardona M., López Cobo M., Vázquez-Prada Baillet M., and De Prato G., TES analysis of AI Worldwide Ecosystem in 2009–2018, EUR 30109 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-16661-0, doi:10.2760/85212, JRC120106. https://publications.jrc.ec.europa.eu/repository/handle/JRC120106 Lane, D.A., Maxfield, R.R. Ontological uncertainty and innovation. Journal of Evolutionary Economics, 15, 3–50 (2005)

Dimension	***Research and development***
Sub-dimension	***Network of collaborations***
Indicator name	***R4: Peer-to-peer collaborations***
Rationale	This measures how many collaborations are developed by players from a geographical area, so indicating the degree to which geographical areas are able to collaborate for R&D purposes. With specific reference to the innovation capacity, this is linked to the capacity of actor to interact between themselves. When multiple perspectives and different notions are brought together and converge towards a common objective, they are very likely to favour the generation of innovations (Lane & Maxfield, 2005).
Definition	Number of weighted collaborations developed by economic players. The weight is based on fractional counting. As what considered are “peer-to-peer” collaborations, each collaboration has a weight that equals one divided by the binomial coefficient determined, with n = the number of players involved in the collaboration and k = 2. The sum of all fractions adds up to 1.
Unit of measurement	Real positive number
Geographical coverage	World
Geographical granularity	Macro areas (top countries plus world regions), EU27 Member States
Breakdown	Profile of collaborating players, as a combination of type of player (firm, research, government) and location of players (local, abroad) as follows: • B2B abroad, which indicates that firms located in the assessed geographical area collaborate with other firms located abroad (i.e., not in the same geographical area); • B2B local, which indicates that firms located in a specific geographical area collaborate with firms located in the same geographical area; • B2R local, which indicates that firms located in a specific geographical area collaborate with research institutes that are located in the same geographical area; • G2B local, which indicates that the governmental institutions of that geographical area collaborate with business players in the same geographical area; • R2R abroad, which indicates that research institutes located in that geographical area collaborate with research institutes located abroad; and • R2R local, which indicates that research institutes located in that geographical area collaborate with research institutes located in the same geographical area. Additional breakdown: Type of R&D activity: patent applications, frontier research publications, and EU-funded projects FP7-H2020 (where relevant).
Data source(s)	JRC AI TES Dataset 2020, available at https://data.jrc.ec.europa.eu/collection/id-0126 See description of the dataset in indicator G1.
Reference date	2009–2020 (one value for the entire period)
Known limitations	
References and Comments	Reference: Samoili S., Righi R., Cardona M., López Cobo M., Vázquez-Prada Baillet M., and De Prato G., TES analysis of AI Worldwide Ecosystem in 2009–2018, EUR 30109 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-16661-0, doi:10.2760/85212, JRC120106. https://publications.jrc.ec.europa.eu/repository/handle/JRC120106 Lane, D.A., Maxfield, R.R. Ontological uncertainty and innovation. Journal of Evolutionary Economics, 15, 3–50 (2005)

Dimension	***Research and development***
Sub-dimension	***Network of collaborations***
Indicator name	***R5: Strategic position in the network of collaborations***
Rationale	This assesses the strategic position of a geographical area in the AI R&D network of collaborations, and hence its influential capacity. The more central an area is (in terms of network of collaborations), the more it is in a dominant position with respect to information exchanges.
Definition	Weighted Betweenness Centrality (Brandes, 2001), normalised in the interval [0,1], in the overall R&D Network. To determine the weight of collaborations, the fractional counting is considered. The geo-based network (i.e., one node per area) is calculated based on the peer-to-peer collaborations between players (which are considered depending on their location). The weight of connections is based on fractional counting. Each collaboration has a weight that equals one divided by the binomial coefficient determined, with n = the number of players involved in that activity and k = 2. Thus the sum of all fractions adds up to 1.
Unit of measurement	Real positive number
Geographical coverage	World
Geographical granularity	Macro areas (top countries plus world regions), EU27 Member States
Breakdown	Potential additional breakdown: Type of R&D activity: patent applications, frontier research publications, and EU-funded projects FP7-H2020 (where relevant).
Data source(s)	JRC AI TES Dataset 2020, available at https://data.jrc.ec.europa.eu/collection/id-0126 See description of the dataset in indicator G1.
Reference date	2009–2020 (one value for the entire period)
Known limitations	
References and Comments	We chose Betweenness Centrality instead of other centrality measures, such as, e.g., Closeness (which is related to efficiency, as it measures the ability of a node to be directly connected with the rest of the network), due to the interest in showing R&D hubs. As we consider R&D activities, in which the circulation of information is the key point for the creation of innovation (Lane & Maxfield, 2005), betweenness is more able to reveal where the important hubs are located. Indeed, betweenness is related to the ability of being in a crucial position, i.e., having a key role in “connecting” nodes, which implies being able to “control” exchanges between other nodes. Reference: Samoili S., Righi R., Cardona M., López Cobo M., Vázquez-Prada Baillet M., and De Prato G., TES analysis of AI Worldwide Ecosystem in 2009–2018, EUR 30109 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-16661-0, doi:10.2760/85212, JRC120106. https://publications.jrc.ec.europa.eu/repository/handle/JRC120106 Brandes, U., A Faster Algorithm for Betweenness Centrality. Journal of Mathematical Sociology 25(2) (2001):163–177. Lane, D.A., Maxfield, R.R. Ontological uncertainty and innovation. Journal of Evolutionary Economics, 15, 3–50 (2005)

T – Technology

Dimension	***Technology***
Sub-dimension	***Performance of AI***
Indicator name	***T1: Performance of AI research***
Rationale	Performance levels for particular AI tasks are measured in terms of different evaluation metrics (accuracy, AUC, EM, F1, BLEU score, etc.), depending on the tasks at hand. Performance metrics may be used as a proxy indicator of progress.
Definition	In order to calculate the performance in each AI tasks (e.g., Image Classification, Face Recognition, Speech Recognition, Text Summarisation, etc.) we average the performance results (when common evaluation metrics are used) related to a particular task over a period of time.
Unit of measurement	Average results in the units required by the evaluation metric (e.g., percentage in [0,1] for accuracy-related metrics)
Geographical coverage	World
Geographical granularity	World
Breakdown	The indicator may be aggregated and summarised by AI tasks (e.g., Image Classification, Facial Recognition, Speech Recognition, etc.) or specific benchmark belonging to a particular task (e.g., Imagenet, COCO, CIFAR-10 for Image Classification). It is not possible to talk about "aggregated" progress, as we are using different dimensions, data, goals, etc.
Data source(s)	AIcollaboratory (http://www.aicollaboratory.org/) See description of the dataset in indicator R3.
Reference date	2017–2020 (one value per year)
Known limitations	Not all the AI tasks can be evaluated for the entire period (2010–2020). Different AI tasks are evaluated using different evaluation metrics making it difficult to compare results among them.
References and Comments	References: Barredo, P., Hernandez-Orallo, J., Martínez-Plumed, F. and O Heigeartaigh, S., "The Scientometrics of AI Benchmarks: Unveiling the Underlying Mechanics of AI Research", 1st International Workshop on Evaluating Progress in Artificial Intelligence (EPAI 2020) @ ECAI 2020, Santiago de Compostela, Spain, 4 September 2020. http://dmip.webs.upv.es/EPAI2020/papers/EPAI_2020_paper_12.pdf Martínez-Plumed, F., Hernández-Orallo, J., Gómez, E., "Tracking AI: The Capability is (Not) Near", Proceedings of the 24th European Conference on Artificial Intelligence (ECAI 2020), Santiago de Compostela, Spain, September 2020. https://ecai2020.eu/papers/1009_paper.pdf

Dimension	***Technology***
Sub-dimension	***Standardisation***
Indicator name	***T2: Standardisation activity engagement***
Rationale	Standardisation activities enable interoperability and foster innovation, efficiency and growth
Definition	Number and maturity level of standardisation initiatives, and the countries engaged in them
Unit of measurement	Number of activities
Geographical coverage	World
Geographical granularity	World, Country
Breakdown	Maturity level
Data source(s)	JRC estimates for AI Watch based on existing worldwide standardisation initiatives
Reference date	2020
Known limitations	
References and Comments	

S – Societal aspects

Dimension	***Societal aspects***
Sub-dimension	***Diversity in research***
Indicator name	***S1: Gender diversity index***
Rationale	We measure diversity in the AI field, to track the representation of female researchers in the field and the impact of gender equality policies. This indicator measures gender diversity of a certain conference and makes an average for the most relevant AI conferences.
Definition	The diversity indices originate from the study of biodiversity of species in an environment. We consider three different *species* (S = 3) in the gender dimension: "male", "female" and "other". We calculate Shannon evenness by means of the Pielou diversity index. For calculating the Gender Diversity Index, we consider three different communities: keynotes (k), authors (a) and organisers (o). The final GDI performs a weighted average among the Pielou index in each community with the following weights: 1/2 for keynotes, 1/3 for authors and 1/5 for organisers.
Unit of measurement	[0, 1] from less to more heterogeneous/diverse
Geographical coverage	World
Geographical granularity	World
Breakdown	This indicator is measured for each scientific conference. We might aggregate for conferences in a given year using statistics, such as the average or the standard deviation, or select only few relevant conferences, such as ICML, NeurIPS.
Data source(s)	divinAI.org DivinAI (Diversity in Artificial Intelligence) is an initiative of the HUMAINT project at Joint Research Centre (EC) and the ICT Department at Pompeu Fabra University, Barcelona. The goal of DivinAI is to research and develop a set of diversity indicators, related to Artificial Intelligence developments, with special focus on gender balance, geographical representation and presence of academia vs companies. The collaborative website collects data on keynote speakers, members of the organisation committee and authors from the most relevant AI conferences worldwide.
Reference date	2017–2020 (one value per year)
Known limitations	These diversity indexes are calculated for each conference.
References and Comments	Reference: Freire, A., Porcaro, L., and Gómez, E., Measuring Diversity of Artificial Intelligence Conferences. https://arxiv.org/abs/2001.07038

Dimension	***Societal aspects***
Sub-dimension	***Diversity in research***
Indicator name	***S2: Geographic diversity index***
Rationale	We measure diversity in the AI field, to track the representation of researchers from different geographical locations in the research field and the impact of some inclusion policies. This indicator represents the geographic diversity (per continent) at AI conferences. It is possible to calculate an average indicator for major AI conferences in a given year.
Definition	The diversity indices originate from the study of biodiversity of species in an environment. We consider as *species* the seven different continents (Asia, Africa, North America, South America, Antarctica, Europe, and Australia). We calculate the Shannon Index for each of the following communities: keynotes (k), authors (a) and organisers (o). The final GeoDI performs a weighted average among the Shannon index in each community with the following weights: 1/2 for keynotes, 1/3 for authors and 1/5 for organisers.
Unit of measurement	[0, 1] from less to more heterogeneous/diverse
Geographical coverage	World
Geographical granularity	World
Breakdown	This indicator is measured for each scientific conference
Data source(s)	divinAI.org See description of the dataset in indicator S1.
Reference date	2017–2020 (one value per year)
Known limitations	These diversity indexes are calculated for each conference.
References and Comments	Reference: Freire, A., Porcaro, L., and Gómez, E., Measuring Diversity of Artificial Intelligence Conferences. https://arxiv.org/abs/2001.07038

Dimension	***Societal aspects***
Sub-dimension	***Diversity in research***
Indicator name	***S3: Business diversity index***
Rationale	We measure diversity in the AI field, to track the representation of researchers from academia vs industry in the research field.
Definition	The diversity indices originate from the study of biodiversity of species in an environment. We consider three different *species* (S = 3) in the business dimension: "academia", "industry" and "research centre". We calculate Shannon evenness by means of the Pielou diversity index. For calculating the Business Diversity Index (BDI), we consider three different communities: keynotes (k), authors (a) and organisers (o). The final BDI performs a weighted average among the Pielou index in each community with the following weights: 1/2 for keynotes, 1/3 for authors and 1/5 for organisers.
Unit of measurement	[0, 1] from less to more heterogeneous/diverse
Geographical coverage	World
Geographical granularity	World
Breakdown	This indicator is measured for each scientific conference
Data source(s)	divinAI.org See description of the dataset in indicator S1.
Reference date	2017–2020 (one value per year)
Known limitations	These diversity indexes are calculated for each conference.
References and Comments	Reference: Freire, A., Porcaro, L., and Gómez, E., Measuring Diversity of Artificial Intelligence Conferences. https://arxiv.org/abs/2001.07038

Dimension	***Societal aspects***
Sub-dimension	***Diversity in research***
Indicator name	***S4: Conference diversity index***
Rationale	Combined conference diversity index
Definition	This index is calculated by the combination of gender, geographic and business indexes using the following formula: CDI = 1/3 *(GDI + GeoDI/2 + BDI)
Unit of measurement	[0, 1] from less to more heterogeneous/diverse
Geographical coverage	World
Geographical granularity	World
Breakdown	This indicator is measured by each scientific conference
Data source(s)	divinAI.org See description of the dataset in indicator S1.
Reference date	2017–2020 (one value per year)
Known limitations	These diversity indexes are calculated per each conference.
References and Comments	Reference: Freire, A., Porcaro, L., and Gómez, E., Measuring Diversity of Artificial Intelligence Conferences. https://arxiv.org/abs/2001.07038

Dimension	***Societal aspects***
Sub-dimension	***Higher education***
Indicator name	***S5: AI in university programmes in the EU***
Rationale	This indicates the intensity with which AI is included in official curricula, as a proxy of supply of AI capacities.
Definition	Proportion of programmes with AI content compared with total number of programmes
Unit of measurement	Number of programmes (percentage)
Geographical coverage	EU27 Member States
Geographical granularity	Country
Breakdown	By level of study (bachelor's degree and master's degree)
Data source(s)	JRC PREDICT's Education offer Dataset A dataset of university programmes addressing advanced digital technologies, including artificial intelligence. Collects information on the programmes (education level, field of education, domain specific areas taught…) and the institutions offering them (name and location of the higher-education institution).
Reference date	2019–20 academic year
Known limitations	Based on courses taught in English: non-English speaking countries have a lower representation.
References and Comments	This indicator could be linked with indicators on the demand side: number of job vacancies advertised by companies. Righi, R., López-Cobo, M., Alaveras, G., Samoili, S., Cardona, M.., Vázquez-Prada Baillet, M., Ziemba, L.W., and De Prato, G., Academic offer of advanced digital skills in 2019–20. International comparison. Focus on Artificial Intelligence, High Performance Computing, Cybersecurity and Data Science, EUR 30351 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-21541-9, doi:10.2760/225355, JRC121680. https://publications.jrc.ec.europa.eu/repository/handle/JRC121680

Dimension	***Societal aspects***
Sub-dimension	***Higher education***
Indicator name	***S6: University places with AI content in the EU***
Rationale	This provides an estimation of the potential future workforce trained with AI skills in a specific AI domain.
Definition	Number of available places in university programmes with AI content by AI domain (ML, AI ethics, Robotics, Computer vision…)
Unit of measurement	Number of places
Geographical coverage	EU27 Member States
Geographical granularity	Country
Breakdown	By level of study (bachelor and master)
Data source(s)	JRC PREDICT's Education places Dataset Estimations based on multiple sources.
Reference date	2019–20 academic year
Known limitations	This indicator only measures the part of workforce that gained skills by means of formal education
References and Comments	This indicator could be linked with indicators on the demand side: number of job vacancies advertised by companies. Reference: Gómez Losada, Á., López-Cobo, M., Samoili, S., Alaveras, G., Vázquez-Prada Baillet, M., Cardona, M., Righi, R., Ziemba, L., and De Prato, G., Estimation of supply and demand of tertiary education places in advanced digital profiles in the EU. Focus on Artificial Intelligence, High Performance Computing, Cybersecurity and Data Science, EUR30377EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-22281-1, doi:10.2760/559530, JRC121683. https://publications.jrc.ec.europa.eu/repository/handle/JRC121683

Dimension	***Societal Aspects***
Sub-dimension	***Higher education***
Indicator name	***S7: AI intensity in university places in the EU***
Rationale	This provides a measure on the size of potential future workforce trained with AI skills.
Definition	Proportion of available places in university programmes with AI content in the total number of places in university programmes
Unit of measurement	Number of places (percentage)
Geographical coverage	EU27 Member States
Geographical granularity	Country
Breakdown	By level of study (bachelor and master)
Data source(s)	JRC PREDICT's Education places Dataset Estimations based on multiple sources.
Reference date	2019–20 academic year
Known limitations	This indicator only measures the part of workforce who gained capabilities in formal education
References and Comments	This indicator could be linked with indicators on the demand side: number of job vacancies advertised by companies. Reference: Gómez Losada, Á., López-Cobo, M., Samoili, S., Alaveras, G., Vázquez-Prada Baillet, M., Cardona, M., Righi, R., Ziemba, L., and De Prato, G., Estimation of supply and demand of tertiary education places in advanced digital profiles in the EU. Focus on Artificial Intelligence, High Performance Computing, Cybersecurity and Data Science, EUR30377EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-22281-1, doi:10.2760/559530, JRC121683. https://publications.jrc.ec.europa.eu/repository/handle/JRC121683

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