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Foreword

This report addresses technological sovereignty in artificial intelligence (AI) within the European Union (EU). AI is widely regarded as a breakthrough technology, potentially dual-use[1], and a strategic asset. AI is viewed as an essential driver of productivity and competitiveness in the near future, making it a key industrial priority amid growing international competition and rivalry. Insufficient investment in AI and related industries could jeopardize both economic growth and security, quickly turning AI development into a matter of national sovereignty.

We define technological sovereignty in AI as the ability of countries to mobilize and integrate AI-related competencies locally (that is, domestically). In other words, we offer a *competence-based* approach to assessing technological sovereignty in AI. Our objective is both descriptive and analytical. Concerning the descriptive section of the report:

- We identify the key AI competencies along a series of steps involved in the production of and innovation in AI, from the most pervasive AI-related techniques, on through more concrete AI-related functions to the most concrete applications. We call this the *Technique-Function-Application value chain* (TFA value chain). We purposefully focus on a stylized value chain limited to AI-algorithms, rather than the whole AI stack that includes data and compute infrastructure, as we are interested in the specific competences that enable core AI innovation.

- We position countries along the TFA value chain in terms of relative special-

[1]Dual-use technology refers to products, technologies, and knowledge that can serve both civilian and military or security purposes. Apart from artificial intelligence, examples include chemicals, biotechnology, nuclear technology, together with computing.

ization, disentangling areas of relative strengths and weaknesses that can serve as a guide to design science, technology and industrial policies.

The report provides ample evidence of country specialization in well-identified areas of AI. We opted to provide as much information as possible, even if it may occasionally feel overwhelming to the reader. We chose to include various descriptive graphs, tables, and names of key actors in the report to satisfy the curiosity of our readership.

From a more analytical viewpoint, we provide two main outcomes:

- We develop country specific measures of integration along the stylized AI value chain, interpreting this metric as a proxy for technological sovereignty in AI. Using this approach, we perform cross-country comparisons of technological sovereignty across the entire value chain.
- We provide evidence of integration enhancing innovation. Since integration within the AI value chain supports future innovation—and given that AI is increasingly established as a foundational technology—this is a strategic area in which technological sovereignty can be achieved.

Throughout the whole *repertoire* of analyses we engage in, we take a *European* perspective, meaning that we offer a study looking beyond the limits of national boundaries, that assesses technological sovereignty in AI at a continental scale. Overall, we find a substantial gap between the reality and the potential of the EU's leadership in AI innovation and production. In reality, a divide persists between the EU and the global frontier, with Europe trailing behind leading innovators. On the potential side, however, there are increasing returns to be gained at the EU level by leveraging coordinated policies, investments, division of labor, and competence building across the continent.

Executive summary

1. Over the past two decades, the income gap between the United States and Europe has widened. This growing gap is mainly due to the lower growth rate in productivity in Europe. It also indicates the increasing difficulty Europe has either integrating advanced technology into its production processes or pushing the technological frontier forward.

2. AI is the latest advance in ICT technology; hence, tracking the dynamics of ICT investments provides insights into Europe's position compared to the global frontier. The EU trails the US in all types of private ICT investments (equipment, services, research and development), and the gap has been increasing over time.

3. When decomposing the growth rate of the different types of ICT investments by sectors, it appears that the main contributors of superior American ICT R&D and equipment investment growth are ICT services, likely driven by large tech corporations (mostly, the so-called GAFAM). Overall, the evidence indicates that the EU's position as a follower results from the slow diffusion of digital technology across the economy, and a lack of large investors (European "champions").

4. Sizeable financial investments are required to cover the European investment gap in ICT (AI's technological backbone) and to escape its "middle technology trap". This situation indicates that a discussion on the continental financing of investments is needed. In addition to resourcing, being able to lead with regard to ICT and AI developments requires competences.

5. Increasing international rivalries and the reliance on overseas resources and platforms have focused political attention worldwide, and in the EU in particular, on autonomy and sovereignty in the domain of technology — *technological sovereignty*. Technological sovereignty can be seen as the *capability* to develop a technology without external dependencies.

6. Rapid advances in AI, estimations of its widespread impact, and the emergence of a full-fledged industry around it have turned the technology into a "strategic asset". Combined with the awareness of the dependency of AI developments on a handful of overseas actors, AI has become a key focus for policies aimed at strengthening technological sovereignty.

7. As of now, the EU approach to AI policy (in particular, the AI Act) has followed the trajectory of its other horizontal regulatory efforts (GDPR, DSA, DMA) with user protection at its center. However, fostering competitiveness and technological sovereignty in AI is also a matter of investment and, thus, of science, technology, and industrial policies. The EU can make major gains by concentrating on the development of competence and the coordination of innovative efforts.

8. AI is a system technology. Its services are deployed on the basis of the alignment and complementary efforts of hardware and software components. Since different AI techniques can fulfill various functions across different applications, dynamic coordination failures may occur when actors favor one technique over others, potentially disrupting the AI value chain.

9. A useful way to capture the "systems-ness" of AI — and to identify the competences that actors have to develop it — is to map its development through

a stylized value chain that encompasses *techniques* (T), *functions* (F), and *applications* (A).

10. Integration reflects the ability to coordinate potentially complementary activities throughout the value chain and develop innovative solutions. The uncertainty, ambiguity, and obsolescence inherent in emerging technologies make investments in specific or co-specialized resources costly and risky for a single firm. However, at the national level, integration can strengthen sovereignty and competitiveness. Integration is an outcome of several stakeholders' expertise and investment. It involves the ability to mobilize complementary resources and generate innovation opportunities for local actors throughout the value chain. In brief, integration indicates an institutional environment that facilitates the coordination of innovation ecosystems and predicts innovative performance, with obvious effects on productivity and employment.

11. Technological sovereignty challenges the classical and modern trade theories by prioritizing strategic autonomy and independence over the economic efficiency gains derived from specialization. While specialization can lead to greater global efficiency and mutual benefits under stable conditions, technological sovereignty focuses on reducing vulnerabilities and ensuring that countries can independently navigate global uncertainties, potentially at the cost of forgoing some benefits of international trade.

12. AI patent and publication production has increased over time, beginning initially in the mid-nineties. The post-2010 period shows an impressive rise in the rate of production of patents and publications. This acceleration is associated with the beginning of the "Deep Learning era", with the joint introduction of the back-propagation technique and faster computing enabled by graphical

processing units (GPU), backed by the availability of large-scale databases such as the ImageNet image dataset.

13. There is a large gap between the EU, the US, and China in terms of patent production and in the number of publications when comparing the EU with the US. The number of EU27 patents is almost a third of the number of US patents. In contrast, the EU27 has 90% of the number of US publications.

14. The EU ranks 17th in per capita patent production, while the EZ ranks slightly higher, in 16th place. This result represents one fifth of US per capita patents, and one twelfth of China's. The EU ranks 13th in per capita AI publications, while the EZ ranks in 12th place. Europe performs better than China in per capita AI-related publications.

15. In the realm of AI, the European paradox may be more severe than originally identified. The gap with the US is both science- and innovation-based. The quest for improving AI competences is, thus, a transversal matter encompassing science, technology, and industrial policies.

16. In virtue of the cumulative nature of knowledge, without achieving a critical mass in AI-related innovation, the EU risks to be unable to close the gap with the global frontier.

17. The top 5 players in AI-related patent production in the world are: Intel (USA, with 27,500 patents corresponding to 17,000 inventions), IBM (USA, 21,500 patents, 13,000 inventions), Samsung (South Korea, 18,500 patents and 9,000 inventions), NEC (Japan, 17,500 patents and 11,000 inventions), and Microsoft (USA, 14,500 patents for 7,000 inventions).

18. There are 3 European companies in the top 20 chart in AI-related patent production: Siemens (Germany, with 10,000 patents corresponding to 5,500 inventions), Philips (the Netherlands,7,000 patents, 3,000 inventions), and Bosch (Germany, 7,000 patents and 2,300 inventions). These three companies produce higher quality patents relative to their worldwide competitors.

19. Chinese universities are among the top 20 public organizations involved in producing AI-related patents, but produce lower quality patents. When focusing on non-Chinese public actors, US and South Korean institutions account for 12 out of 20 positions in the ranking. Looking at Europe, large public research institutes such as CSIP (Spain), CNRS and INSERM (for France), and Fraunhofer (for Germany) account for most AI-related patents. European public actors produce higher quality patents than their non-European counterparts.

20. The top players in AI-related science are essentially American (11 among the top 20 players) and Chinese (4 players). France (Centre National de la Recherche Scientifique — CNRS), India (Indian Institute of Technology System — IITS), the United Kingdom (University of London), Singapore (Nanyang Technological University) and Switzerland (Swiss Federal Institutes of Technology Domain) also appear in the top 20 chart. Digital giants such as Microsoft, Google and IBM appear as major players in AI science. The CNRS ranks fourth worldwide, and is the only organization among the top 20 players belonging to the European Union.

21. In Europe, AI-related knowledge production in scientific papers is led by large institutes in France and Germany *in primis*, specifically, CNRS and INRIA for France, and the network of Max Planck research centres for Germany. The only company involved is the German industrial producer Siemens AG.

22. European actors, both private and public, are followers rather than leaders both in AI patents and publications. While scientific production related to AI in the US shows traces of "industrialization", with private actors competing with universities, in Europe large public research institutes continue to play the major role in AI knowledge production.

23. Concerning AI techniques since 2011, and by decreasing order of specialization, the top five areas of specialization are as follows. In Europe, these are: Ontology engineering; Rule learning; Machine learning; Generative AI; Probabilistic graphical models. In the US, these are: Rule learning; Machine learning; Ontology engineering; Probabilistic graphical models; Expert systems. In China, these are: Support vector machines; Fuzzy logic; Multi-task learning; Classification and regression trees; Deep learning.

24. Concerning AI functions since 2011, the top five areas of specialization in decreasing order are as follows: In Europe, these are: Control methods; Computer vision; Scene understanding and video for robotics; Speaker recognition; Biometrics. In the US, these are: Control methods; Natural language processing; Speech recognition; Text-Speech recognition; Dialogue. In China, these are: Distributed artificial intelligence; Information extraction; Planning and scheduling; Image and video segmentation; Semantics.

25. Concerning AI applications since 2011, the top five areas of specialization in decreasing order are as follows. In Europe, these are: Transportation; Life and medical sciences; Personal devices, computing and HCI; Energy management; Cybersecurity. In the US, these are: Personal devices, computing and HCI; Business; Document management and text processing; Banking and finance; Cybersecurity. In China, these are: Agriculture; Industry and manufacturing;

Telecommunications; Education; Networks.

26. Unlike the US and China, Europe does not display a specific specialization profile with regard to AI techniques, functions, and applications. This lack of specialization is the result of individual EU countries not exhibiting clear patterns of specialization. Therefore, there is no process of Ricardian specialization in European member states, contrary to what we observe in the US or in China. This fact can provide a policy opportunity: through coordination and support, the EU as a whole has a great deal of room for action to steer the direction of AI development towards specific areas.

27. The overall values of concentration along the entire value chain are low. This finding suggests that countries have rather dispersed portfolios of competences across the TFA value chain. There is more concentration of effort in upstream competences, meaning in AI techniques, than in downstream functions and applications. AI techniques offer a range of services — functions and applications. Therefore, countries allocate inventive efforts to fewer AI techniques, especially as some of them become dominant in the field over time. Europe, whether the EU or the EZ, has medium levels of median concentration values, and its constituent countries has medium levels of concentration values, and its constituent countries display levels of concentration values that are similar to other non-European countries.

28. The TFA value chain of AI is becoming more and more structured around better-identified combinations of techniques, functions, and applications that, when linked together, yield services that cannot be reduced to their independent usage. This development grows in successive waves that suggest the possibility for future waves to occur.

29. Contrary to the United States and China, Europe exhibits low levels of integration. Within Europe, Italy displays the highest level of integration, together with countries such as Finland, Sweden, and the Netherlands. France and Germany have low levels of integration.

30. Europe exhibits a relatively high number of AI application domains where it has specialized. However, many of them are not integrated, implying that technological sovereignty is not achieved over these areas of specialization. More fundamentally, whether we focus on Europe as a whole or individual countries, AI application domains with both specialization and integration are rare in Europe, more so than in any other location in the world.

31. The advent of deep learning in 2012 and its subsequent diffusion eventually translated into a significant decrease in integration in the regions considered. This phenomenon illustrates the fact that integration over the AI value chain is an emerging property of the TFA specialization pattern, conditional on exogenous technical changes that countries drive only partially.

32. The locus of integration may vary a great deal with regard to areas of specialization, depending on whether we consider upstream (Γ_{TF}) or downstream (Γ_{FA}) integration. There are both cross-application variations (given the country) and cross-country variations (given the AI application). The heterogeneity in integration throughout the value chain is the expression of local systems of innovation throughout the AI value chain involving specific public and private actors and specific sets of collaborations and interactions.

33. Integration is a source of innovation as it is a significant contributor to patent production. This finding suggests that developing local expertise throughout

the entire value chain increases the innovative capacities of a country in AI-related innovation in specific application domains.

34. Other factors matter for innovation in AI. First and foremost, specialization in specific AI applications and overall knowledge stock are prime factors in patent production. Second, the innovation capacity of a country in AI is associated with the ability to develop a diverse portfolio of expertise in technical domains while concentrating investments in the development of a limited number of specific application domains and functions. A last but important finding relates to the negative effect of the propensity to collaborate with foreign partners, which confirms the important advantage of local innovation networks.

35. Innovation in AI results from integration both upstream (techniques-functions) and downstream (functions-applications). Openness tends to reduce AI innovation, as it weakens the power of integration to produce new knowledge in the realm of AI.

36. When focusing on the organizational origins of integration, we can see how TF integration is fostered by private actors, while TA and overall TFA integration is enhanced by the presence of public assignees. Collaborations between private actors enhance integration overall. Openness and integration are positively related across TF, FA, and TFA, suggesting that AI innovators can develop or expand competences by connecting internationally. In the second stage, the resulting higher level of domestic integration will have a positive effect on innovation.

37. Different countries display different profiles in terms of the types of actors and organizations involved in AI (patent) innovation. Two general regimes seem to

emerge: one innovating through private and international collaborations, and the other through public and private-public co-patenting. Germany and France epitomize the two different regimes, while the EU and EZ seems to innovate as a linear combination of the two. This finding illustrates, once again, the opportunities for AI innovation at the continental level, which could rely on a broader group of innovating organizations.

38. The lack of integration and thus sovereignty in European AI can be seen as a call to (policy) action. Coupled with the evidence of insufficient private investment in ICT infrastructure, databases, and software within Europe, a key insight to derive is that the scope for improvement is vast. Hence, we find limited grounds for optimism regarding the future development of a so-called European AI industry. Based on our findings, we envisage two avenues to follow. On the one hand, the EU needs a "big push" in terms of additional investments. Exogenous shocks in the forms of heavy public programmes, as advocated by Aghion et al. (2024) in the case of France and by Draghi (2024) for the whole Union are more than necessary. On the other hand, the issue is not exclusively quantitative. Efforts in developing a common understanding of the directionality of investments, for instance by allocating scientific and technological funding to directions entailing high returns (Fuest et al. 2024) is also a fundamental challenge to tackle. Our report indicates that a critical yet unrealized factor is the enhancement of EU governance. Strengthening EU governance is necessary to provide increasing coordination between stakeholders within and between European countries and European institutions is needed in order to build a fully integrated continental AI industry, one that would substantially and structurally enhance European sovereignty in AI.

1 Introduction

As the world economy becomes increasingly fragmented and international rivalries re-emerge (Tyson et al. 2023), policy discourse has begun to prioritize and stress the importance of domestic competences, autonomy, and sovereignty in the production of technologies, goods, and services (Crespi et al. 2021). Achieving "technological sovereignty" has become an important pre-condition for increasing competitiveness and innovation. In light of this situation, the European Union (EU), the United States (US) and several national governments have launched a series of exercises to assess their resilience to shocks to the value chains of key products and of strategic dependencies in fundamental inputs and technologies.[2] The rationale for doing so is both economic and (geo)political: countries aim to reduce trade-related dependencies by favoring domestic sourcing and the development of in-house competences, while paying increasing attention to security and defense issues related to possible "technology leakage" to rivals.[3] To increase their autonomy, governments increasingly resort to industrial policy, exploiting a political climate favorable to the intervention of the state in the economy.

Technological sovereignty in Artificial Intelligence (AI) is a critical challenge as AI becomes increasingly integrated into essential infrastructures, economic systems, and social structures (OECD 2019). The 2020's European Commission's Digital Strategy emphasizes the importance of strengthening Europe's technological sovereignty and reducing reliance on foreign technologies in critical areas, including AI (European Commission 2020*a*). AI is a breakthrough technology with transfor-

[2] see, for instance, Arjona et al. (2023) for the EU case

[3] For instance, recently the European Commission assessed risk and leakage in four key technology areas: advanced semiconductors, artificial intelligence, quantum computing, and biotechnologies — see here (last accessed: July 2024).

mative economic and societal potential and is regarded as a major driver of future industrial and economic competitiveness (European Commission 2020*b*). Consequently, it has become a central focus of international rivalries and emerging "arms races" to lead and control its development (Kak & West 2024, Bryson & Malikova 2021).

As a result, the world economy is exploring uncharted territory, with surging tensions between the desire for global coordination and protectionist "races to the bottom". These tensions are particularly interesting to observe at the EU level; while competitiveness is an existential challenge for the Union (Draghi 2024), in practice we witness a continuous clash between the forces supporting state aid and those upholding the principle of guaranteeing the level playing field characterizing European competition policies and underpinning the operation of the single market (Fontana & Vannuccini 2024)..

We contribute to the ongoing discussion about technological sovereignty and competitiveness in Europe by conducting a competence-based analysis. Focusing on AI, we answer the following question: is the European Union *capable* of achieving sovereignty in a fundamental technology that is increasingly considered pivotal and strategic globally? With the adjective "capable", we mean whether the EU, through its member states, has a relative advantage when it comes to specializing in the know-how needed to advance the technology (through innovation) at different stages of its supply chain, from scientific developments to industrial implementation.

AI is a system technology (Vannuccini & Prytkova 2024), with different components evolving in response to difference forces, incentives, and logics. Hence, strengthening competitiveness in this technology is a multidimensional challenge. We decided to focus our study on a key aspect directly influencing how different actors can become competitive in the AI field: innovation. In order to identify strengths and gaps in the European competences to innovate in AI, we conduct an empirical analysis of a measure of the integration of AI inventions based on patent data for the period 1990-2021. We consider this data with regard to a stylized value chain relevant to the production of and innovation in AI, composed of *techniques* (T), *functions* (F), and *applications* (A) — what we label the TFA value chain. It is our choice to work with this stylized structure, which is not a representation of the full technology stack of AI along which value is accrued. Rather, the TFA value chain is an empirically-driven construct that maps and extends the established classification of AI patents provided by the World Intellectual Property Organization (WIPO). It allows us to assign inventive activities to different domains, from those closer to basic science (techniques) to those more related to commercial use (applications) (WIPO 2019). The intuition behind our approach is that greater integration among complementary TFA indicates more widespread competences to produce AI systems domestically, and thus more competitiveness in AI innovation. In turn, the presence of competences can be interpreted as an indicator of autonomy and sovereignty in a specific technological domain. Importantly, with our data we are able to test the role played by different forces in shaping AI-innovation integration. For instance, we can measure whether integration is fostered by overall patent activities, scientific publications, openness, or collaborations between private and public actors. Another advantage of focusing on the forces driving AI innovation is to abstract away from the current patterns of AI adoption by end users. As McElheran et al. (2024) point out, downstream AI implementation is rather limited and heterogeneous, and generally limited to large firms. Concentrating the analysis on AI innovation allows us to identify the root sources of competitiveness and, thus, to make actionable policy suggestions.

With this study, we contribute to the growing literature on AI economics, strategy, and policy. In particular, we provide evidence supporting the recommendation of a more pro-active role of the EU in the AI domain, in line with the suggestions of other recent key policy reports (Draghi 2024, Fuest et al. 2024, Aghion et al. 2024). The novelty of the work is that it takes an original approach to analysis: rather than exploring all of the components that jointly make up current AI systems such as computation, algorithms, data, and talent, we take a more aggregate perspective and focus on AI integration. We maintain that this approach results in a neat explanatory variable that we can use to make sense of the dynamics of innovation in AI. In addition, it can be used as a policy lever that relates to competitiveness and technological sovereignty. We are aware of the system nature of AI technologies and that competitiveness also depends on the investments that countries have made to build complementary (often hardware-related) assets that enable the deployment of AI models. Given that the AI innovation evident in patent data must necessarily be embedded in physical technologies, we are confident that our analysis captures part of the complex nature of this phenomenon. Nevertheless, we are conscious of the limitations of patent data to capture recent advances in AI such as large language models (LLMs). In fact, our data end well before the widespread implementation of the Transformer architecture in AI models.[4] However, the rationale for our focus on patents is that what really matters for competitiveness, autonomy, and the relevance of strategic dependencies, and thus for policy, is the overall AI innovation process that unfolds through the TFA stages. Recent advances in AI occur mostly in the domain of AI-powered business models and final stand-alone products, particularly as interfaces that commercial customers tend to adopt. These software solutions are key to the widespread diffusion of AI. Nevertheless, an assessment of the degree

[4]The Transformer was introduced in 2017, but became the cornerstone of commercial and open-source foundation models only later (Vaswani et al. 2017)).

of sovereignty in AI in the EU must consider to what degree domestic competences to develop AI systems already exist, and how they fare relatively to other areas of the world. In this sense, with our aggregate analysis we have captured more fundamental determinants of technological sovereignty in AI than a granular but less innovation-oriented perspective could offer.

The report is organized as follows. In Section 2, we map the landscape: first, we outline the challenges the EU faces in the domain of digital technology (of which AI is part). Second, we explore the ongoing focus on (technological) sovereignty as a means of assessing the current situation and as a driver of policy initiatives and strategy in the domain of AI and beyond. In Section 3 we argue for a system perspective on AI, from which emerges our choice of measuring sovereignty as competences to innovate in the technology across all elements of the stylized TFA value chain. Section 4 explains the data we use and our methodology in detail. Specifically, we discuss how we identify AI-relevant patents and publications and calculate the countries' specialization in different AI domains. Section 5 presents our measure of integration. In Section 6, we delve into the econometric analysis. First we test whether integration matters at all for innovation. Second, we explore the organizational roots of integration. Section 7 summarizes our findings.

2 The political economy of AI in the European Union

What forces shape the European discourse and action around AI? To ground our analysis, we begin by outlining a series of stylized empirical facts characterizing European digital investments as compared to other areas of the world (subsection 2.1). The evidence illustrates some of the challenges the EU is facing in this domain. It also provides a rationale for discussing sovereignty (and technological sovereignty in particular) as an increasingly major driver of policy initiatives. In subsection 2.2, we unpack the meaning of technological sovereignty and discuss its relevance for the case of AI.

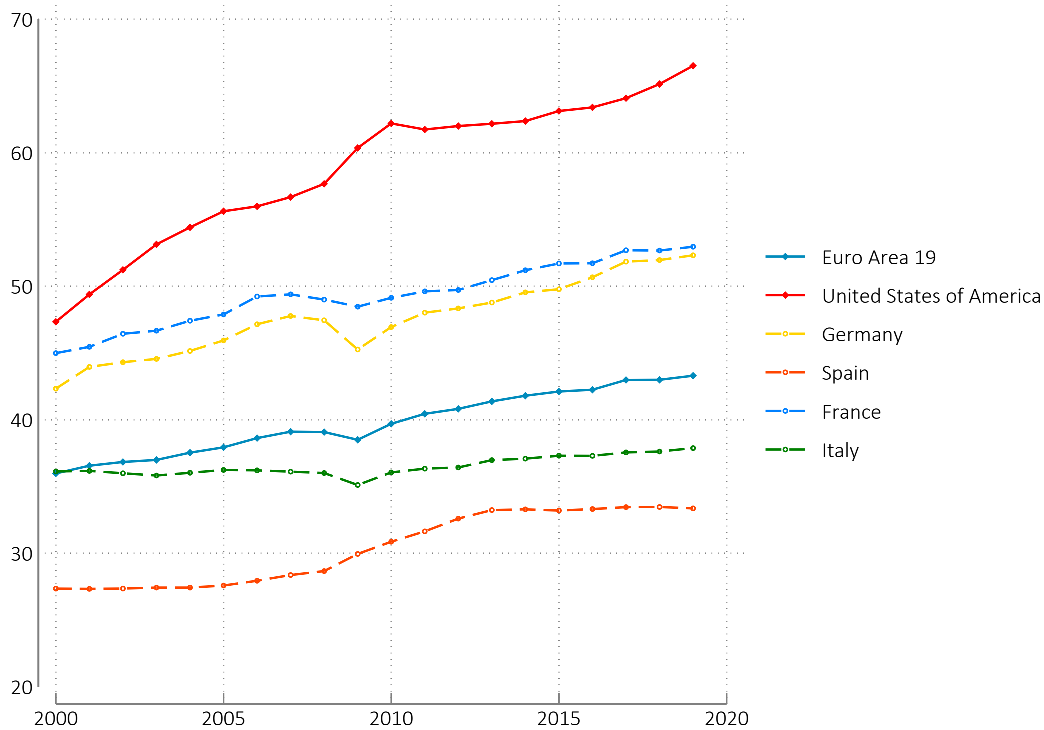
2.1 European economic growth and digitisation: some stylized facts

Despite being the world's largest single market, the EU trails other actors in terms of competitiveness.[5] For instance, Figure 1 plots the dynamics of (hourly) labor productivity for the Eurozone (EZ), the United States (US), and a selection of individual European countries. As argued in Bock et al. (2024), this growing divergence between the Eurozone and the United States translates into a slower growth rate in GDP per capita in the EZ. In fact, over the past two decades, the income gap between the United States and the Eurozone has widened rather than narrowed. This growing disparity began well before the Covid-19 pandemic, reflecting a gradual decoupling in overall economic performance.

Given that productivity proxies for efficiency in the use of technology (among other things) to transform inputs into outputs, the growing gap we observe indicates that Europe is finding it increasingly difficult either to adopt advanced technology in

[5] This subsection is inspired by the OFCE Policy Brief 129 (Bock et al. 2024) and the associated blog on investments.

Figure 1: The dynamics of hourly labour productivity



Sources: EU-KLEMS, Ed. 2023 national account data, and Bock et al. (2024).
Constant 2015 euros per hour, using the 2015 exchange rate: 1€ = 1.1105$.

its productive fabric, or to push the technological frontier forward. These difficulties should be a call to action for Europe to accelerate the development of emerging, economy-boosting technologies such as AI.

Summary Over the past two decades, the income gap between the United States and Europe has widened. This growing gap is mainly due to the lower growth rate in productivity in Europe. It also indicates the increasing difficulty Europe has either integrating advanced technology into its production processes or pushing the technological frontier forward.

To map European strengths and weaknesses in AI development, we take a broader perspective that encompasses digital technology. In fact, according to Carlota Perez and her theorizing on technological revolutions, AI "is better understood as a key development within the still-evolving information-communications-technology (ICT) revolution."[6] Understanding the EU's challenges in ICT can, therefore, shed light on potential deficiencies and gaps related to AI.

ICT has gained momentum and widespread diffusion since the early nineties. This family of technologies includes hardware such as personal computers, laptops, routers, and servers, as well as smartphones and their associated set of applications based on heavy use of the Internet. ICT also includes the whole set of applications and software. All together, ICT (and the Internet) have evolved as a complex system of interconnected technologies (Greenstein 2020) — a property that applies to AI too, as we shall see. ICT hardware and software are key to the development of AI. The use of ICT applications generates large amounts of data that can be exploited statistically, and AI models run on hardware that provides the necessary computing power.

Figure 2 depicts ICT-related investment per employee in the EZ, the US, and the four major EZ countries from 2000 and 2019. It focuses on three types of investments, calculated per employee: (i) investments in ICT equipment (servers, routers, computers, etc.); (ii) investments in ICT services such as software, programs and databases; and (iii) investments in research and development (R&D). We observe the following:

- In terms of R&D investment, the gap between the US and the EZ, which was already large in the early 2000s, is widening in absolute terms (from €1,000 to €2,000 per employee over the period) to represent more than twice the European effort in 2019. What we find most worrying is that this widening

[6] https://www.project-syndicate.org/magazine/ai-is-part-of-larger-technological-revolution-by-carlota-perez-1-2024-03 — last access August 2024).

gap is the result of rather uniform behavior on the part of the main European economies. For both Germany and France, this gap, which was rather small until 2005, is multiplied by 10 for France and by 5 for Germany at the end of the period.

- Concerning investment in ICT equipment, America's singular achievement is even more impressive. Initially close to European levels, this investment is growing steadily in the United States, but remaining constant in the EZ. The comparison is here is quite telling. Investment per job remains at between 500 and 700 euros per year over the entire period in the EZ, whereas it reaches 2,500 euros in the United States, a nearly five-fold increase over the period in question.
- Concerning investment in software and databases, and leaving aside the French case, there is no reason to be optimistic. The US-EZ gap in investment per job in software and databases has increased 12-fold, from €200 to €2,400 over the two decades. France stands out in terms of volume, but the trend is not very positive: French investment has doubled, but US investment tripled during the same period.

Overall, the gap between the EZ and the US with regard to private investment stood at around 150 billion euros in 2000, rising to a worrying 600 billion euros in 2019.

Summary AI is the latest advance in ICT technology; hence, tracking the dynamics of ICT investments provides insights into Europe's position compared to the global frontier. The EU trails the US in all types of private ICT investments (equipment, services, research and development), and the gap has been increasing over time.

In order to understand the sources of these investment gaps, we decompose the investment growth rate as the sum of the sectoral growth rates, weighted by each sector's share of total investment, at the start of the period. We classify all of the sectors that make up the market economy by type of sector as follows: (i) high-tech industries (excluding ICT production); (ii) ICT production industries; (iii) other industries, construction, and public utilities; (iv) high-value-added services (excluding ICT services); (v) ICT services; and (vi) other services. This classification seems relevant to us because it distinguishes ICT production activities (whether manufacturing or services) from other sectors that use ICTs as inputs in their production.

Figure 3 displays the growth rate of each type of investment per employee, distinguishing each sector's contribution. Overall, while Figure 2 indicates that the gap between the US and European countries increases in every sector (except France for investment in software and databases), Figure 3 shows a reinforcing mechanism, with the US investment growth rate higher than all other countries in all ICT types (except for Spain in R&D).[7] The domination of the US investment in R&D both in volume and in growth rate is not surprising. Figure 3 shows that the main contributors to American R&D investments are in the ICT services sectors. It is reasonable to assume that this result is due to the "GAFAMs effect".[8] The returns from the exploitation of large datasets (especially due to cross-domain network externalities), market domination in cloud services, digital advertisement and application markets, and the expected gains from the rise of AI are prompting tech giants to invest massively in R&D.

[7]Focusing on the Spanish exception in the evolution of R&D investment, the results show that Spain exhibits the highest growth rate in our sample. However, this result mainly reveals a catching-up effect: Figure 2 shows that Spain lags behind all other countries when R&D per employee is considered.

[8]The companies included in this acronym are Google (now Alphabet), Amazon, Facebook (now Meta), Apple, and Microsoft.

Growth in investment in databases and software is mainly due to the pull of the services sector in general, regardless of the country. What distinguishes the US from other countries is the significant contribution stemming from high value-added services. This factor suggests that ICTs are spreading throughout economic activities more rapidly in the United States than in Europe. Italy stands out for its low growth rate, with services making virtually no contribution to the growth of this investment. The case of Spain is, again, the outcome of a catch-up effect. Finally, the US-EZ comparison of the sources of growth in investment in ICT equipment is particularly enlightening. Above and beyond the difference in growth rates, the contribution of the various sectors is relatively similar between the two regions of the world, except with regard to ICT services. In the EZ, the contribution of ICT services to growth in investment in ICT equipment remains low, whereas it amounts to 4.5 percentage points in the United States. This fact alone explains the observed investment differential. Our interpretation is that the specific dynamics of investment in ICT equipment in Figure 2 is the result of the massive investment by ICT services, meaning, essentially, those provided by GAFAMs and other large US companies. In other words, intangible investments in R&D and software and databases is evolving in close association with tangible investments in ICTs. Both complement one another and make them operational, productive, and profitable.

It appears that in the US, the ICT services sector is responsible for the observed investment gap, driven by substantial investments in R&D and digital equipment. The other service sectors (essentially high value-added services) are adopting these innovations in their own production processes by investing in software and databases. The overall impression is one of the rapid digitization of the economy, driven by large companies and spreading into the entire US production system. A direct implication of this evidence is that ICT developments require scale (and possibly "champions" capitalizing on investments) and complementarity in order to produce transformative effects.

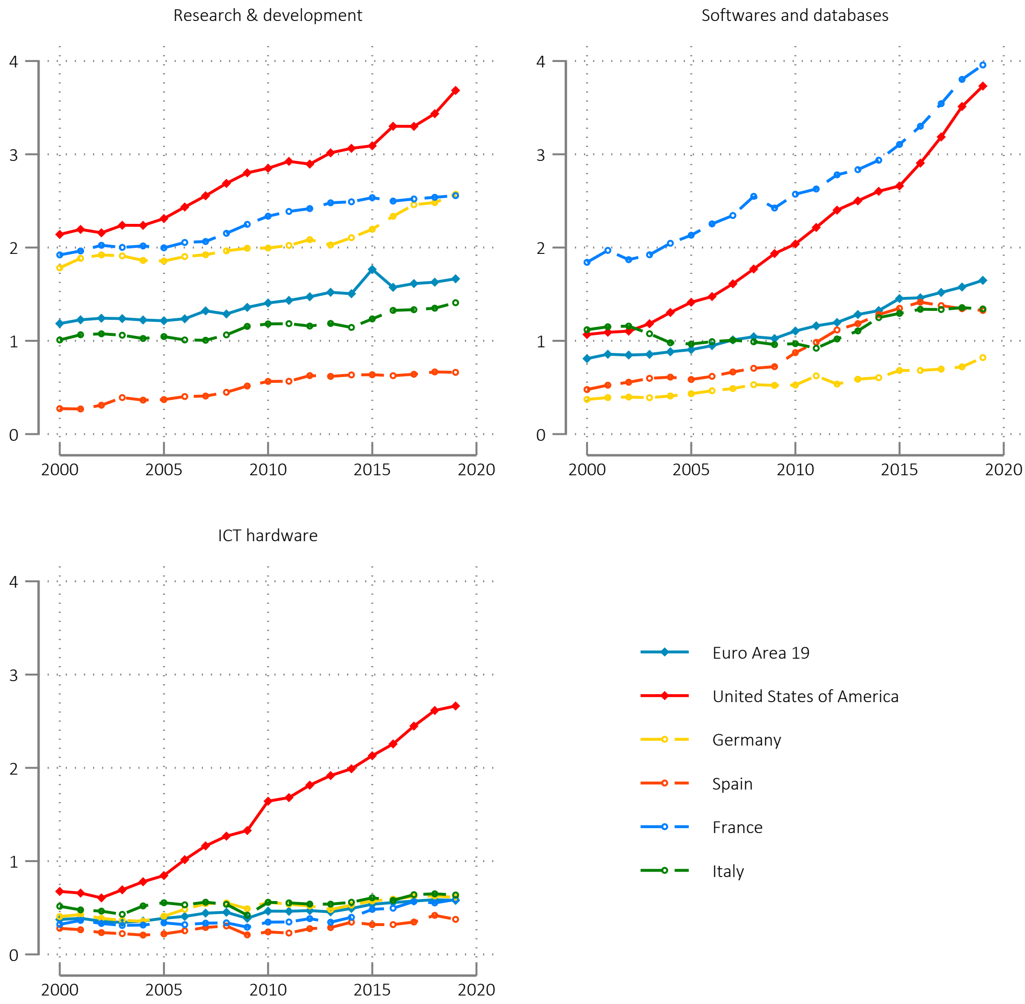
Is Europe on track to achieve ICT-driven economic gains? Unfortunately, the answer is that it is less likely to be able to do so. The European case is worrisome for two reasons. First, the lack of investment in ICT services means that the economy is digitizing slowly. Second, the absence of giants in digital services translates into fewer investments in R&D and ICT equipment, both of which are prerequisites for the development of AI. If large databases are the blood of AI, ICT equipment represent its backbone.

Summary When decomposing the growth rate of the different types of ICT investments by sectors, it appears that the main contributors of superior American ICT R&D and equipment investment growth are ICT services, likely driven by large tech corporations (mostly, the so-called GAFAM). Overall, the evidence indicates that the EU's position as a follower results from the slow diffusion of digital technology across the economy, and a lack of large investors (European "champions").

Catching up would imply increasing private investments in Europe by €630 billion a year, amounting to over 5% of the EZ's GDP, for the set of assets considered here alone (ICT equipment, R&D, software and databases), and assuming that US investment remains constant. This is equivalent to an increase in investment of €61 billion for France, €57 billion for Germany, €28 billion for Italy, and €16 billion for Spain. Without the combination of upstream sectors supplying ICT services and equipment and downstream sectors adopting these innovations, Europe will find it more difficult to capture the fruits of the digitization of the economy.

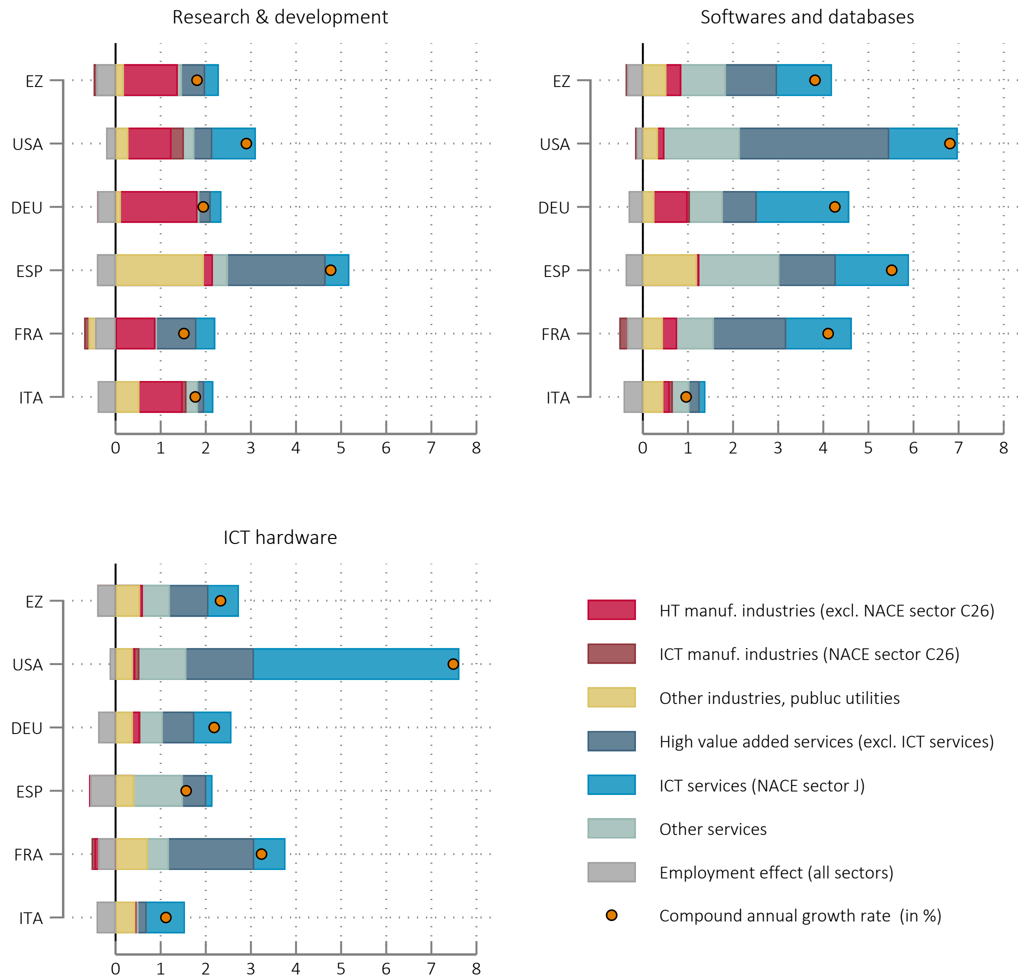
The stylized facts we presented in this subsection are meant to illustrate the challenge facing the EU if it aims to lead and be autonomous in the production

Figure 2: Diverging paths in investment per employee



Sources: EU-KLEMS, Ed. 2023 capital account data, and Bock et al. (2024).
Constant 2015 Keuros per employee, using the 2015 exchange rate: 1€ = 1.1105$.

Figure 3: Sectoral contributions to the compound annual growth rate of investment per employee (2000-2019)



Sources: EU-KLEMS, capital account data, and Bock et al. (2024).
Constant Keuros per employee, using the 2015 exchange rate: 1€ = 1.1105$.

of advanced digital technologies, with AI at the forefront. As some recent high-level reports have highlighted (Fuest et al. 2024), for two decades the EU has been locked in a "middle technology trap" centered on automotive manufacturing and lacking scale and R&D expenditures outside that industry. Massive financial efforts must be made to escape the trap, which open up room to discuss (industrial) policy, resourcing and investments at the continental level (Fontana & Vannuccini 2024). As this theme goes beyond the scope of the report, we now return to our key question: is the EU *capable* of producing a complex breakthrough technology such as AI?

Summary Sizeable financial investments are required to cover the European investment gap in ICT (AI's technological backbone) and to escape its "middle technology trap". This situation indicates that a discussion on the continental financing of investments is needed. In addition to resourcing, being able to lead with regard to ICT and AI developments requires competences.

2.2 On technological sovereignty and the weakness of European AI

The question of whether the EU has the competences to produce AI can be rephrased in terms of whether the EU can develop the technology autonomously, or if it has "sovereignty" over it.

Insert 1. On sovereignty

The notion of sovereignty is a cornerstone of political and legal theory, and as such is subject to a variety of definitions and interpretations. Historically, sovereignty has been defined as the ability of an individual or a governing body, whether as a factual matter or as the outcome of a rule that assigns authority, to act as a sovereign without the jurisdiction of any other individual or entity (Eleftheriadis 2010). In other words, sovereignty is a manifestation of power and of independence in the ability to establish and enforce one's rules. It is "the power to be able" (Ganascia et al. 2018) or, to use the "classic" Schmittian quote, sovereign is the entity "who decides on the state of exception".

When focusing on the particular polity represented by nation-states, sovereignty can be seen as a state's ability to enforce its will, particularly in areas such as economics, defense, and security. As the notion of sovereignty is traditionally linked to the national scale, the very idea of European sovereignty is the subject of discussion. Given that the EU is a novel type of polity, currently somewhere between a federal and a confederal system, the nature of its sovereignty is an ever-evolving matter and an emerging paradigm of analysis in political theory (Elazar 1996).

Increasing international rivalries (OECD 2023) have raised questions about European sovereignty in the context of digital transformations. Furthermore, the COVID-19 pandemic stressed the importance of Europe's digital capacity to ensure Europeans' social and economic well-being. More generally, as we saw in subsection 2.1, the lack of European champions promoting digitalization and, as a consequence, the extensive reliance on foreign digital platforms and related applications, coupled with the persistent lag of European countries' investment in digital technologies, has intensified discussions about the defense of European values, and of its economic independence and industrial competitiveness. The challenge is not only about the ability to regulate the digital economy to ensure data privacy, but also about how to avoid technological dependencies on other regions or monopolistic private companies (European Council 2020).

Discussing European sovereignty over key technologies is, at the core, a matter of *technological* sovereignty, that is, the ability to access relevant technology or components, either domestically or through non-dependent relationships with other economic regions (Edler et al. 2023). Technological sovereignty involves the capacity to make autonomous decisions about technology development, deployment, and regulation without undue influence or dependence on external entities. In a global digital ecosystem that relies on interconnected value chains, technological fragmentation and protectionist strategies could weaken the ability of nations to control their digital destiny, including control over the entire AI supply chain (Larsen 2022). Therefore, access to the necessary technological resources and levers is critical for guaranteeing the EU's economic independence and industrial competitiveness in the long-term. As a matter of principle, technological sovereignty is not a static, nationalistic, defensive concept focused on erecting legal protection barriers. Rather, it should be understood as a dynamic concept associated with building the capability to develop adaptive capacities (Edler et al. 2023). This concept combines the ability to develop the required competences and resources to deliver technologies that are pivotal for competitiveness and growth, along with the capacity to source the complementary technologies and assets needed to produce industrial applications.

Summary Increasing international rivalries and the reliance on overseas resources and platforms have focused political attention worldwide, and in the EU in particular, on autonomy and sovereignty in the domain of technology — *technological sovereignty*. Technological sovereignty can be seen as the *capability* to develop a technology without external dependencies.

Rapid advances in AI and its global scope of application — as well as its potential dual-use nature in the domain of defense — have placed the technology at the forefront of the discussion on technological sovereignty, and the related issue of AI-dedicated industrial policy (Kak & West 2024). While the race to nurture AI national champions can be seen as a rather inward-looking, nationalistic strategy, AI can be considered a "strategic asset" (Ding & Dafoe 2021). Such a view would position AI as a perfect candidate for policy support, especially if this policy is European rather than national. For instance, in the domain of science and innovation, AI can be seen as a *"general-purpose invention in the method of invention"* (Cockburn et al. 2018), as it introduces a new, data-driven, inductive logic to the exploration of knowledge and design spaces. AI can have profound implications for research and development methods and product development processes across many different applications and sectors (LeCun et al. 2015, Cockburn et al. 2018). Given its potential, AI has attracted increasing investments (Maslej et al. 2024). A full-fledged AI industry has emerged. Its implementation is enhancing innovative product capacities and boosting the growth of adopters (Babina et al. 2024). While the real impact of AI on productivity might turn out to be rather modest (Acemoglu 2024), the narrative around AI's transformative impact has intensified the discussions on technological sovereignty. The EU, as a supranational entity, is struggling to become a leading force in AI and is increasingly wary of strategic dependencies (Vicard & Wibaux 2023). This situation reflects concerns about being relegated to an unfavorable position in global value chains and losing strategic autonomy in the global technological system (Reale 2023, European Commission 2021, European Council 2020)[9]. As a result, the European Commission President Ursula von der Leyen emphasized technological sovereignty in her agenda for Europe (Von der Leyen 2019). The idea embraces the need to build capacity in key technologies such as quantum computing, 5G, and AI to reduce the risk of dependency, while promoting technological standards and regulations in line with European values. AI figures prominently amongst the EU policy priorities. One example is the idea of

[9] Annex 1 of the "Statement to accompany the launch of the full EIC"

supporting "AI factories", namely, the provision of AI-optimized computing power to economic actors (mainly startups) to foster innovative activities.[10]

As we mentioned, the attention devoted to technological sovereignty and the concerns about potential dependencies are a direct consequence of re-emerging global rivalries. In particular, the race for technological and industrial supremacy between China and the US might compel European states to import their AI software and applications. The call for technological sovereignty reflects European countries' concerns about losing the ability to act autonomously in a global technological system that is increasingly fragmented and in which trade and industrial policies are used for geopolitical ends. The clearest example is the recent American export bans on semiconductor fabrication equipment. At the same time, and perhaps more concerning, one must consider the increasing power of large tech companies ("Big Tech") to shape the technological landscape as well as different markets. As we documented in subsection 2.1, Big Tech is likely the major element explaining the gap between Europe and the US in ICT (services) investment growth. The anticompetitive and innovation-harming role of Big Tech in AI and beyond is being increasingly placed under the spotlight, as these "intellectual monopolies" shape a novel technological regime around their objectives and appropriate most of the returns on global innovation (Rikap 2023). Big Tech's agenda may not align with long-term national competitiveness or employment objectives (Acemoglu 2021, Acemoglu et al. 2022). In fact, their increased computation capacity, combined with access to large datasets, has provided a disproportionate advantage to large firms such as the already mentioned GAFAM (to which one can add Nvidia and Tesla), which are better positioned than smaller firms to leverage their AI investments and growth opportunities Mihet & Philippon (2019), Calvino & Fontanelli (2023), Babina et al.

[10] https://digital-strategy.ec.europa.eu/en/policies/ai-factories.

(2024). This cumulative advantage has generated increasing polarization in capabilities (both in resources and competences), leading to brain-drains from academia to the private sector and to reductions in the diversity within AI research (Frank et al. 2019, Ahmed & Wahed 2020, Klinger et al. 2020, Ahmed et al. 2023). Furthermore, Big Tech's capital investments in AI-related hardware such as Nvidia's graphical processing units or GPUs are draining the supply of the key inputs of AI systems, which are then allocated exclusively to commercial uses rather than to pursue goals that favor the public interest.[11]

Summary Rapid advances in AI, estimations of its widespread impact, and the emergence of a full-fledged industry around it have turned the technology into a "strategic asset". Combined with the awareness of the dependency of AI developments on a handful of overseas actors, AI has become a key focus for policies aimed at strengthening technological sovereignty.

As we outlined in Insert 1, sovereignty — even in the form of technological sovereignty — is a rather broad notion. Alternatively, one can refer to the idea of *strategic autonomy*. Strategic autonomy is "the ability, in terms of capacity and capabilities, to decide and act upon essential aspects of one's longer-term future in the economy, society and their institutions" (Timmers 2018). The advantage of focusing on strategic autonomy is that policy makers in the EU have already begun to design strategies and actions around the concept. In particular, in the field of trade policy, the European Commission has set forth the idea of *open strategic autonomy* (OSA) as a guiding principle. OSA is conceived as the idea of giving priority to autonomy though without ruling out cooperation if feasible. It is defined as "the

[11]See, for instance, the distribution of compute across private and public actors as provided by https://www.stateof.ai/compute (last access: July 2024).

ability to shape the new system of global economic governance and develop mutually beneficial bilateral relations, while protecting the EU from unfair and abusive practices, including to diversify and solidify global supply chains to enhance resilience to future crises".[12] From this definition, it is clear that for the EU a key dimension of autonomy (and, thus, of sovereignty) relates to the vulnerability of supply chains. This concern aligns with our choice to measure integration throughout the AI knowledge production value chain as an indicator of European sovereignty in AI.

For the EU (and more generally), increasing competitiveness as well as sovereignty in a strategic and transformative technology such as AI means developing competences to innovate that span the entire value chain of the technology. In turn, competence building is an area of intervention for science, technology, and industrial policies. The idea that AI policy is (also) a matter of such policies is just beginning to gain traction. The dominant approach of the EU towards AI and more generally digital technology, platforms, and marketplaces has been that of protecting citizens and favoring market contestability. These principles inspired the most important European horizontal regulation exercises in the field: the General Data Protection Regulation (GDPR), the Digital Markets Act (DMA), and the Digital Services Act (DSA). The AI Act, just entered into effect, is another piece of the same puzzle. In this respect, the EU political economy of AI has been one geared towards the protection of rights, as well as towards addressing one of the challenges to EU technological sovereignty in AI, namely, the dominance of Big Tech in upstream as well as consumer markets.

While EU horizontal regulations in the digital realm have generally been a success and boosted the so-called "Brussels effect", with the rest of the world following

[12] See the 2021 European Commission Staff Working Document — Strategic dependencies and capacities (last accessed: July 2024).

and imitating European legislation, less has been done by the EU on the issues of competitiveness and autonomy, despite the attempt of the European Commission to design and update a coherent industrial strategy (Fontana & Vannuccini 2024). Orchestrating initiatives aimed at addressing the lack of continental champions in the hardware and services layers of ICT have not produced successes yet; for instance, the slow-moving Gaia-X project of a federated European cloud infrastructure[13] testifies to the difficulty of building alternatives to the early American hyperscalers, who enjoy path-dependent gains from their head start in the market.

Overall, we are witnessing an acceleration of public interventions in the economy, especially after the introduction of the Inflation Reduction Act (IRA) and the CHIPS and Science Act in the US (Kleimann et al. 2023). Nevertheless, there have been few specific provisions regarding AI. An exception is the pilot of the National AI Research Resource (NAIRR) launched by the Biden Administration and aimed at sharing computing resources amongst AI actors to lower the entry costs into the field.[14] The European Commission has been working in a similar direction with the already mentioned "AI factories". In line with the NAIRR, the EU initiative consists mostly of sharing high performance computational capacity — a key input into the production of AI systems — re-orienting the existing allocations of the European budget rather than providing additional resources to increase competitiveness and competences with regard to AI. At the moment, the philosophy informing the European Commission's initiative is that of democratizing AI by providing an encompassing AI innovation package.[15]

[13] See, for instance, https://www.politico.eu/article/chaos-and-infighting-are-killing-europes-grand-cloud-project/ (Last accessed: July 2024)

[14] https://nairrpilot.org/. Some have pointed out how the design of this type of policy initiative, which builds on public-private partnerships and licensing agreements, risks favoring Big Tech rather than leveling the playing field: https://foreignpolicy.com/2024/02/12/ai-public-private-partnerships-task-force-nairr/.

[15] See here

Summary As of now, the EU approach to AI policy (in particular, the AI Act) has followed the trajectory of its other horizontal regulatory efforts (GDPR, DSA, DMA) with user protection at its center. However, fostering competitiveness and technological sovereignty in AI is also a matter of investment and, thus, of science, technology, and industrial policies. The EU can make major gains by concentrating on the development of competence and the coordination of innovative efforts.

3 Technological integration as sovereignty in AI

3.1 AI as a complex technological system

More than just a technology, AI is a system technology (Sheikh et al. 2023, Dibiaggio et al. 2022, Vannuccini & Prytkova 2024). In a nutshell, AI systems are "prediction machines" (Agrawal et al. 2022) consisting of a collection of complementary hardware and software components, plus data and talent. As a technological system, AI can be defined as a set of technologies or techniques whose relationships form a coherent whole, ensuring a function or a set of predefined functions dedicated to one or several specific applications (Gilles 1978). The coherence of the system is determined by the compatibility and complementarity of suitable techniques that facilitate the execution of a specific function. Thus, the effectiveness of using AI in industrial or user applications is contingent upon the ability to access complementary technologies and assets. It also depends on the capacity to develop the necessary skills to amalgamate all these components into a unified system.

Each AI technology offers different algorithms or techniques that provide alternative solutions to a class of problems associated with a function. As an emerging technological system, characterized by i) radical novelty, (ii) fast growth, (iii) coherence, (iv) a strong impact, and (v) uncertainty and ambiguity (Rotolo et al. 2015, Bianchini et al. 2022), AI relies on various technological families that may be more or less specific to a function (Corea 2019). In other words, different types of algorithms can be used to perform similar functions. For example, expert systems or logic programming belong to the technological family of symbolic AI. They are rule-based algorithms that emulate human decision-making processes and prove useful in developing applications that require interpretability and transparency, such as medical diagnosis, legal reasoning, or financial analysis. Artificial neural networks (ANNs) such as convolutional networks (CNNs) or feedforward neural networks, which belong to the family of machine learning algorithms, may also be used in the context of medical diagnosis or financial analysis. Thus, the choice of the design and the selection of the algorithms depend on the specific task at hand, the nature of the data, the capabilities of the different techniques, and the problem requirements needed to perform the expected functions in the context of an application.

The frequent evolution of technologies and their associated algorithms broaden the scope of the functions and applications that AI can leverage. Advancements in AI techniques prompt further inventive opportunities in complementary technologies or applications, thereby increasing the incentives for their adoption (Bresnahan 2003, Aghion et al. 2009). New algorithms are often disclosed on open platforms and freely shared, thus often becoming public knowledge[16]. Subsequent spillovers generate positive feedback between technical inventions and the co-invention of functions that create opportunities for further innovations. New functionalities shape the design of products and services, reinforcing complementarities along the value chain (Rosenberg 1982, Mowery 1992, Nelson & Rosenberg 1993). However, in an era of emerging technological development, technological options compete with one another. The technical choices that adopters make and the uncertainty about the performance of the products may lead to a reluctance to invest. The development of downstream phases, including the development of applications and their market launch, hinges on complementary and often irreversible investments. In the context of an emerging technological system, the performance of alternative techniques can vary greatly and is difficult to predict accurately. As the number of potential

[16]The firm's ability to embed algorithms in applications, along with their associated specific complementary investments, ensure that the developers can capture the value of the new algorithms

options increases, each with its own trajectory, anticipating the properties of each technique and its functional performance across all applications becomes daunting. The uncertainty and ambiguity inherent in the dynamics of the structure of complementarities along the value chain, coupled with path-dependent investment trajectories, are likely to generate dynamic coordination failures. Consequently, the more that techniques, functions, and applications are tightly coupled, the greater the cost of sub-optimal design choices as well as the cost of switching from one design to another. These choices can lead to delays in adoption and reductions in the necessary investments throughout the value chain. Thus, the risk of prematurely committing to an inferior design or being locked into sub-optimal options is inherently high, underscoring the need to preserve diversity in the technological environment (David 1985, Arthur 1994, Aghion et al. 2009).

Summary AI is a system technology. Its services are deployed on the basis of the alignment and complementary efforts of hardware and software components. Since different AI techniques can fulfill various functions across different applications, dynamic coordination failures may occur when actors favor one technique over others, potentially disrupting the AI value chain.

3.2 The Technique-Function-Application AI value chain

If the production of AI technology is a systems effort, as we described in 3.1, we must identify the root causes of competitiveness and technological sovereignty in AI or their lack across the entire system. Our approach is to map the competences needed to innovate in AI across a stylized series of steps, which ranges from upstream techniques to functions to downstream applications. We call this structure the Technology-Function-Application (TFA) model, or value chain. This is not a traditional value chain, or a full-stack representation of how value is accrued in the production of AI systems stage by stage. Rather, it is a simplified picture of how AI innovation is developed, from the more generic software developments to their adoption into specific function and practical applications. As we will see, the TFA model is particularly useful as it is tailored on the features of the patent data we use. Our representation of the value chain does not impose a linear model of innovation, whereby new applications necessarily rely on new techniques generating novel or higher-quality functions. As is well-known, innovation often results from learning by using (Rosenberg 1982) as a result of recurrent trials and errors, experimentation processes, and feedback. However, while a direct line from techniques to applications would trivialize the many non-linear circuits driving innovation in AI, the stylized value chain does have the benefit of being able to capture the idea that an AI innovator can *specialize* in one or more stages, and that — as we hypothesize — integrating competences along all stages may result in higher rates of innovation.

The rationale for working with a stylized TFA value chain of AI is grounded in the idea that solving specific AI-related problems (often approximated by what we call functions) involves developing algorithms and methods that build on specific approaches or AI paradigms, such as symbolic or probabilistic AI. Each paradigm can be based on an array of techniques with specific properties, which can be more or less adapted to address certain types of problems. For instance, within the class of deep learning techniques, convolutional neural networks (CNNs) are the state of the art in image recognition tasks, while generative adversarial networks (GANs) have been used extensively to produce images. Reinforcement learning approaches have been successful in the AI-in-science context (e.g., in tasks related to addressing the protein folding problem), while language models such as the already cited Transformer have been pivotal in dealing with prediction tasks involving text embed-ding. While industrial actors have bet on language models becoming the dominant foundational multi-modal design underlying all AI commercial applications, a large variety of techniques continues to exist in the AI world, and involve inventive activities. Therefore, to avoid the risk of ignoring techniques less hyped but still widely developed, we focus on a variety of AI techniques and use data about them that span a long time period.

AI techniques give rise to specific *AI functions*. These functions are employed in different *AI applications*, which approximate techno-economic activities. As a result, we have a many-to-many relational structure: different techniques can feed different functions employed in different applications. Thus, we estimate the strength of the links between technologies depending on the frequency of their use. For example, we assume that the more a function such as image production uses a technique such as GAN, the more useful GAN is for producing images.

Summary A useful way to capture the "systems-ness" of AI — and to identify the competences that actors have to develop it — is to map its development through a stylized value chain that encompasses *techniques* (T), *functions* (F), and *applications* (A).

3.3 Integration, sovereignty, and competitiveness

In such a complex technological environment, integration capabilities become critical. They make the difference between an actor capable of developing the system autonomously and one who is not. Integration consists of shaping, selecting, and combining techniques dedicated to specific application functions (Jacobides et al. 2009), while maintaining the system's coherence. Integration requires specific competences to guarantee coordination across evolving boundaries of technological specializations with circular, interlocking, and often time-delayed relationships (Brusoni et al. 2001). Furthermore, combining different technologies requires dynamic adjustments to ensure compatibility and maintain synergy. Therefore, integration is not just about merging different technologies. It is the ability to coordinate the different yet complementary competences possessed by different stakeholders. More precisely, we define technological sovereignty in AI as in Insert 2.

Insert 2. Technological sovereignty as domestic integration along the AI value chain

In a competence-based framework, technological sovereignty in AI can be summarized as the ability to mobilize and integrated technological competencies domestically along the whole AI innovation value chain that ranges from the elaboration of new or improved algorithms (techniques), the development of new AI-based functions, to the concrete embodiment of AI techniques and functions into new applications.

We claim that integration is a pivotal element in achieving leadership in AI. To justify our claim, we relate the concepts of integration, competitiveness and sovereignty in AI as follows: an actor (a country, or the EU) can display specialization in one, two, all, or none of the layers of the TFA value chain of AI. If the actor exhibits a relative advantage in AI innovation within one of the TFA domains, we regard it as having a comparatively high degree of competence in producing new AI knowledge in that domain. The greater the number of domains this actor specializes in, the more transversal its competences become, leading to greater autonomy in producing all elements of AI innovation, from techniques to industrial implementations. Integrating complementary AI innovation competences in T, F, and A can serve as a proxy for overall competitiveness and autonomy. Specialization in AI-related innovations in a specific industrial application, such as advanced driver-assistance systems (ADAS) for self-driving cars, can be linked to the ability to develop AI-related functions that interpret signals captured from cameras, radar, and lidar sensors (e.g., image recognition combining image identification, image classification, object detection, scene understanding, and specific object recognition) based on specific convolutional neural networks (Fujiyoshi et al. 2019). Missing competences in the domain of convolutional neural networks requires resorting to other actors' competences and therefore reduces autonomy. Given that convolutional neural networks are used in many different functions, lacking expertise in this area reveals potential weaknesses in the ability to develop cutting-edge solutions in several industrial domains.

Beyond missing technological competences, a lack of integration in complementary competences can reduce strategic autonomy. As suggested, integration involves seamless access to the technological competences essential for application development. Developing competences in complementary techniques, functions, and applications requires capabilities not only to design and develop technologies, goods, and services, but also to develop the appropriate supply chain and invest in related resources such as manufacturing and distribution channels. Thus, integration amounts to much more than mixing and matching relevant competences and resources. Integration requires the ability to coordinate complementary activities, if one is to enjoy synergies between the resources throughout the value chain. It also involves the ability to identify and manage compatibility and overcome the other technical challenges required to design innovative solutions.

However, integration is costly and risky. AI-related techniques and functions developed in the context of a specific application may be difficult to redeploy and reuse in another context. Therefore, for a company, investing in an integrated value chain may not be wise for several reasons. First, the uncertainty and ambiguity inherent in emerging technologies increase the obsolescence of the relationships and the level of complementarity among techniques, functions, and applications. Consequently, investments to develop an integrated value chain might be effective in the short run, but might also prevent adaptation and create rigidity in the long run. Second, appropriation may be difficult. As is well known, AI algorithms are information goods, making them easy to reproduce and imitate. Thus, capturing their value relies on investments in specific complementary resources (Teece 1986, 1998). As we explained, when dealing with emerging technologies characterized by uncertainty, ambiguity, and obsolescence, these are risky investments, prompting firms to outsource AI development to partner experts.

Integration at the national level has a different meaning and can be considered as a proxy for and evidence of technological sovereignty and strategic autonomy. Creating networks at the national level has several benefits in the long term. First, promoting the integration of technologies such as AI generates positive externalities downstream. For instance, a new technique may open up innovation opportunities throughout the value chain down to applications. Second, integration is not the result of a single investor's decision. It is an outcome of several stakeholders' expertise and investment. In other words, no single entity incurs the risks associated with integration. Thus, integration capabilities — the ability to connect actors endowed with complementary competences — result from the ability of local actors to develop expertise and invest in complementary resources to explore and exploit innovative solutions. Integration can also have potential spillover effects in a larger ecosystem consisting of startups, partner firms, and downstream customers (Teece 1998). Hence, the ability to mobilize complementary expertise quickly requires specific forms of coordination such as innovation ecosystems including universities, local startups, large corporations, and infrastructures and support services such as technology transfer offices (TTOs) and patent offices that contribute to the innovation capacity of the ecosystem's members.

Furthermore, integration at the national level is also critical if the country wants to benefit from investments throughout the value chain. Missing competences and reliance on the expertise of foreign actors prevent a country from reaping the full rewards of its investments. Given that new techniques may generate upstream and downstream innovation opportunities, downstream application producers might prevent a country from capturing the value of these opportunities. An obvious illustration is the benefits of scientific discoveries by public universities that are exploited abroad by foreign corporations. It is a missed opportunity to capture the value generated by local investment in research and development competences and infrastructure. Giving up the ability to develop new markets or improve products and services also has consequences at the aggregate level. The inability to exploit synergies and spillovers throughout the value chain also creates blinders about seeing the opportunities inherent in local investments in complementary resources such as manufacturing, marketing, or distribution, with significant implications for productivity and employment.

As we will see in Section 4, our data and methodology allow us to operationalize this idea by measuring specialization quantitatively and aggregating it across AI TFA for the EU and the countries in our analysis.

Summary Integration reflects the ability to coordinate potentially complementary activities throughout the value chain and develop innovative solutions. The uncertainty, ambiguity, and obsolescence inherent in emerging technologies make investments in specific or co-specialized resources costly and risky for a single firm. However, at the national level, integration can strengthen sovereignty and competitiveness. Integration is an outcome of several stakeholders' expertise and investment. It involves the ability to mobilize complementary resources and generate innovation opportunities for local actors throughout the value chain. In brief, integration indicates an institutional environment that facilitates the coordination of innovation ecosystems and predicts innovative performance, with obvious effects on productivity and employment.

3.4 Technological sovereignty *versus* productive specialization

Defined as a capability to develop technology without external dependencies, technological sovereignty poses a direct challenge to the classical economic theories that advocate for specialization in international trade, as initially proposed by David Ricardo, further developed in the Heckscher-Ohlin model, and by Paul Krugman's New Trade Theory (inter alia Krugman 1979).

The Heckscher-Ohlin model builds on the concept of comparative advantage by arguing that countries will export goods that utilize their abundant factors of production (e.g., labor, capital) and import goods that require factors they are less endowed with. This model suggests that countries benefit from trading based on their factor endowments, thereby promoting specialization. Krugman (1991) suggests that economies of scale and network effects lead to specialization and trade. It argues that countries can benefit from specializing in certain industries, gaining from increasing returns to scale and resulting in more varied and cheaper products for consumers.

Instead, technological sovereignty focuses on building domestic capabilities and infrastructure to develop technologies independently, regardless of factor endowments. This could lead to the development of industries where a country does not have a natural comparative advantage, driven by strategic considerations like national security, reducing dependency, or long-term economic resilience. In fact, the pursuit of technological sovereignty may limit the potential for exploiting economies of scale in a globally efficient manner.

If countries prioritize self-reliance, they may opt to develop smaller, less efficient industries domestically rather than rely on international trade. This could reduce the overall gains from economies of scale and limit the variety and affordability of goods and services available to consumers, contradicting Krugman's emphasis on the benefits of trade and specialization. Technological sovereignty often arises from concerns about national security, economic independence, or strategic interests. These considerations may prioritize stability, control, and security over the efficiency gains promised by trade and specialization theories. The COVID-19 pandemic and recent geopolitical tensions have highlighted the vulnerabilities of highly specialized global supply chains. Technological sovereignty emphasizes resilience over efficiency, arguing that countries should develop critical capabilities domestically to avoid disruptions and dependencies.

Summary Technological sovereignty challenges the classical and modern trade theories by prioritizing strategic autonomy and independence over the economic efficiency gains derived from specialization. While specialization can lead to greater global efficiency and mutual benefits under stable conditions, technological sovereignty focuses on reducing vulnerabilities and ensuring that countries can independently navigate global uncertainties, potentially at the cost of forgoing some benefits of international trade.

A word should be said about our definition of technological sovereignty and the broader notion of economic sovereignty, as discussed in Rodrik (2011) and Guillou (2023). While both concepts are related, they focus on different aspects of a nation's autonomy. Economic sovereignty refers to a country's capacity to make independent economic decisions without external constraints, encompassing areas like trade, fiscal policies, and regulation to minimize dependence on foreign entities. In contrast, technological sovereignty specifically involves the ability to develop, produce, and innovate new technologies locally, ensuring control over the entire technological process and reducing reliance on foreign technologies. While economic sovereignty covers a wide range of economic policies and decisions, technological sovereignty zeroes in on creating a strong ecosystem for innovation and technological development. Thus, technological sovereignty can be seen as a component of the broader concept of economic sovereignty, providing the technological foundation that supports a nation's overall economic independence and resilience.

4 Data and Methods

Our analysis of competitiveness and sovereignty in AI is based on patent data and publications. We consider the granularity that this type of data offers as most appropriate to address our research question, given our focus on *technology* and *competences*. Many different empirical analyses of AI exist that utilize various sources of data. Examples include information about industries and occupations (Prytkova et al. 2024), firm-level surveys (Rammer et al. 2022), and research grants (Lane et al. 2024). However, most of these works measure AI take-up or its impact on the general economy. We look at the reverse problem: given the potential impact of AI, how can we identify the factors that promote success in developing the technology throughout its complex value chain? In what follows, we describe our data sources, the protocols we used to identify the relevant documents, and the type of quantitative analysis we conducted using them.

4.1 Data

The basic unit of information for our analysis is the patent document. A patent grants its owner(s) rights over a piece of intellectual property, usually a technological invention, preventing others temporarily from using the technology without a licensing agreement. Therefore, patents should be seen as strategic elements of the owners' technology portfolios. They are a tool for increasing the incentive to develop novelty, given the expected monopoly rents they provide to the inventor. Nevertheless, filing a patent is costly. In addition, patenting is not always an inventor's first choice for protecting intellectual property. The propensity to patent varies across industries by virtue of the type of knowledge that is produced. Therefore, not all inventions are patented (Mezzanotti & Simcoe 2023). However, patent data provide the broadest coverage of inventive activities in all technological domains. In addition, patents remain a good measure of innovation output when focusing on large companies and R&D firms.

Patenting requires information disclosures, meaning that the technological content of patents must be made public. This requirement is key, because it provides access to a source of data that is both rare and unique in terms of the richness of the information it contains. By looking at a patent, we have access to a description of its technological content through standardized classifications of technologies, patent owners and locations, the nationality of the inventors, year of invention, etc. In this report, we use PATSTAT as our main source of information regarding patents and present it in Insert 3

Insert 3. Presentation of PATSTAT

Our source of information is PATSTAT, Autumn 2023 edition. It is produced by the European Patent Office. PATSTAT is a systematic database of patent applications and contains bibliographic data on more than 140 million patent documents from major industrialized and developing countries. More precisely, PATSTAT retrieves all patents from the United States Patent and Trademark Office (USPTO), European Patent Office (EPO), and World Intellectual Property Organization (WIPO). The systematic nature of the database makes it very attractive, although it is not exhaustive, either geographically or temporally. A very attractive feature of PATSTAT is the organization of information into relational tables which makes its use very intuitive.

PATSTAT Global is a comprehensive repository that houses bibliographic data covering over 140 million documents from major industrialized and developing countries. In addition to a unique identifier, each patent is defined by: (i) the year it was first filed; (ii) its owner(s) (individuals, public laboratories or companies) and their addresses; (iii) its inventors' names and addresses; (iv) its technology class vector; (v) its title and abstract; (vi) references to prior patents and scientific publications relevant to the invention in question; and (vii) its patent family.

We wish to stress that the patents' quality may vary a great deal from one patented invention to another. By quality, we mean the economic value of the patents. We do not evaluate the technological novelty embodied in the invention. In general, there are two ways to account for the inventive activity of an organization or a country that results in intellectual property patent applications. First of all, we can focus on patent families. In the terminology of PATSTAT, a patent family means all patents referring to the same invention. For example, counting the number of patent families is tantamount to counting the number of inventions, regardless of their potential economic value. Second, we may instead focus on the patents themselves and count the number of patents, not families. A direct interpretation of patent counting is that it is the number of families, with each family being weighted by the number of patents. Given that inventions with more economic value will yield families with more patents, calculating the number of patents is similar to counting a quality-weighted measure of the number of inventions, the adjective "weighted" meaning weighted by the economic value of the invention.[17]

[17]See Insert 4 for more details on what a patent family is and why it matters.

Insert 4. What is a patent family, and why is it important?

The patent family is a generic term in PATSTAT that qualifies the invention. In a nutshell, a family groups a particular invention that is filed as different patents in different jurisdictions under one record. For example, a fictitious company named SPO-DGSCHAIR decides to protect its invention in France exclusively using the National Institute of Intellectual Property (INPI). The company then decides to extend its protection to Brazil, the United States, South Africa, and China. In PATSTAT, doing so would result in four additional patents, although all relate to the same invention, namely, the same family. In this work, we distinguish the number of patents from the number of families. Our rationale is not so much to distinguish inventions from patents; rather, comparing patents and families can help us appreciate the economic value of the invention.

Let us imagine that in order to follow up on the success of its invention, SPO-DGSCHAIR decides to extend its protection to Japan, and to all of the countries in the Eurozone. Doing so would mean increasing the number of countries to 21 (the 19 countries of the Eurozone, including France and Germany, the United States, and Japan). There would thus be 21 patents for a single invention. Obviously, expanding the protection of its intellectual property to a large number of countries is an indication of the economic value that the company hopes for or expects. This value would have to be distinguished from another invention protected in only one country. Thus, the size of the family, meaning the number of patents protecting the same invention, is an indication of the economic value of the invention.

It must be stressed that AI-related inventions do not readily lend themselves to patenting. As mentioned, patenting is a strategy. Organizations vary in their propensity or incentives for revealing their inventive activities. For instance, while Google (or its parent organization Alphabet) is well-known for being a leading actor in AI, it is listed as only the 10th most frequent inventor in 2. One of the reasons, beyond strategy, is that AI algorithms are software technology, and software can be patented only when embedded in a tangible (hardware) solution using AI. In this sense, as we anticipated in 1, our data might not cover some of the most recent advances in AI software. However, it will capture hardware-embedded technology that is pivotal to countries' physical production, products and services and, thus, productivity improvements.

Our study uses AI patents for 1990-2021. We are aware that using a long time span for the analysis can hide signals related to *current* trends and protagonists in AI innovation. Nevertheless, we opted for measuring AI innovation and competences over an extensive time span, because gaining competence is a non-trivial process characterized by path dependence. Understanding gaps in European technological sovereignty requires a structural, long-term view, that can be achieved only by factoring in AI developments along a decades-long trajectory.

In addition to patents, our study also uses scientific publications to track the evolution of AI-related scientific discoveries. We retrieved all papers in the Elsevier Scopus database (2023 edition) that were presented at international AI conferences. Scopus is one of the largest and most reliable abstract and citation databases offering a comprehensive platform for academic research. It contains more than 90 million records published and provides global and regional coverage of scientific journals, conference proceedings, and books (Baas et al. 2020). Scopus provides comprehensive information about the publications, author and institution profiles, including the year of the publication, and the name and the geographic location of the author(s)' affiliation. This information indicates the global distribution of research contributions and collaborations. Focusing on scientific conferences, Scopus includes content from 149,000 conferences and provides access to more than 11 million conference papers. To select publications concerned exclusively with AI, we relied on conferences identified as the main AI conferences by Baruffaldi et al. (2020). From Scopus, we retrieved all available proceedings of these conferences. We obtained 330,362 publications from conference proceedings from 1989 to 2023.

4.2 Identifying AI patents and publication

The essential information that makes it possible to identify AI patents is the description of the patent by means of its title, its summary, and its technology classes. We used information from three patent classification systems (for details, see Insert 5).

Insert 5. Patent classifications

There are three major patent classification systems that differ in their detail and structure: the International Patent Classification (IPC), the Cooperative Patent Classification (CPC), and the File Index / File forming terms (FI/F).

The IPC is a hierarchical classification system used primarily to classify and search patent documents according to the fields of technology to which they belong. It thus serves as a tool for the orderly classification of patent documents, and as the basis for the selective dissemination of information and the study of prior art in given fields of technology. The classification system contains approximately 70,000 entries identified by classification symbols that can be assigned to patent documents. These different classification sites are organized according to a hierarchical structure in the shape of a tree. The highest level consists of eight sections corresponding to very broad technical areas. These sections are subdivided into classes, subclasses, groups, and subgroups.

The CPC is an extension of the International Patent Classification, and is jointly managed by the European Patent Office and the United States Patent and Trademark Office. It is divided into nine sections, classes A-H of the International Classification, plus a class Y which includes new technological developments from the various sections of the International Patent Classification.

Finally, the terms FI and F (File Index / File forming terms, or FI/F terms) refer to the Japanese patent classification system. They contain 190,000 and 360,000 entries respectively that allow for the efficient search of patent documents. It should also be noted that the IFs and Fs are based on the International Patent Classification.

Another method of accessing the technological content of patents is using keywords that a simple elaboration on technological classes would not be able to grasp. Keyword-based approaches are increasingly used in order to navigate data in a more explorative and unstructured manner (Ott & Vannuccini 2023, Cockburn et al. 2018). This is indeed the path we followed for our exercise with AI. In addition, in our identification of AI patents, we used the title and summary of the patent to detect the presence of AI technologies.

Our selection of AI patents is inspired by the methodology developed by WIPO

(WIPO 2019), to which we added an additional step. The WIPO methodology consists of three building blocks of data from different selection strategies. Each block builds upon the previous one.

1. Step 1: List of CPC codes specific to AI technologies/functions/applications
2. Step 2: Specific list of keywords in the titles and summaries of the patents
3. Step 3: Specific lists of CPC codes, IPC codes, and FI/F terms controlled by another specific list of keywords

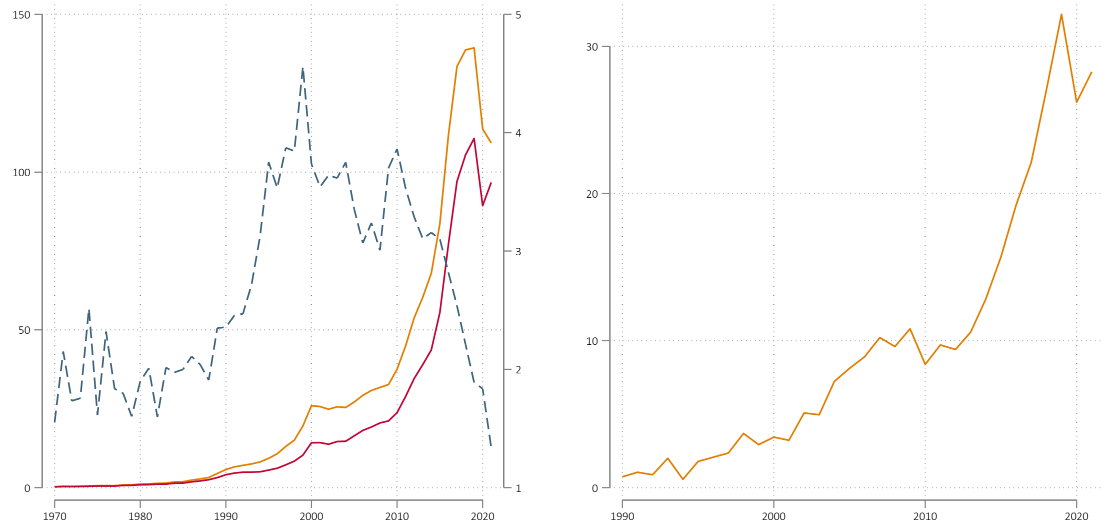
The combination of the three datasets obtained through these steps results in a sample that represents all patents considered potential AI patents. Steps 2 and 3 are based on a search in the abstracts and titles of the patents of the keywords that the WIPO proposed. We also added a number of terms such as generative AI techniques that have emerged more recently. Although the majority of patent titles and abstracts are written in English (approximately 80% for titles and approximately 90% for abstracts), some are written in other languages. Given that the keywords in the WIPO list are in English, it is difficult to search through texts written in other languages. Of the 36 languages used, we selected those which, according to the WIPO report, are spoken in countries that play a relatively important role in the development of AI (WIPO 2019). We translated the keywords into the following 11 languages: French, German, Spanish, Portuguese, Italian, Russian, Chinese, Japanese, Korean and Dutch. The last step was to apply Steps 2 and 3 to Japanese patents that do not use a patent classification system based on the CPC or IPC codes. To do so, we first retrieved the AI patents using the Japanese FI/F classification terms. We then performed a full join on the patent IDs in order to retrieve the corresponding IPC and CPC codes.

This procedure allowed us to identify 96% of the patents from the Japanese patent classification. In Step 2 we used the list of keywords from Step 1 to select the patents. The third step was to select a list of patents by IPC, CPC, and FI/F terms, and then filter them using the keyword list in Step 2. Finally, we built our own patent databases by categorizing the patents into the AI TFA categories using an algorithm we developed. We began by classifying a patent into a category/subcategory if the CPC/IPC code allowed it through the WIPO classification. If not, we searched for a series of keywords related to the category and subcategory in the abstract and/or title of the patent. In this way, we built three databases of patents that corresponded to the three categories of AI we considered: techniques, functions, and applications.

We also used this method to classify scientific publications about AI into the three categories of TFA. However, there were three major differences in our approach. First, given that our publications came from conferences devoted to AI, we did not have to determine which publications were relevant. Second, unlike patents, publications are not classified in technology classes (IPC, CPC, FI/F classes). Hence, we relied exclusively on our search for AI-related keywords in the titles and summaries of the publications. Last, we did not consider publications associated with application domains (the "A" in the TFA representation). We made this choice because publications usually focus primarily on advancing knowledge — in our case, introducing new (or advanced) techniques and functions — rather than specific production issues. Therefore, we assumed that scientific publications would be concerned with the development of techniques and functions.

Figure 4 displays the evolution of the number of AI patents filed since 1970 (Panel 4a) and publications (Panel 4b). The two panels exhibit a similar trend with an increasing rate of patent and publication production. Both panels show an initial phase starting in the mid-nineties, and the post 2010 decade indicates an impressive

Figure 4: The dynamics of AI-related patents and publications



(a) Patents (b) Publications

Sources: EPO PATSTAT (Ed. Autumn 2023) for patent data. SCOPUS for publication data. Authors' own calculations. The left axes in Figure 1a are in thousands of patents (orange line), of families (dark red line), and of publications (orange line, Figure 1b). The dotted blue line depicts the average family size (Figure 1a, right axis).

rise in the rate of production of patents and publications. It is difficult to identify precise reasons for these changes, other than the fact that they reflect the combined increase in intensive margin (an increase in the use of patents by countries that have traditionally already used this strategy of the appropriation of technologies), and extensive margin (the use of intellectual property in countries that until then made little use of this strategy). Of course, one explanation for the post-2010 acceleration can be linked to the beginning of what AI researchers have called the "Deep Learning era" (Sevilla et al. 2022), with the joint application of the backpropagation (a machine learning technique to train neural network algorithms) and graphics processing unit (GPU) computing to the image recognition task in the ImageNet competition. This marks the resurgence of interest in the so-called connectionist (that is, simply put, neural-network based) AI after previous "AI Winters" (Vannuccini & Prytkova 2024). The observed drop in the number of patent applications and publications after 2020 is simply a consequence of the time-consuming activity of retrieving all publication and patent data systematically. Therefore, it does not necessarily reflect a real downward trend in the publication of AI-related documents. Altogether, we observe that:

Finding 1. AI patent and publication production has increased over time, beginning initially in the mid-nineties. The post-2010 period shows an impressive rise in the rate of production of patents and publications. This acceleration is associated with the beginning of the "Deep Learning era", with the joint introduction of the back-propagation technique and faster computing enabled by graphical processing units (GPU), backed by the availability of large-scale databases such as the ImageNet image dataset.

Table 1 provides the full list of techniques and functions used to classify patents and publications in the Technique-Function-Application framework. Figures 5 and 6 display the frequencies of the patent documents and publications, respectively.

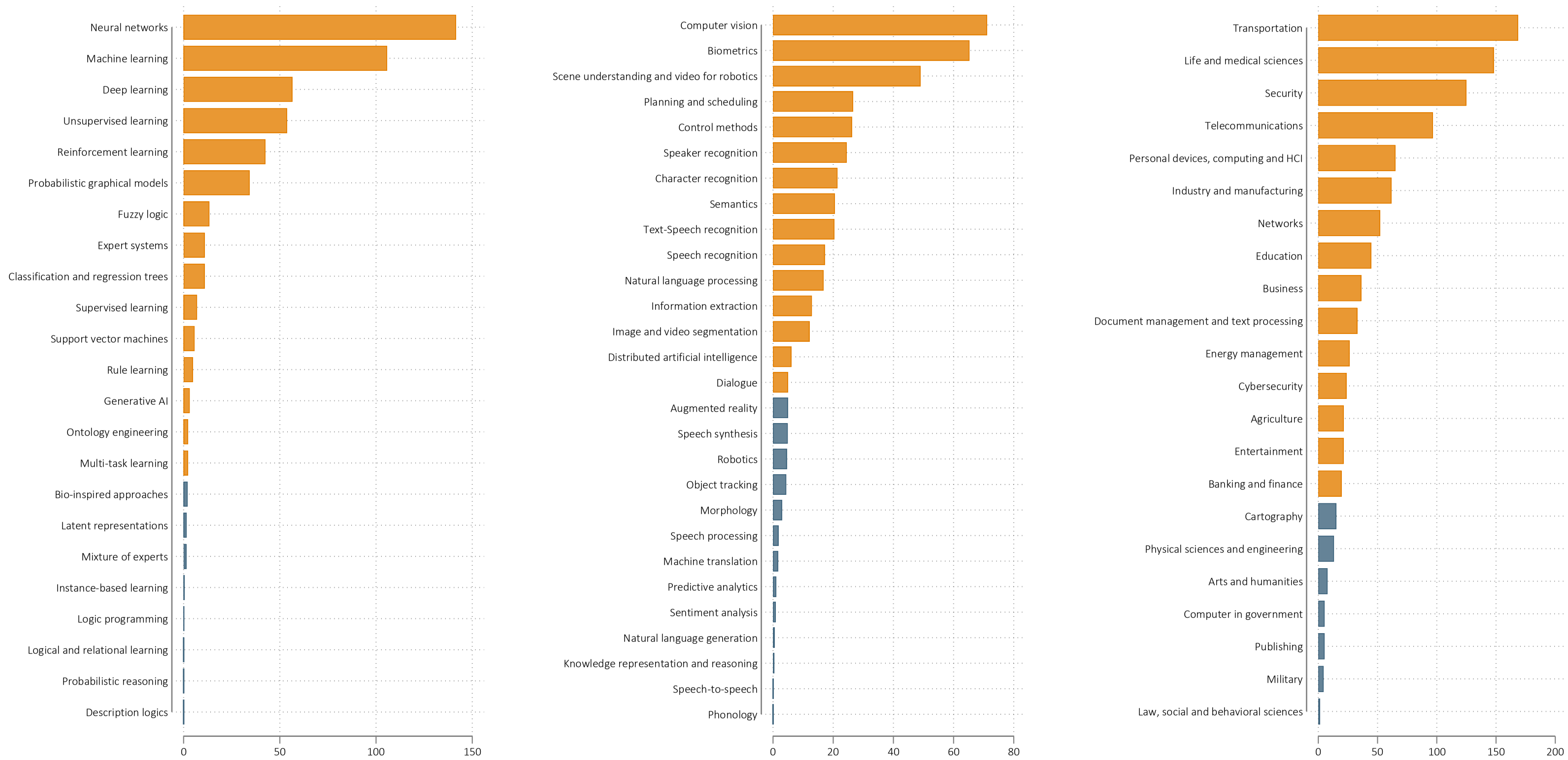
Not surprisingly, both figures 5 and 6 indicate over-dispersed distributions in the number of patents and publications dedicated to techniques and functions. Figures 5 also show that all applications do not use AI with the same intensity. The fields of transportation, life and medical sciences, security, and telecommunications are clearly dominant in their use of AI. These differences may affect the estimation and interpretation of specialization in each domain. Becoming an expert in deep learning requires much more investment and resources than acquiring a specialization in fuzzy logic. Although this issue is beyond the scope of this report, investing in the least crowded technical or functional domains might be a positioning strategy for taking the lead in niche areas, if any returns (scientific or economic) are to be expected from that positioning.

Table 1: List of AI techniques, functions, and applications used in this report

AI Techniques	AI Functions	AI Applications
Bio-inspired approaches	Augmented reality	Agriculture
Classification and regression trees	Biometrics	Arts and humanities
Deep learning	Character recognition	Banking and finance
Description logics	Computer vision	Business
Expert systems	Control methods	Cartography
Fuzzy logic	Dialogue	Computer in government
Generative AI	Distributed artificial intelligence	Cybersecurity
Instance-based learning	Image and video segmentation	Document management and text processing
Latent representations	Information extraction	Education
Logic programming	Knowledge representation and reasoning	Energy management
Logical and relational learning	Machine translation	Entertainment
Machine learning	Morphology	Industry and manufacturing
Mixture of experts	Natural language generation	Law, social and behavioral sciences
Multi-task learning	Natural language processing	Life and medical sciences
Neural networks	Object tracking	Military
Ontology engineering	Phonology	Networks
Probabilistic graphical models	Planning and scheduling	Personal devices, computing and HCI
Probabilistic reasoning	Predictive analytics	Physical sciences and engineering
Reinforcement learning	Robotics	Publishing
Rule learning	Scene understanding and video for robotics	Security
Supervised learning	Semantics	Telecommunications
Support vector machines	Sentiment analysis	Transportation
Unsupervised learning	Speaker recognition	
	Speech processing	
	Speech recognition	
	Speech synthesis	
	Speech-to-speech	
	Text-Speech recognition	

WIPO and author's own elaboration.

Figure 5: Top patent frequencies in AI techniques, functions, and applications



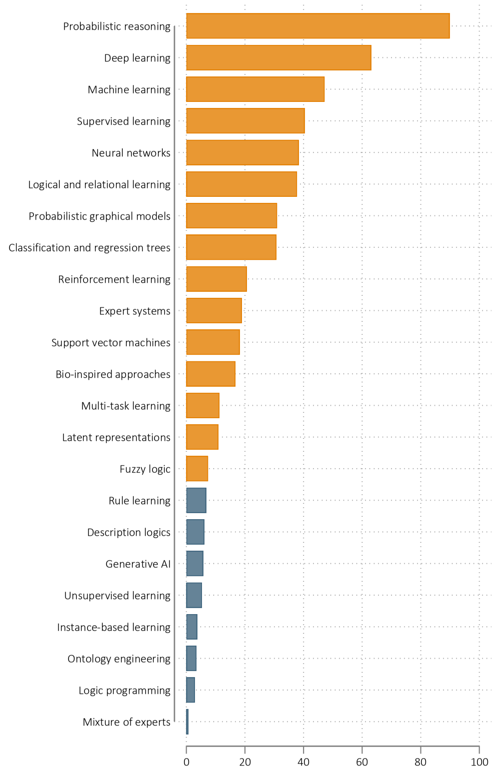
(a) AI techniques

(b) AI functions

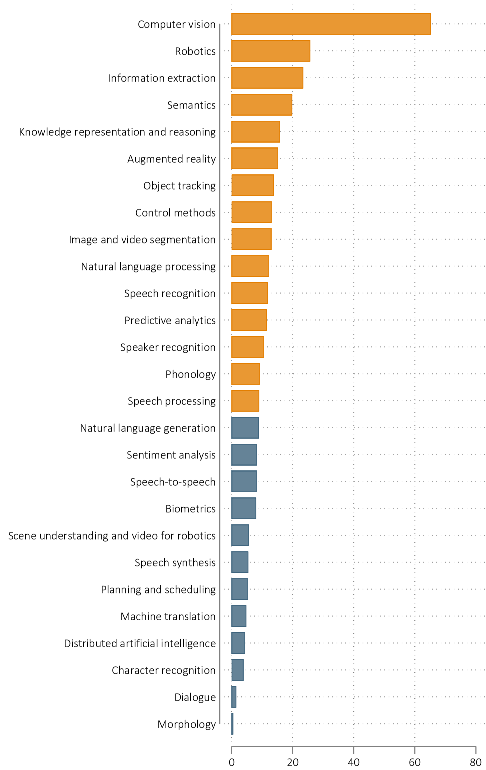
(c) AI applications

Source: EPO PATSTAT (Ed. Autumn 2023). Authors' own calculations. The top 15 frequencies appear in orange. The unit of the horizontal axis is in thousand of patents.

Figure 6: Top publication frequencies in AI techniques and functions



(a) AI techniques



(b) AI functions

Source: SCOPUS data. Authors' own calculations. The top 15 frequencies appear in orange. The unit of the horizontal axis is in thousand of publication.

4.3 Location of invention

An important issue is to determine the location of the invention (in terms of country), and the public or private organization that owns the invention. As our interest is to locate and map AI-related competences, we use the country of residence of the inventors identified by their personal address referenced in PATSTAT rather than the country of the IP office (see insert 6).

Insert 6. Location of patents: IP office or inventors' country of residency?

The location of patents can be determined by looking either at the location of the office to which the intellectual property application is being sent, or by the location of the inventor. Given that an inventor can submit a patent application in a country other than that in which he or she lives, we cannot interpret these two pieces of information in the same way.

An inventor files a patent application with the aim of obtaining rights over his or her intellectual property. The patent gives its holder exclusivity to exploit the patented invention for a limited period (generally between 15 and 20 years), with the obligation to fully disclose the technical content of the invention. An inventor therefore decides to patent an invention for two major reasons: (i) the anticipated market is sufficiently large in terms of potential demand; (ii) the probability of being imitated by a competitor is high. In other words, assigning a patent to a country on the basis of the geographical area of protection primarily reflects the country's potential demand and only secondarily the presence of those who have the ability to imitate the invention, meaning, the supply side. Conversely, locating a patent according to the inventor's residency primarily reflects the supply side (the local competences) and only secondarily the potential demand.

In our opinion, the strategic challenge for countries is to develop the scientific and technical skills that allow them to participate in the global effort to develop AI. The fact that a patent is being developed by inventors from a particular country implies that complementary investments, in terms of infrastructure, researchers, engineers, national innovation system, networks, the underlying education and professional training system, etc., have been made in the first place.

The issue with using the inventors' country of location is that that information is missing in around 50% of AI patents. Therefore, we proceeded sequentially as follows.

1. *PATSTAT*. With variable "psn_country_code", PATSTAT provides information on the inventor's location. Of 1,580,115 patents, we located the inventor's residency for 783,556 patents.

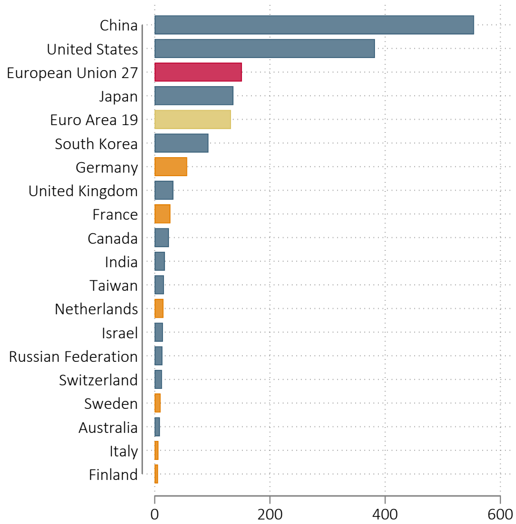
2. *OECD REGPAT database. January 2024.* REGPAT is an OECD database that provides the location of nearly 19 million patents from PATSTAT (Maraut et al. 2008). The ultimate goal of REGPAT is to link patents to NUTS3 regions, and therefore countries.

3. To complement this approach, we considered patents with only one inventor and a family size of 1 (only one IP office). We also assigned the country of the IP office as the country of invention.

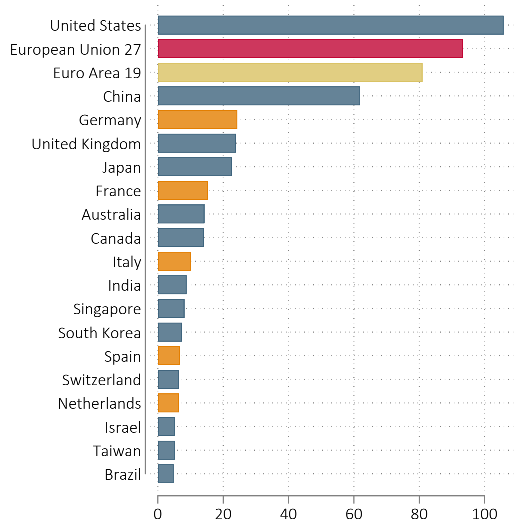
By concatenating the different sources of information, we obtained 1,415,828 patents (93%) with a geographic location. It should be noted that a patent can have several inventors. For example, a patent involving an American resident, a German resident, and a French resident will be counted identically in the three countries of the United States, Germany, and France. Concerning publications, the information contained in Scopus allowed us to determine the location of the scientists more straightforwardly, using the address of the affiliation of the authors. As for the patents, we did not use weights to allocate publications to countries. If a publication was written by authors from different countries, we counted the publication as many times as there were countries rather than allocating weights to the countries.

Figure 7 provides preliminary evidence of the distribution of AI-related competences across countries. Although Europe is a collection of countries rather than a country in itself, we considered it as a country. Europe, whether the European Union or the Eurozone, has its own institutions, constitution-like treaties, and is backed by a house of representatives whose members are chosen through European-

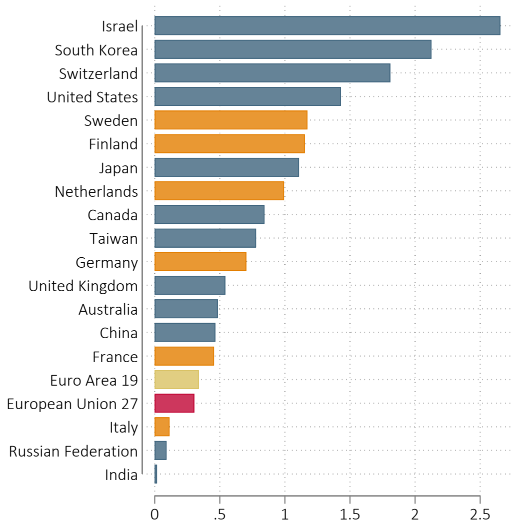
Figure 7: Country frequencies in AI-related patents and publications



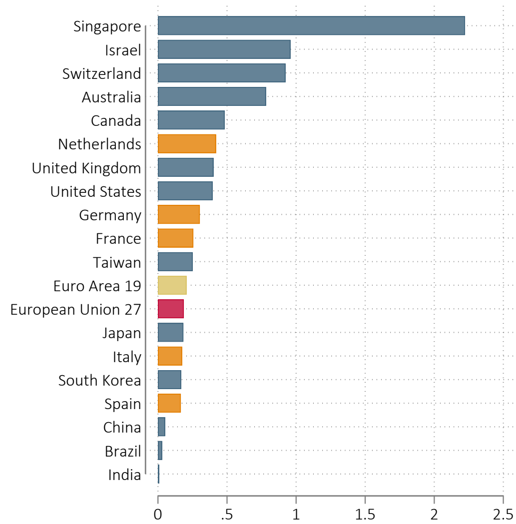
(a) Patents



(b) Publications



(c) Patents per capita



(d) Publications per capita

Sources: EPO PATSTAT (Autumn 2023 edition) and Scopus (2023 edition). The number of inhabitants per country is derived from the Penn World Tables version 10 (Feenstra et al. 2015). Number of patents and of publications per million inhabitants. Authors' own calculations.

wide elections. Therefore, given the objective of the report, we considered Europe as giving rise to two countries: the European Union (the EU, with 27 member states) and the Eurozone (the EZ, with 19 member states). We constructed the statistics on patents and publication in the EU and the EZ by aggregating the information about the individual member states.[18]. The top panel ranks countries according to their contribution in terms of frequencies. The bottom panel normalizes the figures by providing the number of patents and publications per million inhabitants.

Overall, the EU and the EZ rank high both in terms of publications and patents when looking at absolute frequencies. However, there is still a gap between the EU and both China and the US. The gap is far greater when it comes to patents. The number of EU27 patents is almost a third of the number of US patents. In contrast, the EU27 has 90% of the number of US publications. Even when discounting for possible strategic and inflationary behaviors in publications and patenting from EU competitors — as we cannot assume that the same strategies are not pursued by European actors — the EU lags behind the US in AI-related knowledge generation and inventions over the period covered by our data. Europe is very close to the US in terms of scientific publications and far outranks China in this area.

Finding 2. There is a large gap between the EU, the US, and China in terms of patent production and in the number of publications when comparing the EU with the US. The number of EU27 patents is almost a third of the number of US patents. In contrast, the EU27 has 90% of the number of US publications.

When we normalize the measures in terms per inhabitants, the results for Europe are far more dire. The EU ranks 17th in patent production per capita, while the EZ ranks slightly higher, in 16th place. This result represents one fifth of the patents per capita in the US. In the same fashion, the EU ranks 13th in per capita AI publications, while the EZ ranks in 12th place. Europe performs better than China

[18] We excluded the United Kingdom from all EU statistics.

in per capita AI-related publications. Therefore, the gap becomes more pronounced when accounting for country size in AI patents and publications.

Finding 3. The EU ranks 17th in per capita patent production, while the EZ ranks slightly higher, in 16th place. This result represents one fifth of US per capita patents, and one twelfth of China's. The EU ranks 13th in per capita AI publications, while the EZ ranks in 12th place. Europe performs better than China in per capita AI-related publications.

These findings can be read through the critical take of Dosi et al. (2006) on the European paradox. Traditionally, the paradox describes the gap between European frontier science and its sub-optimal industrial application. The term is often used to highlight failures in technology transfer and commercialization when compared to the US. However, our results suggest that in the case of AI the paradox may be more severe than originally conceived: the EU under-performs — relative to the US — both in patent and publication production. The take-home message is that the EU gap with the frontier is both science and innovation-based, rather than only innovation-based. In addition, the quest for improving AI competences is a transversal matter encompassing science, technology, and industrial policies. In other words, a European AI policy should focus on supporting the basic knowledge production of AI as well.

Finding 4. In the realm of AI, the European paradox may be more severe than originally identified. The gap with the US is both science- and innovation-based. The quest for improving AI competences is, thus, a transversal matter encompassing science, technology, and industrial policies.

Another element to consider is the long-term impact of this gap. As knowledge is for a large share cumulative, a lower accumulation of inventions compared to other areas of the world might turn into a persistent disadvantage. If a critical mass of knowledge production is needed to improve competitiveness and catch-up with the frontier, Europe might never be able to fill the gap formed over the decades.

Finding 5. In virtue of the cumulative nature of knowledge, without achieving a critical mass in AI-related innovation, the EU risks to be unable to close the gap with the global frontier.

4.4 Actors

Innovation is seldom an individual activity; rather, it is the product of interactions between a multiplicity of actors with complementary resources and skills. As with many other high-tech products, the development of AI systems relies on four types of actors: universities and public research laboratories, which act as producers and repositories of basic scientific knowledge; large companies, mostly from high-tech and digital industries, which are also increasingly involved in fundamental AI research to shape the direction of the evolution of the technology (Ahmed et al. 2023); investors, with a strong commitment from banks and venture capitalists, and startups, generally small in size and developing AI applications building on received knowledge and existing systems. The different policy initiatives observed in countries active in AI development aim, among other things, at supporting the interplay between these four types of actors. In a sense, policies designed to orchestrate and coordinate these interactions fall under the classic efforts to build national and sectoral systems of innovation (Malerba 2002), which is a useful perspective to take when discussing technological sovereignty in AI. As the AI industry itself evolves with the technology, there are different taxonomies of AI actors in the literature. For instance, Jacobides et al. (2021) distinguish among actors based on how AI systems are produced and implemented (e.g., for re-sale or for in-house adoption). For our purposes, we maintain the distinction outlined above between the four main supply-side actors, as we can map the information contained in patent and publication data directly to these types of actors.

In particular, in our analysis, we differentiate between private companies and research institutes, regardless of whether the latter are public or private. On one hand, private companies are key drivers of innovation. They seek economic gains by creating new markets or increasing their share of existing ones. On the other hand, the scientific community is a key part of the development of AI. AI is a science-based domain, where the development of new algorithms combines upstream research in statistics and computer science and downstream innovation closer to potential market applications. Due to this significant overlap between fundamental and applied knowledge in AI, public research institutions, including universities and research institutes, are active players. To this end, we exploited the PATSTAT variable "psn_sector", which may take the following labels: (i) natural person; (ii) business; (iii) indeterminate; (iv) governmental organization; (v) non-profit organization; (vi) university; and (vii) hospital. Using this approach allows us to classify a patent assignee as either a private company or a research organization, including universities, public or private research institutes.

Tables 2, 3, 4, 5, 6 and 7 list the major private or public players in AI in the world and in Europe. Table 2 identifies the top 20 private actors in the world active in AI innovation. Over our period of analysis, the semiconductor company Intel and the American giant IBM accounted for more than 20,000 patents each, representing

Table 2: The top 20 worldwide private actors in AI patent production

Applicant	Nationality	# Patents	# Family	Quality
Intel	United States	27,470	17,161	1.60
IBM	United States	21,502	13,246	1.62
Samsung	South Korea	18,696	8,922	2.10
NEC	Japan	17,541	11,336	1.55
Microsoft	United States	14,487	6,865	2.11
State Grid Corp.	China	12,416	9,805	1.27
LG	South Korea	10,472	5,111	2.05
Siemens	Germany	10,208	5,508	1.85
Sony	Japan	9,499	4,720	2.01
Google	United States	9,287	3,739	2.48
Hitachi	Japan	8,895	6,126	1.45
Baidu Online Technology	China	7,870	5,873	1.34
Toshiba	Japan	7,813	5,918	1.32
Huawei	China	7,339	4,407	1.67
Fujitsu	Japan	7,317	5,120	1.43
Philips	Netherlands	7,247	2,964	2.45
Bosch	Germany	6,882	2,312	2.98
Nippon	Japan	6,559	5,512	1.19
Canon	Japan	6,414	4,458	1.44
Tencent Technology	China	6,337	4,135	1.53

Source: PATSTAT Autumn 2023 Edition. Calculations of the Authors.

30,000 patent families[19] that protect inventions embodying AI-related components. The South Korean high-tech manufacturer Samsung was ranked third, with almost 19,000 patents. Software producers such as Microsoft and Google ranked lower but still accounted for 25,000 patents. In total, of the top 20 companies, there were 4 US companies, 13 Asian companies (among which 7 were Japanese, 4 Chinese, and 2 South Korean), and only 3 European companies (2 German companies and 1 Dutch). However, European companies produced higher quality patents[20]

It is important to stress that the actors we identified with our patent analysis do not necessarily earn revenues from AI products and services targeting final users. Rather, they are large, established corporations, active in the business-to-business

[19] See Insert 4 for a definition of what a patent family is, and why it is important.

[20] the average invention quality is defined simply as the ratio of the number of patents over the number of families. See Harhoff et al. (2003) for more details.

Table 3: The top 20 European private actors in AI patent production

Applicant	Nationality	# Patents	# Family	Quality
Siemens	Germany	10,208	5,508	1.85
Philips	Netherlands	7,247	2,964	2.45
Bosch	Germany	6,882	2,312	2.98
Nokia	Finland	2,756	1,340	2.06
Bayer Healthcare	Germany	2,584	989	2.61
Audi	Germany	2,462	893	2.76
Volkswagen	Germany	2,312	673	3.44
Airbus	France/Germany/Spain	1,453	770	1.89
Alcatel	France	1,190	763	1.56
Thales	France	1,079	555	1.94
Ericsson	Sweden	965	471	2.05
Accenture	Ireland	918	437	2.10
Continental Automotive	Germany	791	189	4.19
Sap	Germany	744	489	1.52
StMicroelectronics	Switzerland/France	638	375	1.70
Valeo	France	610	184	3.32
Schaeffler Technologies	Germany	396	15	26.40
Here Global	Netherlands	393	191	2.06
Thomson	France	293	170	1.72
Infineon Technologies	Germany	214	64	3.34

Source: PATSTAT Autumn 2023 Edition. Calculations of the Authors.

domain. These actors are engaged in building the backbone of the AI technology systems on which other actors can develop their solutions. The fact that EU companies are under-represented in the ranking illustrates the European weakness in AI production. Lacking continental-sized AI champions Fontana & Vannuccini (2024), the EU foregoes its place on the technological frontier.

Finding 6. The top 5 players in AI-related patent production in the world are: Intel (USA, with 27,500 patents corresponding to 17,000 inventions), IBM (USA, 21,500 patents, 13,000 inventions), Samsung (South Korea, 18,500 patents and 9,000 inventions), NEC (Japan, 17,500 patents and 11,000 inventions), and Microsoft (USA, 14,500 patents for 7,000 inventions).

Table 4: The top 20 worldwide public actors in AI patent production

Applicant	Nationality	# Patents	# Family	Quality
Nanjing University	China	12,667	10,633	1.19
Chinese Academy Of Sciences	China	7,432	6,069	1.22
Zhejiang University	China	7,265	6,200	1.17
Wuhan University	China	5,685	4,789	1.19
Shandong University	China	5,470	4,438	1.23
Harbin University	China	5,145	4,318	1.19
Hangzhou University	China	4,467	3,881	1.15
Beijing University Of Technology	China	4,353	3,675	1.18
Chongqing University	China	4,171	3,613	1.15
Jiangsu University	China	3,988	3,216	1.24
University Of Electronic S&T Of China	China	3,919	3,443	1.14
Tianjin University	China	3,753	3,130	1.20
Tsinghua University	China	3,584	2,910	1.23
Southeast University	China	3,445	2,972	1.16
Xidian University	China	3,410	2,986	1.14
Dalian University	China	2,916	2,369	1.23
Beihang University	China	2,870	2,440	1.18
South China University Of Technology	China	2,796	2,288	1.22
Huazhong University	China	2,286	1,863	1.23
Guangdong University Of Technology	China	2,209	1,816	1.22

Source: PATSTAT Autumn 2023 Edition. Calculations of the Authors.

Finding 7. There are 3 European companies in the top 20 chart in AI-related patent production: Siemens (Germany, with 10,000 patents corresponding to 5,500 inventions), Philips (the Netherlands,7,000 patents, 3,000 inventions), and Bosch (Germany, 7,000 patents and 2,300 inventions). These three companies produce higher quality patents relative to their worldwide competitors.

Table 3 zooms in on the top 20 European AI (private) innovators as defined through their patenting activities. Germany accounts for the lion's share of the top actors. As with the worldwide ranking, the top AI innovators are high-tech hardware producers, with the mixed presence of actors in ICT and telecommunication devices, heavy industry, automobile and aerospace, and semiconductors. A salient feature of European innovators is that they produce higher quality patents relative to their

Table 5: The top 20 non-Chinese public actors in AI patent production

Applicant	Nationality	# Patents	# Family	Quality
Northwestern Polytechnical University	United States	2,057	1,712	1.20
Industry Academic Cooperation Foundation	South Korea	1,989	1,227	1.62
Electronics And Telecom. Res. Institute	South Korea	1,767	1,233	1.43
CSIP	Spain	1,709	923	1.85
CNRS	France	1,052	424	2.48
Advanced Institute Of S&T	South Korea	861	540	1.59
University Of California	United States	726	369	1.97
Seoul National University	South Korea	619	375	1.65
INSERM	France	591	259	2.28
Industrial Technology Res. Institute	Taiwan	523	368	1.42
National Dong Hwa University	Taiwan	432	347	1.24
UCL Business London	United Kingdom	423	258	1.64
University Res.& Bus. Foundation	South Korea	395	266	1.48
US Navy	United States	387	278	1.39
Massachusetts Institute Of Technology	United States	361	174	2.07
Fraunhofer-Gesellschaft	Germany	355	103	3.45
Korea Electronics Technology Institute	South Korea	313	183	1.71
CEA	France	291	113	2.58
Carnegie Mellon University	United States	225	105	2.14
IUCF Hanyang University	South Korea	220	144	1.53

Source: PATSTAT Autumn 2023 Edition. Calculations of the Authors.

worldwide competitors.

Finding 8. The top 5 players in Europe in AI-related patent production are: Siemens, Philips, Bosch, Nokia (Finland, 2,700 patents and 1,300 inventions), and Bayer Healthcare (Germany, 2,500 patents and 1,000 inventions). The top European AI innovators are high-tech hardware producers, with a mixed presence of actors in ICT and telecommunication devices, heavy industry, automobile and aerospace, and semiconductors. European companies produce higher quality patents relative to their worldwide competitors.

Tables 4 and 5 shift the focus from private to public actors. The worldwide ranking (Table 4) is dominated by Chinese universities. National policies such as "Made in China 2025" and subsidies and financial incentives from local governments

Table 6: The top 20 worldwide actors in AI publication production

Applicant	Status	Nationality	# Pub.
University of California System	University	United States	9,990
Chinese Academy of Sciences	PPRI	China	8,350
Carnegie Mellon University	University	United States	6,955
Centre National de la Recherche Scientifique (CNRS)	PPRI	France	6,259
Microsoft	Entreprise	United States	6,152
Tsinghua University	University	China	5,261
Massachusetts Institute of Technology (MIT)	University	United States	4,500
Swiss Federal Institutes of Technology Domain	PPRI	Switzerland	4,086
University of Illinois System	University	United States	3,965
Google Incorporated	Entreprise	United States	3,794
International Business Machines (IBM)	Entreprise	United States	3,786
Stanford University	University	United States	3,627
Nanyang Technological University	University	Singapore	3,556
University of Texas System	University	United States	3,409
University System of Georgia	University	United States	3,270
University of Chinese Academy of Sciences, CAS	University	China	3,258
University of London	University	United Kingdom	3,253
Peking University	University	China	3,084
Indian Institute of Technology System (IIT System)	University	India	2,993
University of Illinois Urbana-Champaign	University	United States	2,887

Source: SCOPUS 2023 Edition. Calculations of the Authors. PPRI: Public/Private Research Institute.

explain the over-representation of Chinese universities (Sun 2003). To gain a clearer view of the positions of other actors, we excluded Chinese universities from the ranking in Table 5. US and South Korean institutions accounted for 12 out of 20 positions in the ranking. Looking at Europe, large public research institutes such as CSIP (Spain), CNRS and INSERM (for France), and Fraunhofer (for Germany) made it to the ranking. Again, we observe that European public actors produce higher quality patents than their non-European counterparts.

Table 7: The top 20 European actors in AI publication production

Applicant	Status	Nationality	# Pub.
Centre National de la Recherche Scientifique (CNRS)	PPRI	France	6,259
Max Planck Society	PPRI	Germany	2,226
Inst. Nat. Recherche en Informatique Appliquée (INRIA)	PPRI	France	2,115
Technical University of Munich	University	Germany	2,042
University Paris Saclay	University	France	1,905
Helmholtz Association	PPRI	Germany	1,510
Katholieke Universiteit Leuven	University	Belgium	1,326
Aalto University	University	Finland	1,280
University of Amsterdam	University	Netherlands	1,236
Technische Universität Wien	University	Austria	1,174
Sorbonne University	University	France	1,160
Delft University of Technology	University	Netherlands	1,064
University of Munich	University	Germany	1,032
Consiglio Nazionale delle Ricerche (CNR)	PPRI	Italy	1,015
Institut Polytechnique de Paris	University	France	977
Eindhoven University of Technology	University	Netherlands	954
Sapienza University Rome	University	Italy	938
IMT - Institut Mines-Telecom	PPRI	France	917
Siemens AG	Entreprise	Germany	909
Communauté Université Grenoble Alpes	University	France	909

Source: SCOPUS 2023 Edition. Calculations of the Authors. PPRI: Public/Private Research Institute.

Finding 9. Chinese universities are among the top 20 public organizations involved in producing AI-related patents, but produce lower quality patents. When focusing on non-Chinese public actors, US and South Korean institutions account for 12 out of 20 positions in the ranking. Looking at Europe, large public research institutes such as CSIP (Spain), CNRS and INSERM (for France), and Fraunhofer (for Germany) account for most AI-related patents. European public actors produce higher quality patents that their non-European counterparts.

Table 6 ranks the top actors worldwide in the domain of AI publications rather than patents. The top players in AI-related science are essentially American (11 among the top 20 players) and Chinese (4 players). France (Centre National de la Recherche Scientifique — CNRS), India (Indian Institute of Technology System —

IITS), the United Kingdom (University of London), Singapore (Nanyang Technological University), and Switzerland (Swiss Federal Institutes of Technology Domain) also appear in the top 20 chart. The CNRS ranks fourth worldwide, and is the only organization among the top 20 players belonging to the European Union. While AI research occurs essentially within the university system, the world ranking provides a glimpse of the ongoing process of the "industrialization" of AI outlined by Ahmed et al. (2023), with some of the GAFAM at the forefront of AI-related scientific production (with all this implies in terms of the "direction" of research, likely more attuned to commercial priorities).

Finding 10. The top players in AI-related science are essentially American (11 among the top 20 players) and Chinese (4 players). France (Centre National de la Recherche Scientifique — CNRS), India (Indian Institute of Technology System — IITS), the United Kingdom (University of London), Singapore (Nanyang Technological University) and Switzerland (Swiss Federal Institutes of Technology Domain) also appear in the top 20 chart. Digital giants such as Microsoft, Google and IBM appear as major players in AI science. The CNRS ranks fourth worldwide, and is the only organization among the top 20 players belonging to the European Union.

Finally, Table 7 ranks the top European actors in AI publications. Overall, large institutes in France and Germany lead the AI-related knowledge production in scientific papers, specifically CNRS and INRIA for France, and the network of Max Planck research centers for Germany. France has 7 top players (e.g. CNRS; INRIA; and Université Paris Saclay), Germany has 5 players (e.g., Max Planck Society; Technical University of Munich), the Netherlands has 3 players ((University of Amsterdam, Delft University of Technology, and Eindhoven University of Technology) and Italy has 2 players (CNR and University of Rome La Sapienza). Other contributing countries are, by decreasing order of contributions, Belgium (Katholieke

Universiteit Leuven), Finland (Aalto University), Austria (Technische Universität Wien). The only company is the German industrial producer Siemens AG.

Finding 11. In Europe, AI-related knowledge production in scientific papers is led by large institutes in France and Germany *in primis*, specifically, CNRS and INRIA for France, and the network of Max Planck research centres for Germany. The only company involved is the German industrial producer Siemens AG.

A final caveat should be expressed. In general, the types of actors that are emerging as the top AI patent holders reflect both the censoring of our data to 2021 as well as one of the limitations of the dataset we use: only embedded AI is patented. As a result, the actors that focus only on the development of AI algorithms, such as the widely known OpenAI, Anthropic, the French unicorn Mistral, and the booming set of startups created in the last few years are not part of the picture. The fact that the main AI actors currently under the media spotlight are not included in our data does not mean that our analysis is missing key structural dynamics in AI innovation. On the contrary, it allows us to focus on industrial innovation in AI, which is the fundamental repository of knowledge and competences capable of promoting widespread productivity improvements in user sectors and, thus, international competitiveness.

Finding 12. Our overall impression is that European actors, both private and public, are followers rather than leaders both in AI patents and publications. While scientific production related to AI in the US shows traces of "industrialization", with private actors competing with universities, in Europe large public research institutes continue to play the major role in AI knowledge production.

4.5 Country specialization

A country is considered specialized when it develops a particular expertise relative to other countries. Specialization relates to the concentration of resources — investments, human capital, distinctive skills — in given areas. It is different from the notion of critical mass in that specialization does not require massive investments in absolute terms. Rather, it refers to the allocation of resources among a portfolio of possible destinations. Specialization in sciences or in techniques has been the focus of attention of scholars in the literature on technical change, whether in firms (Cantwell 1989, Dibiaggio & Nesta 2005) or countries (Nesta & Patel 2004).

One measure which has been used extensively is the so-called relative specialization index. Let $P_{c,d}$ be the number of patents held by country c in AI domain d, representing alternatively the technique t, the function f, or the application a domains. For a given year, the relative specialization advantage RSA is defined by:

$$RSA_{c,d} = \frac{P_{c,d}/\Sigma_d P_{c,d}}{\Sigma_{b \neq c} P_{c,d}/\Sigma_{b \neq c}\Sigma_d P_{c,d}}, \tag{1}$$

where $d \in \{t, f, a\}$, $t = \{1, 2, \cdots, t, \cdots, T\}$, $f \in \{1, 2, \cdots, f, \cdots, F\}$, and $a = \{1, 2, \cdots, a, \cdots, A\}$.

The specialization index is the ratio of two proportions. The first — the numerator — is specific to the actor. The second — the denominator — is relative to all of the actors active in the field of interest, AI in our case. The numerator represents the proportion of patents belonging to a given AI domain. The denominator represents the same proportion (the share of patents belonging to a domain) for all other countries. In other words, the RSA measures the share of a domain's AI patents in all AI patents for a given country relatively to the same share for the rest of the world. For example, between 2011 and 2021, France was granted 419 patents in the AI technique "Probabilistic graphical models", for a total number of AI-related patents of 4846. This equates to 8.5% of patents in this AI technique. Meanwhile, in countries other than France, this proportion amounts to only 6.4%. Therefore, relative to other countries, France enjoys a specialization advantage of 1.35 (the ratio of 8.5 over 6.4), indicating that the domestic share of innovation in a domain is relatively higher than the corresponding share for the rest of the world.

This index belongs to the zero-infinity interval (i.e. $nRSA \in [0\ ;+\infty[$), and its pivotal value is unity. If this index exceeds unity, the focal country is more specialized in the field compared to the rest of the world. Conversely, if the index is lower than unity, the country is less specialized in the AI domain of interest relative to the rest of the world. Without altering the interpretation of the indicator, and in order to facilitate the visualization of the results, we normalized the specialization index as follows:

$$nRSA_{c,d} = \frac{RSA_{c,d} - 1}{RSA_{c,d} + 1}, \tag{2}$$

where $nRSA_{c,d} \in [-1\ ;+1[$, with a threshold value of nullity indicating whether a country enjoys a relative specialization advantage ($nRSA > 0$) or disadvantage ($nRSA < 0$). Applying this transformation to the previous example yields a $nRSA$ of $+.15$. Being positive, the index implies that France indeed enjoys a specialization advantage in "Probabilistic graphical models". Conversely, a value of $-.64$ informs us that in "Generative AI", France suffers from *dis-specialization* relative to other countries.

As mentioned, one must not confuse specialization with critical mass in AI-related patents. Critical mass relates to an absolute number of patents, concealing substantial investments in both human capital, production equipment, and complementary assets. In this respect, major players such as the United States or China have reached a critical mass in nearly all AI domains. Instead, specialization relates to the composition of AI-related patents among the different AI techniques, functions, and application. Therefore, a country can be highly specialized without holding a large number of patents. Returning to our example, although France enjoys a relative specialization in "Probabilistic graphical models", its absolute number of patents in this techniques is far smaller than that of Japan (1,117). Nevertheless, the latter has a negative specialization index $nRSA = -.05$.

Figures 8, 9 and 10 display country specific $nRSA$ for the top 15 AI techniques, functions, and applications for three periods: 1990-2000, 2001-2010, and 2011-2021. We do not intend to comment on all countries or AI domains. Instead, we focus on the three major geographic areas: Europe, the US, and China. We wish to stress the following points.

First, the EU and the EZ have very similar specialization profiles in all AI techniques, functions, and applications domains. Second, and more strikingly, relative specialization changes abruptly in techniques, and to a lesser extent, functions. In contrast, it exhibits more persistence over time with regard to applications. This difference is not surprising. AI applications are downstream applications close to economic activities, whereas techniques refer in general to upstream research activities. The AI value chain ranging from techniques to applications *via AI functions* requires investments in complementary assets that become more significant from one phase to another, yielding a natural persistence in the trajectories chosen by public or private players active in downstream AI applications (David 1985, Arthur 1989). In other words, the persistence of specialization in application activities may stem from the sunk costs necessary to run these activities, while the turbulence in upstream specialization is facilitated by the more intangible nature of innovations in techniques and functions, which are less embedded and, thus, more flexible. An alternative and complementary explanation has to do with the progressive upgrading and substitution of the underlying techniques and functions powering innovation in a certain AI application. By virtue of path dependence, the EU retains the capability to innovate in applications in the long term. However, it does so by leveraging new AI techniques and functions, sometimes produced domestically, and sometimes sourced internationally. From this perspective, the turbulence in AI techniques and functions results from a continuous exploration process as the AI field itself evolves rapidly, which eventually feeds the specific applications in which the EU has a specialization advantage.

The analysis of specialization profiles in AI techniques shows that the EU is involved in head-to-head competition with the US more than with China. The EU is not very concentrated compared to other countries such as the US, China, or Japan. Europe specializes in rule machine learning, learning and ontology engineering and, to a lesser extent in expert systems and probabilistic graphic models. These are areas where the US is also very present, generally demonstrating higher levels of specialization. Interestingly, the EU specializes slightly more than the US and slightly less than China in generative AI. The major difference between the EU and the US is that the US industrial profile has changed dramatically from 1990 to 2022. The US used to be more diversified with high levels of specialization in support vector machines, multi-task learning, supervised and unsupervised learning, classification and regression trees, and expert systems, all areas where the level of specialization is now below 0. The Chinese profile has been more stable over time and concentrated in different areas. For instance, China displays the highest levels of specialization in support vector machine, fuzzy logic, and multi-task learning. China also specializes in generative AI, classification and regression trees, deep learning, and reinforcement learning. It is worth highlighting the similarity between France and Germany in their profiles, with the noticeable exception of generative AI, where France is absent. It is also interesting to see how diversified China and Europe and its member states are. Unlike China, the EU, Germany, and France, all other countries are very specialized with only three or four techniques exhibiting positive levels of RSAs.

Finding 13. Concerning AI techniques since 2011, and by decreasing order of specialization, the top five areas of specialization are as follows. In Europe:

1. Ontology engineering
2. Rule learning
3. Machine learning
4. Generative AI
5. Probabilistic graphical models

In the US:

1. Rule learning
2. Machine learning
3. Ontology engineering
4. Probabilistic graphical models
5. Expert systems

In China:

1. Support vector machines
2. Fuzzy logic
3. Multi-task learning
4. Classification and regression trees
5. Deep learning

Focusing on the specialization profile in AI-related functions, the significant drop of the EU in control methods, text-speech recognition, speech recognition, speaker recognition, dialogue, and distributed artificial intelligence is striking. The EU keeps specializing in control methods (but less than the US) and computer vision. Character recognition and natural language processing are the only domains with higher levels of specialization in 2022 than in 1990 (but their respective RSA remain below 0). Overall, the EU specialization profile in AI functions is quite weak, with only three domains showing RSAs significantly greater than 0 (namely, control methods, computer vision and, to a lesser extent, scene understanding and video for robotics). The US concentrates on AI dedicated to control methods, natural language processing, text-speech and speech recognition. It also exhibits high levels of specialization in dialogue and computer vision. The figure also shows that, over time, the EU dramatically reduced its attention to information extraction, planning and scheduling, image and video segmentation, and scene understanding and video for robotics. Finally, China has dramatically increased its positions in information extraction, image and video segmentation, planning and scheduling and semantics. It remains inactive in distributed artificial intelligence and has almost withdrawn completely from control methods. Looking at countries within the EU, Germany has a very strong position in control methods, whereas France concentrates more on character recognition. However, they both share high levels of specialization in computer vision, and scene understanding and video for robotics. It is easy to suspect a relationship between a specialization in AI functions and AI industrial applications.

Finding 14. Concerning AI functions since 2011, the top five areas of specialization in decreasing order are as follows: In Europe:

1. Control methods
2. Computer vision
3. Scene understanding and video for robotics
4. Speaker recognition
5. Biometrics

In the US:

1. Control methods
2. Natural language processing
3. Speech recognition
4. Text-Speech recognition
5. Dialogue

In China:

1. Distributed artificial intelligence
2. Information extraction
3. Planning and scheduling
4. Image and video segmentation
5. Semantics

The European pattern of specialization in applications in both the EU and the EZ is quite balanced with a relatively high degree of specialization in AI devoted to the life sciences and entertainment. Interestingly, the profile of EU industry specialization has evolved over the 20 years of observations. The specialization in network industries, business, and, to a lesser extent agriculture, has declined, but the specialization in cybersecurity has increased. Also interesting is the lack of distinctiveness in specialization compared to the US. Indeed, the US is also specialized in entertainment and even more concentrated on the life sciences and cybersecurity than the EU. It also shares its weakness in energy maintenance and its moderate position in banking and finance. The difference is that at one point the US shared the leadership in energy management with China, but became one of the weakest countries in this domain. Finally, compared to Europe, the US is more specialized than Europe in the application category labelled industry and manufacturing. China has a very different profile with very high levels of specialization in AI devoted to agriculture, telecommunications, industry and manufacturing, networks, neural networks, and education. Note that China's profile has remained stable over time. The only significant progress made over the last 20 years is in business, document management and text processing, and energy management at the expense of personal devices, computing and HCI (human-computer interaction), and entertainment.

Finding 15. Concerning AI applications since 2011, the top five areas of specialization in decreasing order are as follows. In Europe:

1. Transportation
2. Life and medical sciences
3. Personal devices, computing and HCI
4. Energy management
5. Cybersecurity

In the US:

1. Personal devices, computing and HCI
2. Business
3. Document management and text processing
4. Banking and finance
5. Cybersecurity

In China:

1. Agriculture
2. Industry and manufacturing
3. Telecommunications
4. Education
5. Networks

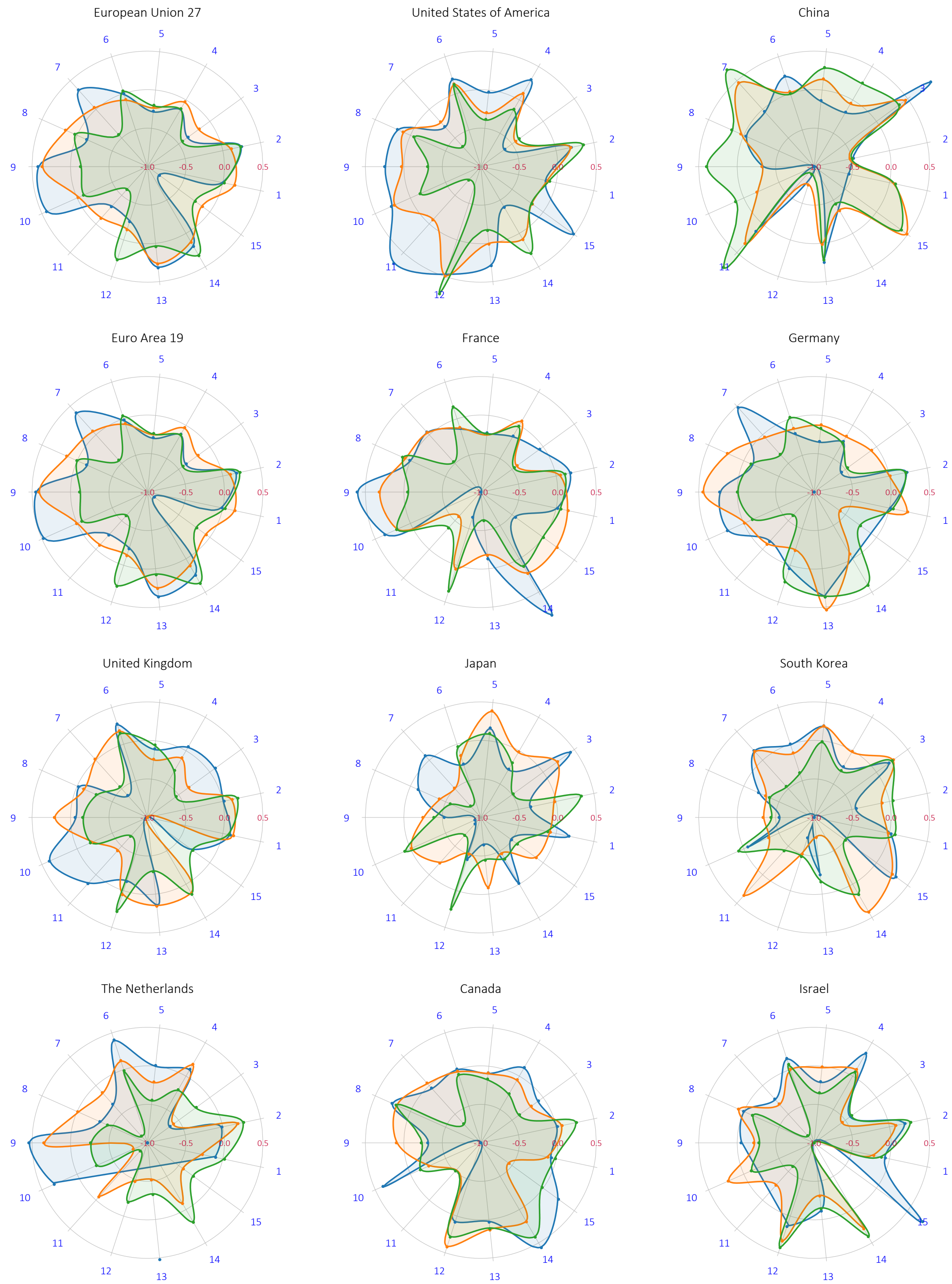
One last remark concerns the values taken by our specialization measure. Recall that positive values of the index denote specialization, with values closer to 1 implying significant specialization. One salient feature in the observed levels of specialization is that Europe has systematically lower values, most of them closer to 0, and sometimes below 0. These results suggest that Europe, unlike the US and China, does not exhibit a specific specialization pattern with regard to AI techniques, functions, and applications. After a closer look at individual countries, these lower levels of specialization are the result of individual EU countries not exhibiting clear patterns of specialization, more than the result of blending together countries with different — and pronounced — specialization patterns.

Finding 16. Unlike the US and China, Europe does not display a specific specialization profile with regard to AI techniques, functions, and applications. This lack of specialization is the result of individual EU countries not exhibiting clear patterns of specialization. Therefore, there is no process of Ricardian specialization in European member states, contrary to what we observe for the US or China. This fact can provide a policy opportunity: through coordination and support, the EU as a whole has a great deal of room for action to steer the direction of AI development towards specific areas.

The $nRSA$ index is a measure that characterizes the degree of specialization of a country in a single AI domain. Alternatively, one could define specialization as a measure of the concentration of patents across the various AI domains–techniques, functions, and applications. To measure this concentration, we use the simple Herfindahl-Hirschman Index (HHI), defined as:

$$HHI_c = \sum_d \alpha_{c,d}^2 \tag{3}$$

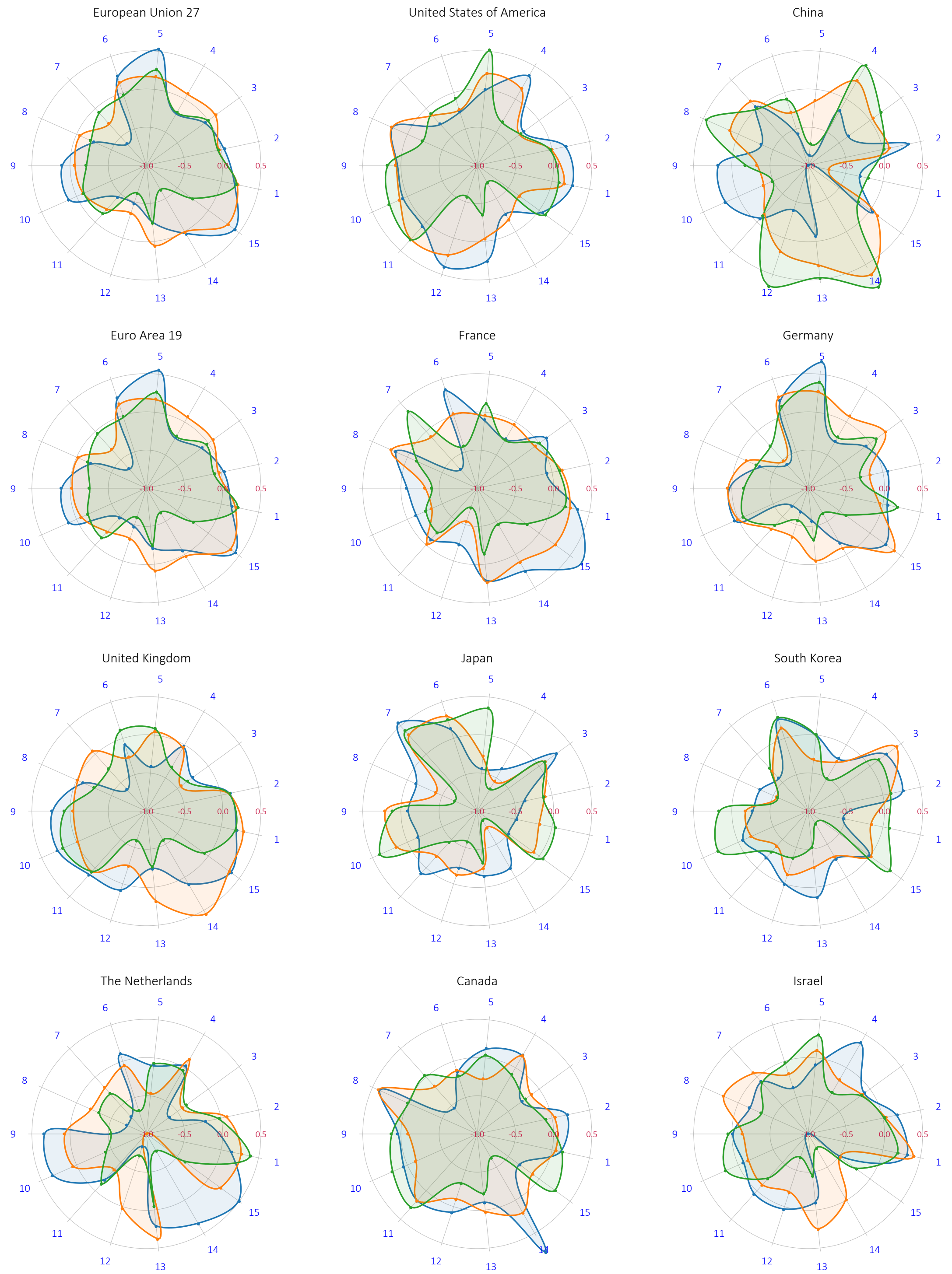
Figure 8: Normalized $nRSA$ in AI techniques (patent data)



1. Neural networks; 2. Machine learning; 3. Deep learning; 4. Unsupervised learning; 5. Reinforcement learning;
6. Probabilistic graphical models; 7. Fuzzy logic; 8. Expert systems; 9. Classification and regression trees; 10. Supervised learning;
11. Support vector machines; 12. Rule learning; 13. Generative AI; 14. Ontology engineering; 15. Multi-task learning.

Blue area is for period 1990-2000. Orange area is for period 2001-2010. Green area is for period 2011-2022

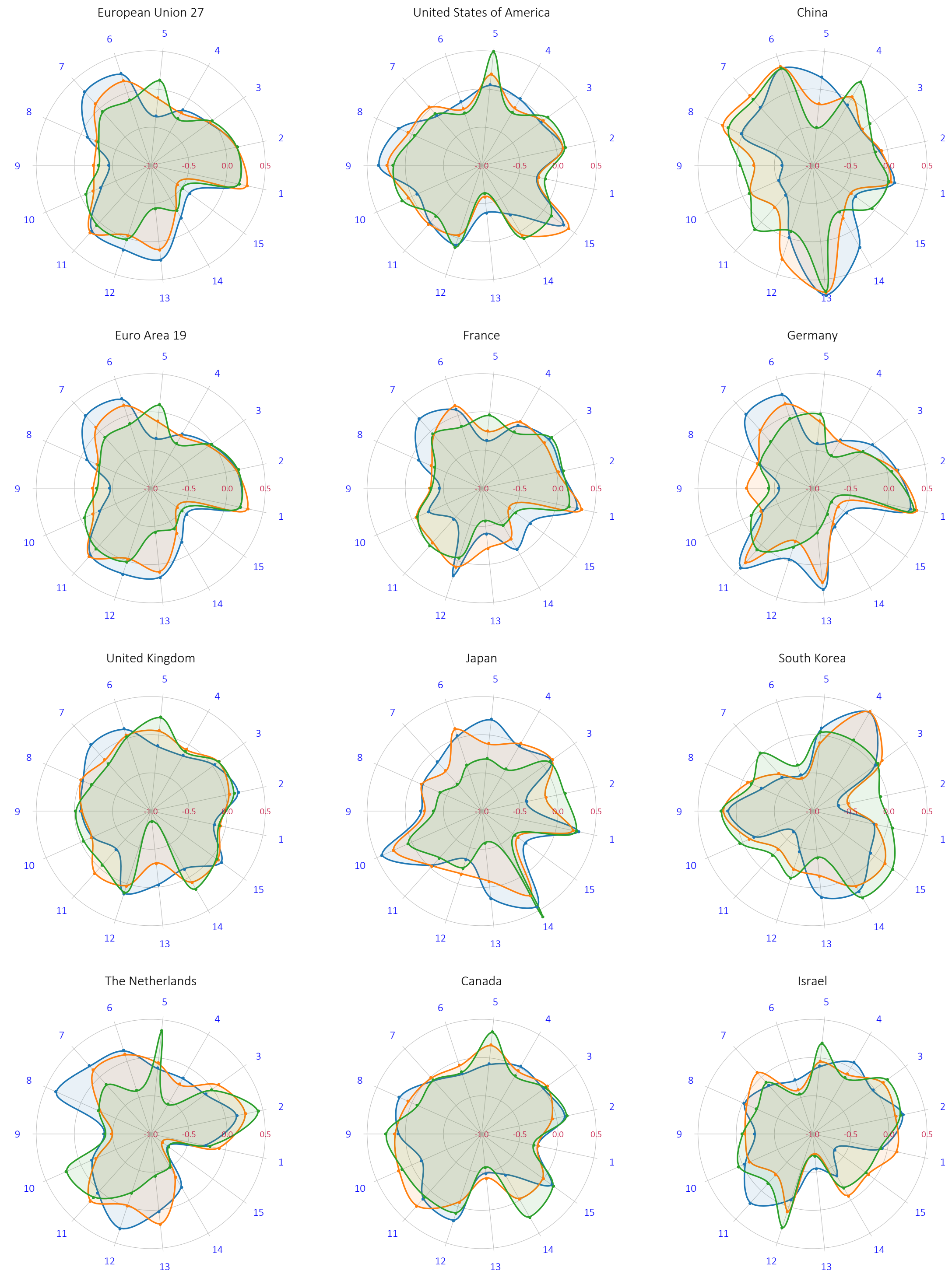
Figure 9: Normalized $nRSA$ in AI functions (patent data)



1. Computer vision; 2. Biometrics; 3. Scene understanding and video for robotics; 4. Planning and scheduling; 5. Control methods; 6. Speaker recognition; 7. Character recognition; 8. Semantics; 9. Text-Speech recognition; 10. Speech recognition; 11. Natural language processing; 12. Information extraction; 13. Image and video segmentation; 14. Distributed artificial intelligence; 15. Dialogue.

Blue area is for period 1990-2000. Orange area is for period 2001-2010. Green area is for period 2011-2022

Figure 10: Normalized $nRSA$ in AI applications (patent data)



1. Transportation; 2. Life and medical sciences; 3. Security; 4. Telecommunications; 5. Personal devices, computing and HCI; 6. Industry and manufacturing; 7. Networks; 8. Education; 9. Business; 10. Document management and text processing; 11. Energy management; 12. Cybersecurity; 13. Agriculture; 14. Entertainment; 15. Banking and finance.

Blue area is for period 1990-2000. Orange area is for period 2001-2010. Green area is for period 2011-2022

where $\alpha_{c,d} = P_{c,d}/\Sigma_d P_{c,d}$, and where d is any of the particular AI techniques, functions, and applications. This index is a measure of the concentration of patents in particular fields. Its maximum value of 1 indicates that the actor's patent production is concentrated in a single field, while a minimum value closer to 0 indicates that the patent production is diversified.[21] If a country has a uniform distribution of patents across AI domains, its degree of specialization is low. If, on the contrary, its technological profile is very pronounced, its values come closer to unity.

Table 8 displays the concentration measures along the TFA value chain for a limited number of countries. The top group displays the four main geographic areas of interest: Europe (the EU and the EZ), China, and the United States. We then grouped the countries together based on their geographic and economic homogeneity. The second group consists of European countries. The third group includes Asian countries. The last group consists of other OECD countries.

We note the following. First, overall, the values of the concentration index indicate rather low levels of concentration across the entire value chain, implying that countries have rather dispersed portfolios of competences across the AI TFA value chain. Second, all countries exhibit higher levels of concentration in upstream competences, meaning in their AI techniques, than in downstream functions and applications. One way to interpret this finding is to imagine that countries "bet" on one (or a subset of) technique(s) to become the dominant underlying engine of AI systems in a given period, and therefore allocate inventive efforts in a more concentrated fashion. Alternatively, the result could reflect the progressive formation of a

[21] When the number of categories reaches infinity, the lower bound is indeed 0. In our case, the number of categories is fairly low: 23 for AI techniques, 27 for AI functions, and 22 for AI applications. Therefore, we must adjust the HHI index as follows: $nHHI_c = \frac{HHI-n^{-1}}{1-n^{-1}}$. Doing so ensures the comparability of the measures across domains, and normalizes their range to the 0-1 interval. To keep the notation simple, we called our normalized $nHHI$, based on its non-adjusted value HHI.

Table 8: HHI index per country (period 1990-2021)

	Patents			Publications	
Country name	T	F	A	T	F
European Union 27	0.094	0.057	0.076	0.037	0.037
Euro Area 19	0.093	0.055	0.078	0.037	0.037
China	0.097	0.074	0.049	0.051	0.039
United States	0.101	0.047	0.051	0.045	0.042
Finland	0.118	0.048	0.057	0.042	0.032
France	0.088	0.063	0.075	0.043	0.038
Germany	0.094	0.061	0.101	0.040	0.044
Italy	0.098	0.052	0.077	0.036	0.034
Netherlands	0.112	0.065	0.098	0.039	0.036
Spain	0.086	0.069	0.095	0.035	0.033
Sweden	0.118	0.091	0.065	0.040	0.048
India	0.125	0.042	0.043	0.038	0.027
Japan	0.112	0.066	0.062	0.044	0.045
Singapore	0.129	0.101	0.063	0.044	0.037
South Korea	0.114	0.095	0.077	0.056	0.049
Taiwan	0.108	0.105	0.052	0.048	0.034
Australia	0.086	0.063	0.093	0.041	0.044
Canada	0.099	0.047	0.048	0.042	0.047
Israel	0.117	0.066	0.078	0.047	0.041
Switzerland	0.112	0.075	0.090	0.049	0.055
United Kingdom	0.115	0.062	0.060	0.035	0.034

See equation 3 for details about the HHI index. T: AI techniques; F: AI functions; A: AI applications. Source: PATSTAT Autumn 2023 Edition. Calculations of the Authors. Countries are grouped by geographic and cultural homogeneity. The top group displays the four main geographic areas of interest. The second group consists of European countries. The third group includes Asian countries. The last group consists of other OECD countries.

"dominant design" in AI techniques over time, with a few approaches preferred over others. Third, Europe, whether the EU or the EZ, has medium levels of concentration values, and its constituent countries display levels of concentration values that are similar to other non-European countries.

Finding 17. The overall values of concentration along the entire value chain are low. This finding suggests that countries have rather dispersed portfolios of competences across the TFA value chain. There is more concentration of effort in upstream competences, meaning in AI techniques, than in downstream functions and applications. AI techniques offer a range of services — functions and applications. Therefore, countries allocate inventive efforts to fewer AI techniques, especially as some of them become dominant in the field over time. Europe, whether the EU or the EZ, has medium levels of median concentration values, and its constituent countries has medium levels of concentration values, and its constituent countries display levels of concentration values that are similar to other non-European countries.

5 Measuring integration

Our conception of sovereignty is rooted in the idea that the portfolio of competences of countries must be complementary to one another in order to yield services that cannot be reduced to their independent use. Applied to the AI TFA framework, sovereignty can be measured as the aggregate level of complementarity between the various AI domains of expertise in AI techniques, functions, and applications. This implies that one must quantify complementarity between techniques and functions on one hand, and between functions and applications on the other. One can then aggregate the complementarities over the value chains in which countries enjoy a specialization advantage.

5.1 Complementarity between AI TFA domains

We exploited the fact that a single patent can be jointly assigned to techniques, functions, and applications. For example, a patent might use the techniques of "Probabilistic graphical models" to produce "Computer vision" services for "Transportation". Our intuition is that this combination constitutes a consistent, coherent (Nesta & Saviotti 2005) value chain. More specifically, if we combined the techniques, functions, and applications randomly, the number of possible combinations to be analyzed would be extensive. Thus, the 23 techniques combined with the 27 functions might yield 22 applications, giving rise to more than 13,000 possible value chains. Therefore, we claim that the actual combinations are meaningful and suggest an order led by synergies.

Our goal is to develop a statistical measure of complementarity that exploits joint frequencies. Similar to Teece et al. (1994), we base our measure of complementarity on the survival principle. We assume that combinations of techniques and functions, and of functions and applications that are more productive are more complementary. We also maintain that they will occur more frequently than less productive ones. Hence, we first counted the frequency of joint occurrences of techniques and functions (what we call TF co-occurrences), and of functions and applications (what we call FA co-occurrences). We then compared the observed TF and FA joint frequencies with their expected ones, should such joint frequencies occur randomly. An observed number of joint frequencies greater than their expected value reveals a positive association, a "mutual" attraction, or, one could say, a complementarity between techniques and functions (alternatively, between functions and applications). Conversely, should the expected frequencies exceed the observed ones, we would conclude that the two AI domains exclude one another, and hence are not complementary to one another. Insert 7 provides the statistical details of our approach.

Insert 7. Measuring complementarity

AI techniques and functions are complementary when their combination leads to services that are not reducible to their independent use. To assess complementary techniques and functions, we follow Nesta (2008) and quantify complementarity between any AI technique $t \in \{1, 2, \cdots, t, \cdots, T\}$ and any AI function $f \in \{1, 2, \cdots, f, \cdots, F\}$. Let the technological universe consist of K patent applications. Let $P_{tk} = 1$ if patent k is assigned to AI technique t, and 0 otherwise. The total number of patents assigned to technique t is thus $O_t = \sum_k P_{tk}$. In the same vein, let $P_{fk} = 1$ if patent k is assigned to AI function f, and 0 otherwise. The total number of patents assigned to function f is thus $O_f = \sum_k P_{fk}$. The number O_{tf} of observed joint occurrences of AI technique t with AI function f is $\sum_k P_{tk} P_{fk}$.

Given this setting, let us now define a random variable X_{tf} as the number of patents assigned to both technique t and function f under the assumption of random joint occurrence. Then, X_{tf} can be considered a hypergeometric random variable of mean μ_{tf} and variance σ^2_{tf} as follows (population K, number of successes O_t and sample size O_f):

$$\mu_{tf} = E(X_{tf} = x) = \frac{O_t O_f}{K} \tag{4}$$

$$\sigma^2_{tf} = \mu_{tf} \left(\frac{K - O_t}{K} \right) \left(\frac{K - O_f}{K - 1} \right) \tag{5}$$

If the actual number O_{tf} of co-occurrences observed between AI technique t and AI function f greatly exceeds the expected value σ^2_{tf} of random joint occurrences, then technique t and function f are highly complementary. Inversely, when $O_{tf} \leq \mu_{tf}$, AI technique t and AI function f are deemed as excluding one another, meaning they do not complement one another. Thus, complementary τ is defined as follows:

$$\tau_{tf} = \frac{O_{tf} - \mu_{tf}}{\sigma_{tf}} \tag{6}$$

Typically, τ_{tf} is a real number that can be positive or negative and may be thought of as the degree of complementarity between couples of techniques and functions. The same logic can be applied to quantify how AI functions apply to specific AI-related applications. Define AI applications a such that $a \in \{1, 2, \cdots, a, \cdots, A\}$. Now let $P_{ak} = 1$ if patent k is assigned to AI application domain a, and 0 otherwise. The total number of patents assigned to AI-related application a is thus $O_a = \sum_k P_{ak}$. We then define μ_{fa}, σ^2_{fa} and τ_{fa} as, respectively:

$$\mu_{fa} = E(X_{fa} = x) = \frac{O_f O_a}{K} \tag{7}$$

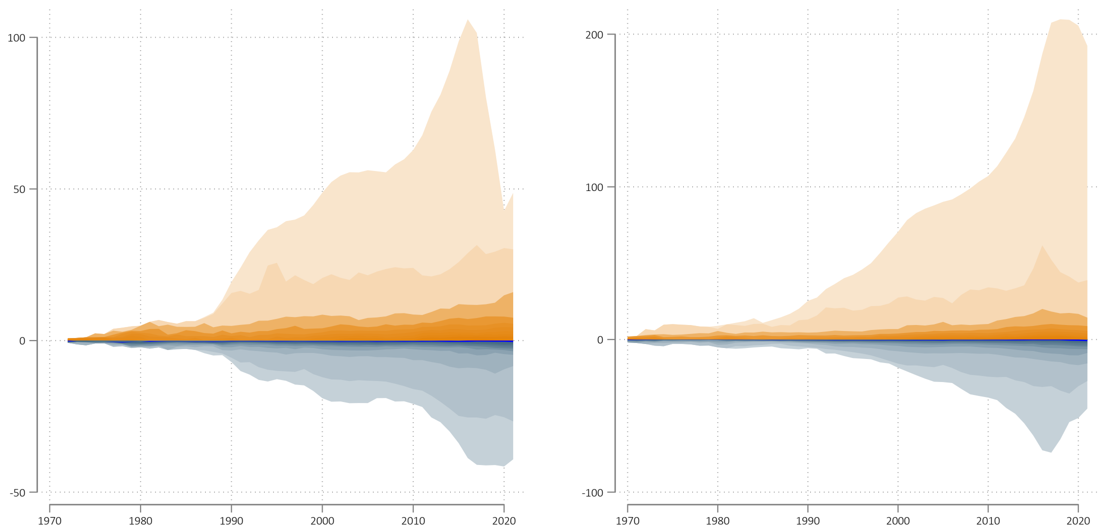
$$\sigma^2_{fa} = \mu_{fa} \left(\frac{K - O_f}{K} \right) \left(\frac{K - O_a}{K - 1} \right) \tag{8}$$

$$\tau_{fa} = \frac{O_{fa} - \mu_{fa}}{\sigma_{fa}} \tag{9}$$

Again, τ_{fa} is a real number that can be positive or negative and may be thought of as the degree of complementarity between couples of functions and applications.

Figure 11 displays the evolution of the distribution of τ_{tf} (panel a) and τ_{fa} (Panel b) over the period of 1970 to 2020. Overall, the two panels display a strikingly similar pattern in which, initially, complementarities, and their lack thereof, are poorly defined. This pattern spans more than two decades, from 1970 to 1990. This initial period corresponds to the phase in which ICT technologies became increasingly pervasive in productive activities.

Figure 11: The dynamics of complementarity



(a) Techniques-Functions (TF) τ (b) Functions-Applications (FA) τ

These graphs display the distribution of complementarity measures τ over time, from the minimum to the maximum measures, and by darkening each every fifth percentile towards the median. Orange (resp. blue) colors depict positive (resp. negative) complementarity measures τ. Source: EPO PATSTAT (Ed. Autumn 2023). Authors' own calculations.

From the early nineties to the late 2010s, we observe an increase in the variability of complementarities. Significant positive ones grow and, as in a mirror, negative ones become clearer. This process exemplifies the fact that complementarities between AI techniques and AI functions, and between AI functions and AI applications, become gradually identified, and others are ruled out as a result of experimentation. This second phase matches the systematization of AI developments in scientific and applied fields. During this period AI continues to advance despite the lack of the widespread attention paid to it that it will receive from 2010 onwards.

Starting in the early 2010s, the last phase corresponds to the rise of deep learning-driven AI as a well-bounded technology. It builds on the access to larger datasets and better computational capabilities. These are the two conditions needed for AI algorithms to be trained and expanded for a variety of potential uses. It is thus not surprising to witness an increase in the range of the distribution, reaching very high positive and negative values. These results indicate that the TFA landscape is consolidating around better-identified sets of techniques, functions, and applications, and determinations about how to combine them in a way that yields services that cannot be reduced to their independent usage.

Finding 18. The TFA value chain of AI is becoming more and more structured around better-identified combinations of techniques, functions, and applications that, when linked together, yield services that cannot be reduced to their independent usage. This development grows in successive waves that suggest the possibility for future waves to occur.

5.2 Integration as a measure of technological sovereignty

The fact that a country specializes in several AI techniques, functions, and applications raises the question of the consistency of specializations throughout the AI value chain. For example, medical applications are essentially based on image and video segmentation and, to a lesser extent, control methods and computer vision (functions). However, image and video segmentation is largely based on unsupervised learning and fuzzy logic techniques. Therefore, a coherent value chain for a country specializing in medical applications suggests specialization in the relevant functions and techniques. The degree of integration is an indicator of the complementarity of the innovation chain. It assesses a country's ability to create and benefit from the value produced from its areas of specialization.

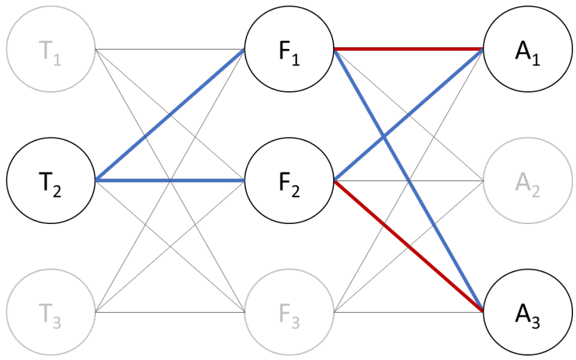
The information contained in patents and their breakdown into AI techniques, functions, and applications can be used to characterize the degree of integration of the AI innovation value chain. We interpret technological sovereignty in AI as the capacity to mobilize local AI-related competences to develop AI-related innovations: a country will exhibit a degree of integration when it masters the competences that appear to be complementary in the AI value chain. There are two ideas in this intuitive definition. First, countries must exhibit specialization in some AI-related areas, whether technical, functional, or application-related. Second, these exhibited levels of specialization between techniques and functions, and between functions and applications, must be complementary. Given this setting, and abstracting from the country and time indexes, we measured the overall TFA integration for a single application domain Γ_{TFA} as in the following:

$$\Gamma_{TFA,a} = \sum_{t \in T} \tau_{tf} \times \alpha_t \times \xi_t + \sum_{f \in F} \tau_{fa} \times \alpha_f \times \xi_f \tag{10}$$

where τ_{tf} and τ_{fa} are defined as in Equations 6 and 9, respectively. Variables α_t and α_f represent shares of techniques and functions in overall patents, i.e. $\alpha_t = P_t / \sum_t P_t$ and $\alpha_f = P_f / \sum_f P_f$, respectively. Last, variables ξ_t and ξ_f represent indicator variables, taking value 1 if the normalised value of RSA in technique t and function f are positive, 0 otherwise, i.e. $\xi_t = \mathbb{1}(RSA_t > 0)$ and $\xi_f = \mathbb{1}(RSA_f > 0)$, respectively.

To better understand the spirit of the measure, Figure 12 represents the AI innovation value chain with three AI techniques, three AI functions, and three AI applications. The result is 27 possible technique-function-application chains with the total number of possible chains amounting to 1,000. Now let us imagine a

Figure 12: AI innovation value chain for a fictitious country



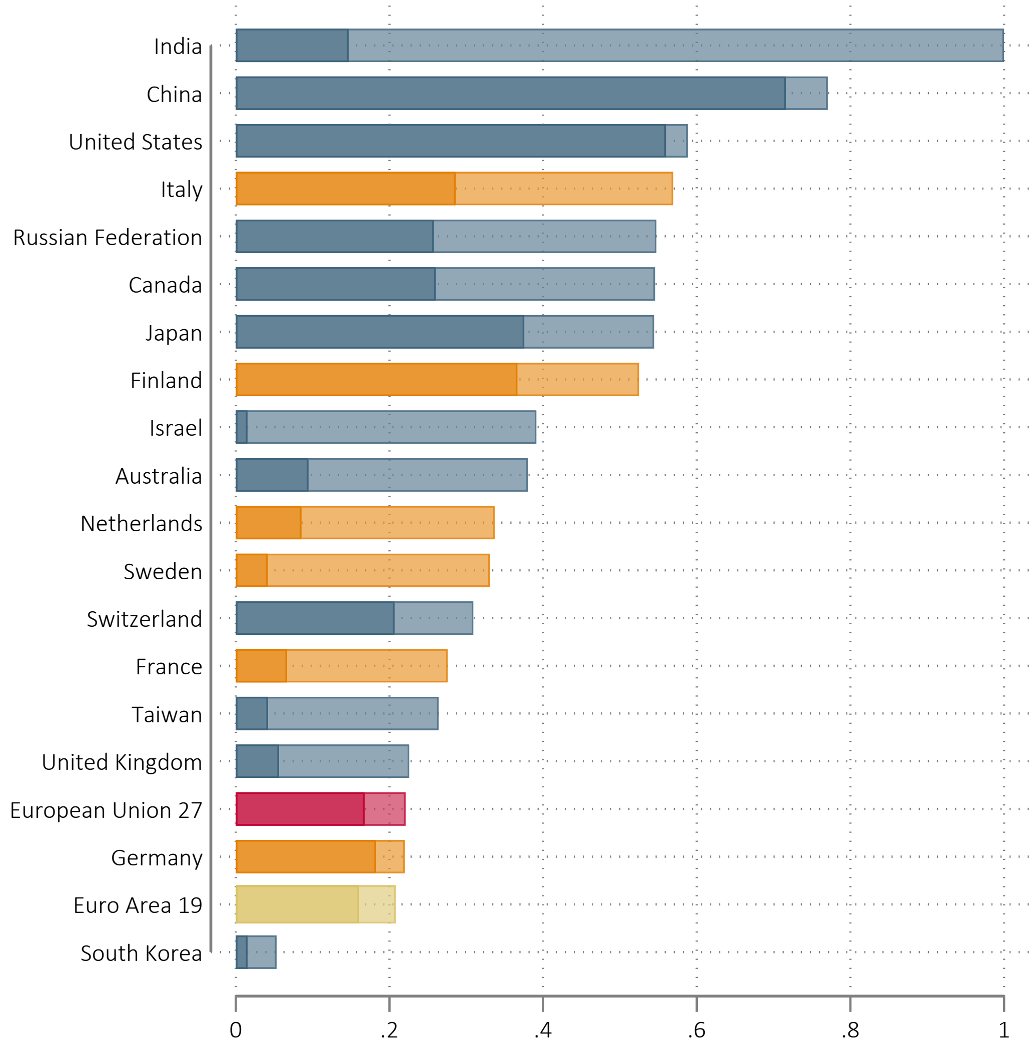
country specializing in technique T2, functions F1 and F2, and applications A1 and A3, implying that $\xi_{T1} = 1$, $\xi_{F1}, \xi_{F2} = 1$, and last $\xi_{A1} = 1$ and $\xi_{A3} = 1$. The edges between the vertices represent the degree of complementarity between the techniques, functions, and applications (τ_{tf} and τ_{fa}). Edges in bold represent complementarities that are relevant for this country because they correspond to the revealed areas of specialization. As Figure 12 indicates, there is a positive association between technique T2 and the functions F1 and F2 (blue edges). In addition, there is a negative association between the function F1 and the application A1 (red edge), but a positive association with the function A3 (blue edges), unlike the function F2. Overall, the degree of integration is the sum of the observed complementarities (the bold edges) linking the vertices corresponding to areas of AI specialization. This degree of integration can be either positive or negative, depending on whether countries specialize in areas that complement or exclude one another. We interpret this measure as indicating the complementarity between the TFA domains.

Take the European Union as an example. As we have already seen, the EU specializes in “Ontology engineering”, “Rule learning”, “Machine learning”, “Generative AI”,“probabilistic graphical models”. It also specializes in “control methods” and “computer vision”. Last, it serves “ Transportation”, “Life and medical sciences", "Personal devices, computing and HC", "Energy management" and "Cybersecurity" as destination markets. In total, for the EU, there are 7 techniques with positive specializations, 2 functions and 5 applications with positive specializations too, yielding $7 \times 2 \times 5 = 70$ possible value chains. In addition, "Ontology engineering", a technique in which the EU has its strongest comparative advantage, is never combined with "Control methods", and is only poorly complementary to "Computer vision", a function in which the EU has also developed a comparative advantage. Finally, "Computer vision" and "Control methods" are both highly complementary to "Transportation", and also to " Life and medical sciences". The degree of integration is simply the sum of the degrees of complementarity observed (between techniques and functions, then between functions and applications) along these 70 possible chains.

An important feature of our measure of integration is that it can be decomposed into two parts such that $\Gamma_{TFA,a} = \Gamma_{TF,a} + \Gamma_{FA,a}$, where $\Gamma_{TF,a} = \sum_{t \in T} \tau_{tf} \times \alpha_t \times \xi_t$ and $\Gamma_{FA,a} = \sum_{f \in F} \tau_{fa} \times \alpha_f \times \xi_f$. Doing so improves our ability to determine whether the locus of integration is located more in upstream integrations ($\Gamma_{TF,a}$) or downstream integrations ($\Gamma_{FA,a}$).

Figure 13 displays the levels of integration among the top patenting countries over the TFA AI value chain. The yellow-red bar allows us to distinguish between TF integration and FA integration: the length of the bar up to the yellow-red bar represents the value of the integration over techniques and functions (TF integration), while the remainder of the bar represents the integration over functions and applications (FA integration). Mean values are normalized to 1 for the frontier value (India). As the figure indicates, Europe, whether the EU or the EZ, exhibits one of the lowest levels of integration. The United States and China belong to the other end of the spectrum, with values of integration reaching 60% and 80% of the

Figure 13: Mean TFA Integration across countries (1991-2021)



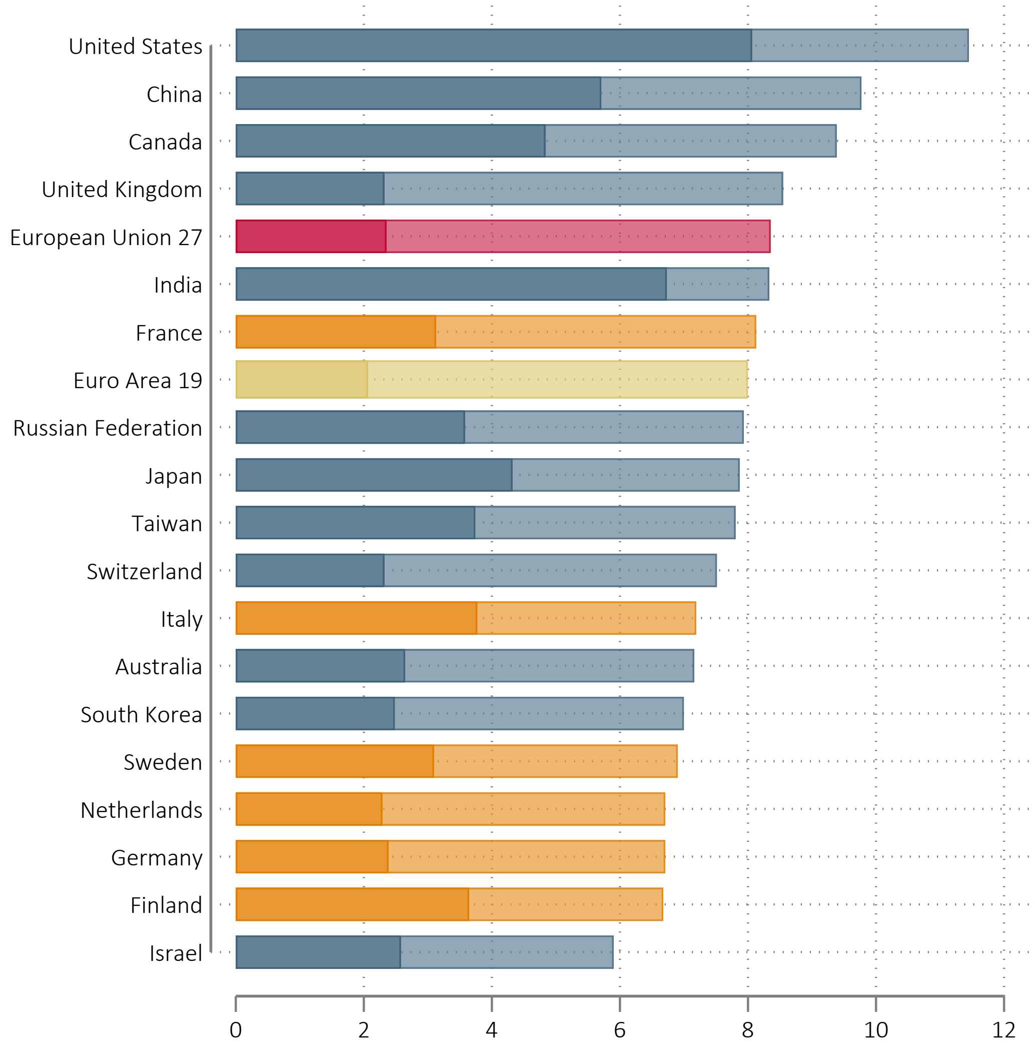
The overall bar represents the value of integration over the Technique-Function-Application value chain (TFA integration). The darkened left hand side of the bar represents the value of integration over techniques and functions - TF integration). The light-color right-hand-side of the bar represents the value of integration over functions and applications (FA integration). Mean values are normalized to 1 for the frontier value (India). Source: EPO PATSTAT (Ed. Autumn 2023). Authors' calculations.

highest value in the dataset belonging to India. Within Europe, Italy displays the highest level of integration, together with countries such as Finland, Sweden, and the Netherlands. France and Germany have low levels of integration and drive the overall poor performance of Europe regarding integration.

Finding 19. Contrary to the United States and China, Europe exhibits low levels of integration. Within Europe, Italy displays the highest level of integration, together with countries such as Finland, Sweden, and the Netherlands. France and Germany have low levels of integration.

Bearing in mind that what we wish to characterize is AI value chain sovereignty, one may want to characterize it from the AI application domain where countries specialize and wonder whether it is locally integrated. In other words, one key aspect determining integration is the number of application areas where countries specialize and see whether these exhibit positive values of integration. Figure 14 displays the number of AI application domains, averaged over the 1991-2021 period, where countries exhibit actual specialization ($nRSA > 0$). Europe exhibits a relatively high number of AI application domains where it has specialized, with a value of about 8 domains, out of 22 possible application fields. However, only few of them are not integrated, implying that technological sovereignty is not achieved in most application areas where Europe has specialized. Conversely, the USA exhibits not only a high number of application domains where it specializes (around 11 on average), but also an impressively high share of them is integrated (around 8 on average), implying technological sovereignty. Last, most European countries have a relatively low number of AI application domains where they specialize, but their share is also, on average, lower. Altogether, whether we focus on Europe as a whole or individual countries, AI application domains with both specialization and integration are rare in Europe, more than in other location in the world.

Figure 14: Mean number of AI applications areas with positive $nRSA$ (1991-2021)



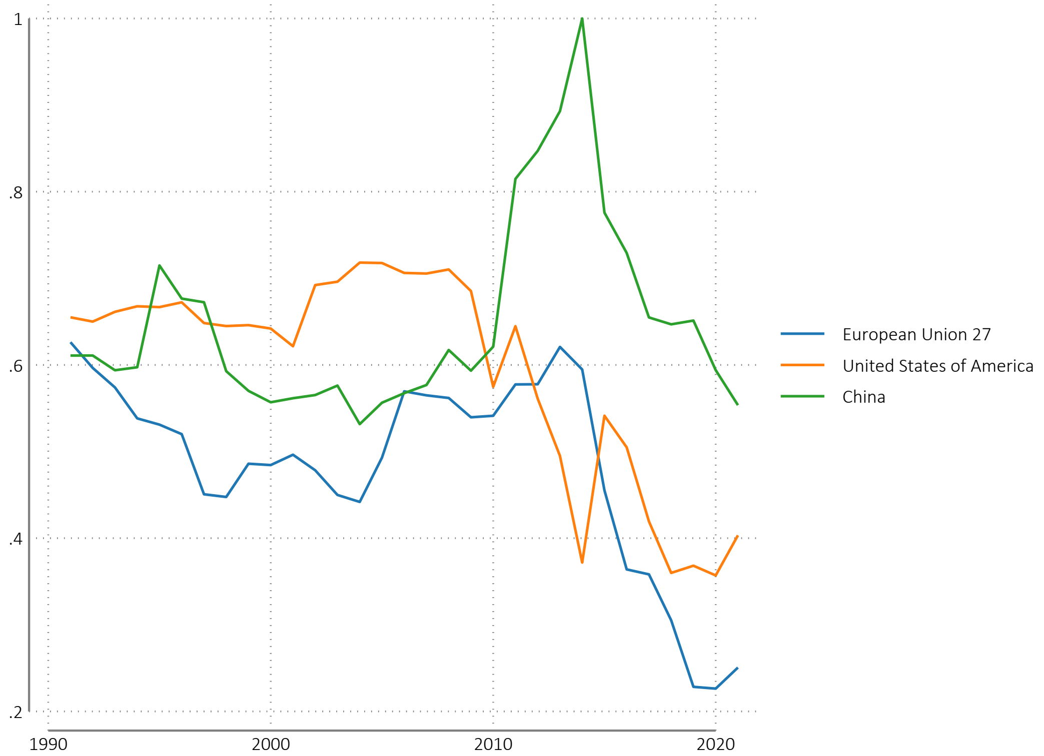
The overall bar represents the mean number of AI application domains where countries exhibit specialization ($nRTA > 0$). The darkened left hand side of the bar represents the number of integrated AI application domains. Source: EPO PATSTAT (Ed. Autumn 2023). Authors' calculations.

Finding 20. Europe exhibits a relatively high number of AI application domains where it has specialized. However, many of them are not integrated, implying that technological sovereignty is not achieved over these areas of specialization. More fundamentally, whether we focus on Europe as a whole or individual countries, AI application domains with both specialization and integration are rare in Europe, more so than in any other location in the world.

Figure 15 displays the dynamics of TFA integration between 1991 and 2021 for the three major geographic areas: Europe, the United States, and China. As the figure illustrates, while all three regions exhibited a similar level of integration until 2010, the dynamics followed somewhat different paths until 2015, with China's level of integration rising and that of the US and Europe declining substantially. We find it striking that the advent of deep learning in 2012 and its subsequent diffusion eventually translated into a significant decrease in integration in the three regions. This phenomenon illustrates the fact that integration over the value chain is an emerging property of the TFA specialization pattern, conditional on whether these TFA domains complement one another. It may very well be that the specialization of countries remained unchanged, whereas the diffusion of deep learning into a range of functions and applications redefined the most promising combinations of AI techniques, functions, and applications.

Finding 21. The advent of deep learning in 2012 and its subsequent diffusion eventually translated into a significant decrease in integration in the regions considered. This phenomenon illustrates the fact that integration over the AI value chain is an emerging property of the TFA specialization pattern, conditional on exogenous technical changes that countries drive only partially.

Figure 15: The dynamics of AI TFA Integration in major geographic areas



The mean values are normalized by the frontier value (India). Source: EPO PATSTAT (Ed. Autumn 2023). Authors' own calculations.

Another appealing feature of our measure of integration is that it can indicate whether each AI application in which a country specializes is rooted in a integrated value chain. Using previous findings on specialization in AI applications, we are now in the position to quantify each in terms of its normalized integration scores, as displayed in Table 9.

We have three main observations. First, the integration scores are all positive. This result implies that all value chains display positive complementarities on average, although some connections throughout the AI value chain may well be negative. Second, the locus of integration may vary a great deal, whether we consider upstream (Γ_{TF}) or downstream (Γ_{FA}) integration. For example concerning "Transportation"

Table 9: Integration score by top AI application specializations, by geographic area

AI application	Γ_{TFA}	Γ_{TF}	Γ_{FA}
		Europe	
Transportation	0.499	0.005	0.494
Life and medical sciences	0.334	0.067	0.267
Personal devices, computing and HCI	0.287	0.135	0.152
Energy management	0.266	0.067	0.199
Cybersecurity	0.295	0.125	0.169
		United States of America	
Personal devices, computing and HCI	0.330	0.064	0.265
Business	0.296	0.148	0.148
Document management and text processing	0.313	0.137	0.176
Banking and finance	0.296	0.157	0.140
Cybersecurity	0.302	0.214	0.088
		China	
Agriculture	0.327	0.216	0.111
Industry and manufacturing	0.370	0.069	0.301
Education	0.303	0.124	0.179
Networks	0.332	0.177	0.155
Telecommunications	0.306	0.136	0.170

Period 2011-2021. See equation 11 for details about the Γ index. TFA: techniques-functions-application integration; TF: techniques-functions integration; TF: functions-application integration. Source: PATSTAT Autumn 2023 Edition. Calculations of the Authors.

in Europe, the locus of integration is clearly located in the functions to applications complementarities, as previously observed. In contrast, the complementarities between techniques and functions are very poor. A similar pattern is evident concerning "Energy management" in Europe, "Personal devices, computing and HCI" in the US, and "Industry and Manufacturing" in China. Conversely, the locus of integration is located upstream in "Cybersecurity" in the US, and to a lesser extent in "Agriculture" in China. All other areas have a somewhat more balanced pattern in which there is integration throughout the entire value chain. Third, as exemplified by "Personal devices, computing and HCI" or by "Cybersecurity", two countries with significant specializations can exhibit different integration patterns. For example, with regard to " Cybersecurity", integration in Europe is more balanced throughout the TFA value chain than in the US, where integration is essentially upstream (TF integration). In a similar fashion, with regard to "Personal devices, computing and HCI", whereas integration in Europe is more balanced, that of the US leans more towards downstream complementarities (FA integration). Our interpretation is that this heterogeneity conceals local systems of innovation throughout the AI value chain involving specific public and private actors and specific sets of collaborations and interactions.

Finding 22. The locus of integration may vary a great deal with regard to areas of specialization, depending on whether we consider upstream (Γ_{TF}) or downstream (Γ_{FA}) integration. There are both cross-application variations (given the country) and cross-country variations (given the AI application). The heterogeneity in integration throughout the value chain is the expression of local systems of innovation throughout the AI value chain involving specific public and private actors and specific sets of collaborations and interactions.

6 Technological integration and innovation

Taking stock of our argument and findings, we have measured technological sovereignty as technological integration, that is, the ability to mobilize *local* competences that appear to be complementary throughout the TFA AI innovation value chain. We have found that China and the US have high levels of integration, higher than any other country in the world, with the exception of India. Should Europe be considered a country, it has a lower level of integration, implying that it might be unable to mobilize *locally* the competences needed throughout the AI value chain. In the realm of *AI applications* Europe's relative advantage in specialization rests on the required sets of *AI functions*, that themselves rely on locally available *AI applications*. We have also identified the areas of AI applications in which Europe's advantage in specialization is unlikely to hold in the long run, insofar as it is not supported by locally available complementary competences in AI functions and techniques. It is, one could argue, footloose specialization in AI applications.

What remains unclear is whether and to what extent sovereignty, defined as technological integration, and its measurement, actually matters for innovation in AI. The next section explores whether integration represents a source of innovation, above and beyond the chief role of the major determinants of patent production such as knowledge stocks, specialization, and country size.

6.1 Is integration a source of innovation?

To explore whether integration represents a source of innovation, we estimated a patent production function whereby new patents in a given area of AI applications a stem from the relative specialization in AI application a ($nRSA_a$), the existing stock of AI-related knowledge stock in patents and publication, measures of the concentration of patents across techniques, functions, and applications, and of course, integration as measured in Equation 10. Insert 8 provides more details on the estimating procedure and the series of control variables.

Insert 8. Estimation of the patent production function

We consider a Cobb-Douglas patent production function whereby new patents stem from an existing stock of knowledge, the latter being composed of both a stock of patents and of publications. The inclusion of these two variables might seem somewhat redundant at first glance. However, we maintain that these two variables embody distinctive competences and types of actors. Therefore, when introduced together, they characterize different combinations of incentive structures supporting the creation of innovation (Dasgupta & David 1994). Abstracting from subscript c accounting for country c, the model reads as follows:

$$k_{a,1} = AK_0^{\beta_K} S_0^{\beta_S} \mathbf{C_0}^{\mathbf{B_C}} \exp(\mathbf{B_Z Z_0} + \upsilon_{a,1}), \tag{11}$$

where k_a represent innovation in AI application a, and K and S represent overall patent and publication stocks (irrespective of the application domain a). Subscripts 0 and 1 indicate the timing of innovation, whereby additional patents in 1 come from existing stocks at the beginning of the period (hence, period 0). Note that we forward the dependent variable one year to avoid any spurious correlation between the dependent variable and the vector of explanatory variables. We decompose the disturbance term $\upsilon_{a,1}$ into a year specific effect controlling for common shocks across countries, a country-application fixed effect to control for unobserved but stable differences between country-domains of application, and an *iid* disturbance term such that, respectively: $\upsilon_{a,1} = \kappa_y + \iota_c + \varepsilon$.

Knowledge stocks, whether using patents or publications, are measured using the permanent inventory method whereby new patents feed an existing stock of past patents given a rate of obsolescence ϱ – set to 15% – such that $K_t = (1-\varrho)K_{t-1} + k_t$, where k_t are new patents (when computing the patent stock) or new publications (when computing the publication stock).

Vector Z includes the variables of interest: the level of expertise E and the level of integration Γ, both being specific to application a, so that $\mathbf{B_Z Z} = \beta_E E_{a,0} + \beta_\Gamma \Gamma_{a,0}$. What we call the level of expertise E is the relative specialization advantage RSA in application a. Integration is measured as in Equation 10, and reflects the complementarity of the value chain between the various domains of techniques and functions with application a. Finally, vector $\mathbf{C}$ represents a vector of controls, namely, population and GDP per capita to control for both country size and wealth. We augment vector $\mathbf{C}$ with the various measures of concentration HHI to control for the concentration of expertise across techniques, functions, and applications. We also include a variable "Openness" to control for international interactions between the national innovation system and other countries.[a]

Taking the log-transformation of Equation 11 allows us to estimate the coefficient using least squares estimation methods.

[a]This variable is computed as the share of co-patents with foreign institutions over the overall number of patents for country c, relative to (i.e. divided by) the same share pertaining to all other countries.

Our intuition is that more integrated countries will be better equipped to produce AI innovations, so that integration should support the production of new patents in AI applications. Given that knowledge creation draws on knowledge stocks, we expect the coefficient associated with patent stocks and publication stocks to be positive. We also expect the coefficient for the degree of expertise to be positive, implying that specialization in a given domain of applications has a positive effect on the creation of future innovations.

Table 10 provides the results of specification 11. We introduce the variables of interest sequentially, with the results appearing in Columns (1) to (4). In Column (1), we introduce the main control variables of knowledge stocks (patent and publication stocks), together with the normalized specialization index ($nRSA$). An important difference between $nRSA$ and the knowledge stock variables is that the latter do not pertain to AI applications specifically. Hence, their parameter estimates can be interpreted as the effects of knowledge capital in science and technology in general on the generation of AI-related patents. Instead, specialization is AI application specific, so that its parameter estimate must be interpreted as the effect of expertise in the given application on the generation of future innovations.

Not surprisingly, all parameters are positive and significant, implying that the level of expertise in AI applications and overall knowledge stocks are key ingredients of future innovation in AI-related patents. Regarding specialization ($nRSA_a$), a 1% increase in $nRSA$ leads to a 46% increase in patent generation. By the same token, a 1% increase in overall patent stocks leads to a 0.46% in AI-related patents in specific applications. The significance of publication stocks in patent generation corroborates the idea that innovation in AI is science-based. Hence, a 1% increase in publication stocks leads to a 0.1% increase in AI-related patents. Finally, the parameter estimates of the patent stocks is more than three times as large as that

Table 10: TFA local integration and the production of quality-weighted innovation

	(1)	(2)	(3)	(4)
$nRSA_a$	0.464***	0.452***	0.442***	0.445***
	(0.056)	(0.056)	(0.056)	(0.056)
Patent Stock (ln)	0.359***	0.360***	0.291***	0.294***
	(0.031)	(0.031)	(0.031)	(0.031)
Publication Stock (ln)	0.107***	0.106***	0.105***	0.102***
	(0.032)	(0.032)	(0.032)	(0.032)
TFA Integration (Γ_{TFA})		0.022**	0.024**	0.074***
		(0.010)	(0.009)	(0.021)
Openness			-0.262***	-0.260***
			(0.035)	(0.035)
TFA Integration × Openness				-0.023***
				(0.008)
T Herfindahl (patents)	-1.431***	-1.430***	-1.210***	-1.188***
	(0.442)	(0.443)	(0.423)	(0.425)
F Herfindahl (patents)	2.128***	2.181***	1.449***	1.538***
	(0.461)	(0.463)	(0.461)	(0.463)
T Herfindahl (publications)	0.750**	0.745**	0.892***	0.884***
	(0.303)	(0.302)	(0.290)	(0.289)
F Herfindahl (publications)	0.758***	0.750***	0.708***	0.706***
	(0.163)	(0.163)	(0.160)	(0.159)
Population (ln)	0.037	0.052	0.596**	0.556**
	(0.269)	(0.269)	(0.272)	(0.272)
GDP per capita (ln)	1.425***	1.419***	1.439***	1.434***
	(0.099)	(0.099)	(0.095)	(0.095)
R-squared	0.857	0.857	0.859	0.859
Within R-squared	0.197	0.197	0.206	0.207
Log Likelihood	-7,840	-7,837	-7,791	-7,787
LR test	-	5.44**	91.44***	8.78***

$N = 8,268$. Dependent variable: Quality-weighted number of innovation (number of patents). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a full vector of unreported year fixed effects and country-field of application fixed effects. Constant is omitted for the sake of clarity. The LR test is carried out comparing the unrestricted model (m) with the restricted model ($m-1$).

of the publication stocks. This result is in line with the idea that experience in patenting matters for future patent generation. Such experience includes problem-solving activities specific to the development of inventions, above and beyond the mere scientific challenges that it may embody. It also includes know-how in writing patents, legal competences in intellectual property rights, etc. Beyond experience, publications and patents do not necessarily come from the same institutions. For instance, universities and public research institutions may focus their effort on publishing much more than patenting. Similarly, while the number of private companies involved in scientific research is limited, the number of private firms involved in patenting is much larger. This factor might affect the relationship between publication stocks and patenting output. These aspects cannot be accounted for by looking at scientific capabilities only, as evidenced in the publication stocks. These conclusions hold for all models (Columns 1-4) displayed in Table 10, given the stability of the parameter estimates.

One major finding of our study is the significant and positive effect of integration. It confirms our intuition that integration as such is a positive input in patent creation. There are a number of reasons for this result. First, as suggested earlier, when the necessary expertise throughout the value chain is developed locally, organizations find it easier and cheaper to identify and coordinate their activities rather than searching for similar competences abroad. Second, the result also suggests the existence of local clusters where the sharing of information, of human capital, and their associated positive externalities act as positive ingredients for future innovation (Romer 1990). Another important element is that value chain integration reduces uncertainty, allowing for further complementary investments throughout the value chain (Amendola & Gaffard 1998).

Observe that the previous remark holds irrespective of the diversity of the countries' portfolio throughout the AI value chain. More specifically, all models control for the diversity of the countries in terms of AI techniques and functions, whether stemming from technologies (as assessed by patents) or from science (as measured in publication data). It is noteworthy that all concentration measures display positive coefficients, implying that more concentrated investments around key techniques and functions matter. The only exception to this contention relates to techniques as measured in the patent data. Conversely, the diversification of AI techniques in the patent data acts as a positive input for future innovation. Bear in mind that Table 8 has revealed that the concentration of investments in upstream competences is extensive, contrary to investments in downstream functions and applications. In fact, these results show that efforts to diversify investments into more AI techniques would be beneficial for innovation in AI applications.

Finally, in Columns (3-4), we introduce Openness, a variable measuring the propensity of the country to engage in international collaborations in patent activity. In Column (3), Openness figures negatively, implying that more international collaborations generate fewer patents pertaining to the country. This result does not mean that international collaborations are detrimental to innovation in AI. Rather, we interpret this result as a confirmation of the importance of local innovation systems. A strong propensity to collaborate with foreign partners reveals a lack of equivalent expertise locally. As explained, searching for partners abroad is costly and less stable relative to relying on local networks of partners. Furthermore, openness also results in a loss of innovative opportunities for local partners throughout the supply chain. Knowledge spillovers and innovation options generated by the collaboration may benefit customers and suppliers in the partner's country.

Finding 23. Integration is a source of innovation as it is a significant contributor to patent production. This finding suggests that developing local expertise throughout the entire value chain increases the innovative capacities of a country in AI-related innovation in specific application domains.

Finding 24. Other factors matter for innovation in AI. First and foremost, specialization in specific AI applications and overall knowledge stock are prime factors in patent production. Second, the innovation capacity of a country in AI is associated with the ability to develop a diverse portfolio of expertise in technical domains while concentrating investments in the development of a limited number of specific application domains and functions. A last but important finding relates to the negative effect of the propensity to collaborate with foreign partners, which confirms the important advantage of local innovation networks.

A key feature of our measure of integration is that it allows us to identify the distinctive role of upstream versus downstream integration. To do so, we simply need to rewrite Vector **Z** as $\beta_E E_{a,0} + \beta_{\Gamma_{TF}} \Gamma_{TF,a,0} + \beta_{\Gamma_{FA}} \Gamma_{FA,a,0}$. Coefficients $\beta_{\Gamma_{TF}}$ and $\beta_{\Gamma_{FA}}$ and their difference will provide information about the locus of integration as a source of future innovation. Table 11 re-runs the analysis exploiting the possibility of separating the upstream and the downstream integration effects. The signs, magnitude, and significance of the coefficients for the key variables tested ($nRSA$, patent and publication stocks, Openness) are stable compared to the results of the regressions with aggregate TFA integration. In this new setup, both the TF and FA integrations are positive and significant, indicating that AI inventions are enabled both by the alignment of competences between techniques and functions and between functions and applications. Models (7) and (8) consider TF integration based on publications rather than patents. Our goal is to capture the more science-based competences embodied in the technique-functions pairs, and possibly to identify the different actors involved. The coefficient related to TF integration based on publications loses its statistical significance, but re-acquires it when the interaction term with Openness is introduced in specification (8). One way to interpret the result is that TF integration feeds innovation, but only when the competences are developed domestically rather than by sources far from the local context. FA integration based on patents reveals similar insights. Openness affects innovation negatively both overall and when interacted with the integration terms. This result suggests that sourcing knowledge outside the local innovation systems reduces invention incentives and weakens the power of integration to produce new knowledge. All in all, this evidence supports the idea that technological sovereignty can enhance innovative performance.

Finding 25. Innovation in AI results from integration both upstream (techniques-functions) and downstream (functions-applications).
Openness tends to reduce AI innovation, as it weakens the power of integration to produce new knowledge in the realm of AI.

6.2 The determinants of integration as sovereignty in AI

If integration — and, thus, technological sovereignty — favors innovation in AI, what factors favor integration? With our data, we can explore the organizational origins of integration at a granular level. Doing so illustrates the key modalities through which integration is built, and may also represent an actionable policy lever. In Table 12, we relate TFA integration (Model (9)), TF integration (Model (10)), and FA integration (Model (11)). We can distinguish between private and public actors

Table 11: Partitioning upstream TF and downstream FA integration and the production of quality-weighted innovation

	(5)	(6)	(7)	(8)
$nRSA_a$	0.441***	0.445***	0.443***	0.444***
	(0.056)	(0.056)	(0.056)	(0.056)
Patent Stock (ln)	0.269***	0.272***	0.290***	0.282***
	(0.031)	(0.031)	(0.031)	(0.031)
Publication Stock (ln)	0.097***	0.093***	0.111***	0.135***
	(0.032)	(0.033)	(0.033)	(0.034)
TF Integration (Γ_{TF})	0.062***	0.069***		
	(0.013)	(0.019)		
FA Integration (Γ_{FA})	0.016*	0.064***	0.017*	0.069***
	(0.009)	(0.020)	(0.009)	(0.021)
Openness	-0.281***	-0.279***	-0.259***	-0.246***
	(0.035)	(0.036)	(0.035)	(0.035)
TF Integration × Openness		-0.004		
		(0.008)		
FA Integration × Openness		-0.022***		-0.024***
		(0.008)		(0.008)
TF Integration (publications)			0.010	0.080***
			(0.010)	(0.018)
TF Integration (pub.) × Openness				-0.031***
				(0.008)
R-squared	0.859	0.859	0.859	0.859
Within R-squared	0.209	0.210	0.206	0.209
Log Likelihood	-7,779	-7,775	-7,792	-7,777
Model Comparison	(5) vs. (3)	(6) vs. (4)	None	(8) vs. (7)
LR test	24.82***	24.84***	-	30.21***

$N = 8,268$. Dependent variable: Quality-weighted number of innovations (number of patents). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a full vector of unreported year fixed effects and country-field of application fixed effects. The constant is omitted for the sake of clarity. The vector of control variables includes the series of Herfindahl indexes of AI techniques and AI functions derived from patents and publications, and population and GDP per capita entered in logs. Models (7) and (8) use relatedness measures and shares of techniques and functions derived from publication data.

and combinations thereof (private-private, public-public, and public-private collaborations). Indicators of Openness and knowledge stocks (patents and publications) are included as well. With regard to TFA integration (Model (9)), collaborations amongst private actors are related to more integration. Private actors seem to play a positive role in enhancing TF integration, with public assignees being characterized by a significant but negative coefficient. FA integration is positively related to the presence of public actors. The stock of patents is significantly related to integration in all specifications, negatively for TFA and FA and positively for TF. These results suggest that prior knowledge is important for connecting complementary competences at the more technological level, while it hinders integration at the more market-proximate layer of the value chain. Interestingly, Openness has a positive and significant effect on TFA, TF, and FA integration. A possible interpretation of this result, especially when compared to the innovation analysis, is that an "open first, closed then" strategy might be at work. Local actors can develop or diversify their competences in AI by interacting with international partners. Once the competences are formed, local integration favors the production of new knowledge. In a nutshell, AI innovators trade openness at the competence-development stage for less openness at the innovation stage.

Finding 26. When focusing on the organizational origins of integration, we can see how TF integration is fostered by private actors, while TA and overall TFA integration is enhanced by the presence of public assignees. Collaborations between private actors enhance integration overall. Openness and integration are positively related across TF, FA, and TFA, suggesting that AI innovators can develop or expand competences by connecting internationally. In the second stage, the resulting higher level of domestic integration will have a positive effect on innovation.

Table 12: The determinants of integration as sovereignty in AI

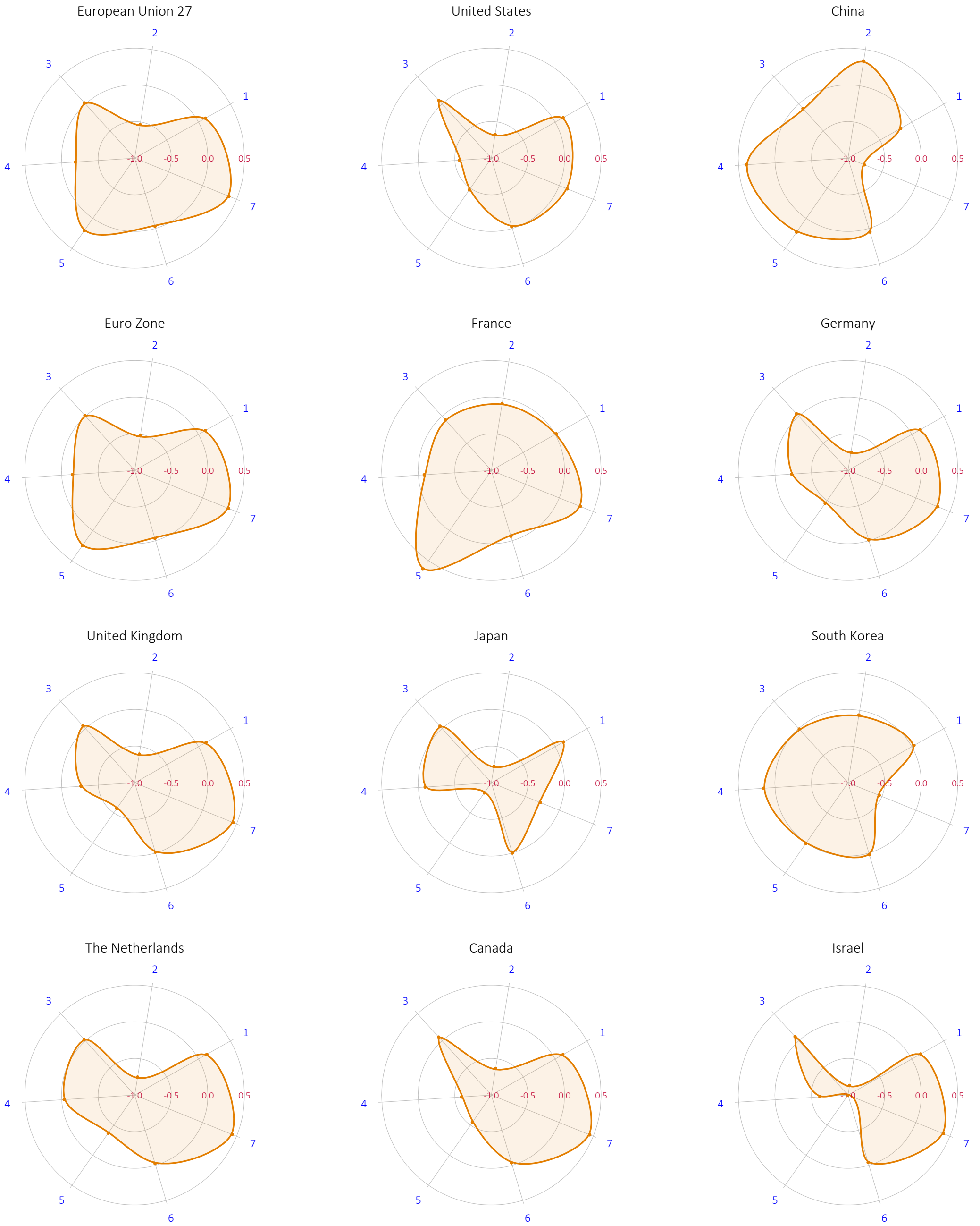
	(9)	(10)	(11)
Private assignee (ln)	0.038	0.280***	0.004
	(0.049)	(0.039)	(0.049)
Public assignee (ln)	0.066**	-0.093***	0.080**
	(0.033)	(0.025)	(0.033)
Private-Private coll. (ln)	0.153***	0.388***	0.105***
	(0.034)	(0.025)	(0.034)
Public-Public coll. (ln)	-0.008	-0.083***	0.002
	(0.018)	(0.016)	(0.018)
Public-Private coll. (ln)	-0.028	0.033*	-0.035
	(0.022)	(0.017)	(0.022)
Openness	0.160***	0.340***	0.120***
	(0.040)	(0.030)	(0.040)
Patent Stock (ln)	-0.192***	0.113***	-0.204***
	(0.041)	(0.038)	(0.041)
Publication Stock (ln)	0.038	-0.007	0.043
	(0.036)	(0.028)	(0.036)
R-squared	0.451	0.632	0.441
Within R-squared	0.010	0.103	0.080
Log Likelihood	-9,263	-7,608	-9,335

$N = 8,268$. Dependent variable: TFA integration in model (9). TF integration in model (10). FA integration in model (11). Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a full vector of unreported year fixed effects and country-field of application fixed effects. The vector of control variables includes patent stocks, publication stock, population and GDP per capita, all entered in logs. Constant is omitted for the sake of clarity.

We can delve into more detail about the organizational aspects that are relevant to the production of AI innovation. Figure 16 depicts each country's performance in AI patenting on a normalized scale, using seven different organizational types: patents assigned to private or public companies, combinations of their collaborations (private-private; public-public; private-public), solo patents, and international collaborations. The major insight that can be derived from a visual inspection of Figure 16 is that there are two broad "regimes" a country can fall into: one roughly oriented around the axis connecting private-private collaborations and international co-patenting, and the other placing more weight on public and public-private patenting. The US, Canada, the UK, Germany, and Israel tend to fall into the first category. China, South Korea, and France tend to come closer to the second. Interestingly, the EU and EZ seem to represent the joint features of the two "classic" engines of the integration of the Union: France and Germany, with public and international co-patents playing a pivotal role in AI innovation.

Finding 27. Different countries display different profiles in terms of the types of actors and organizations involved in AI (patent) innovation. Two general regimes seem to emerge: one innovating through private and international collaborations, and the other through public and private-public co-patenting. Germany and France epitomize the two different regimes, while the EU and EZ seems to innovate as a linear combination of the two. This finding illustrates, once again, the opportunities for AI innovation at the continental level, which could rely on a broader group of innovating organizations.

Figure 16: The organizational characteristics of countries in AI-related patent production



1. Private companies; 2. Public research organization; 3. Private copatents; 4. Private-Public copatents; 5. Public copatents; 6. Solo patents; 7. International copatents;

7 Conclusion

In a world characterized by increasing geo-political and geo-economic rivalries, the idea the countries should strive to increase autonomy and resilience in the production of key, economy-impacting technologies is rapidly gaining momentum. The ongoing discussion has revolved around the notion of sovereignty, and in particular technological sovereignty, as a handful of key, enabling and breakthrough technologies are considered strategic assets to lead in the global context. In a nutshell, a consensus is emerging around the fact that addressing the competitiveness challenge requires not to dismantle globalization, but to improve domestic capabilities and resilience — and that, in turn and especially for Europe, imposes the need of financing substantial fresh investments (Draghi 2024).

In this report, we contribute to this ongoing debate by assessing sovereignty in a specific technology — artificial intelligence — and in a well-defined context — the European Union. We decided to adopt a rather focused approach by defining AI sovereignty as a set of competencies that enables countries to gain control over the entire AI innovation value chain. The rationale for that relies on the fact that AI has the potential to become an ubiquitous element of future economic activities, and thus a required tool in the toolbox of countries' technological capabilities. Given that, our definition of AI sovereignty emphasizes a fundamental yet often overlooked aspect: the competency dimension of sovereignty. We propose a quantitative indicator to measure AI sovereignty: the *integration* of innovation competences along a stylized AI value chain. Following our analysis, we derived a large set of findings, which can be summarized in the following conclusions.

1. Of all geographic areas covered, the EU is the least integrated, implying that

Europe masters too few AI value chains. This is in sharp contrast with the United States and China. Neither do individual member states countries exhibit a high level of integration.

2. Compared with other major area such as China and the United States, the EU lags behind in terms of patent production and, to a lesser extent, in terms of scientific contribution.

3. Because integration enhances future innovation, lack of integration represents a problem for the EU, implying that the gap with other major areas in the world is most likely to widen in the years to come.

4. Accumulation of patents and publications is slower in Europe compared to other areas of the world. This implies that the gap of the EU to the frontier might become permanent; without reaching a minimum critical mass, the EU is poised to lose the race to become a major player in the field of artificial intelligence.

5. Closing the integration gap would require not only additional public and private investments into a series of complementary assets and scientific projects as well as the involvement of a wide variety of actors, but also some form of continental coordination between European actors, in order to form a complementary, Europe-wide AI value chain.

The lack of integration (and thus sovereignty) in European AI can be seen as a call to (policy) action. Coupled with the evidence of insufficient private investment in ICT infrastructure, databases, and software within Europe, a key insight to derive is that the scope for improvement is vast. Hence, we find limited grounds for optimism regarding the future development of a so-called European AI industry. Based on our findings, we envisage two avenues to follow. On the one hand, the EU needs a "big push" in terms of additional investments. Exogenous shocks in the forms of heavy public programs, as advocated by Aghion et al. (2024) in the case of France and by Draghi (2024) for the whole Union are more than necessary. On the other hand, the issue is not exclusively quantitative. Efforts in developing a common understanding of the directionality of investments, for instance by allocating scientific and technological funding to directions entailing high returns (Fuest et al. 2024) is also a fundamental challenge to tackle. Our report indicates that a critical yet unrealized factor is the enhancement of EU governance. Strengthening EU governance is necessary to provide increasing coordination between stakeholders within and between European countries and European institutions is needed in order to build a fully integrated continental AI industry, one that would substantially and structurally enhance European sovereignty in artificial intelligence.

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