fteval JOURNAL
for Research and
Technology Policy Evaluation

July 2025, Vol. 57, pp. e10, 1-27
DOI: 10.22163/fteval.2025.702
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ENHANCING EU POLICY THROUGH COMPLEXITY METRICS: A NEW LENS FOR RESEARCH AND INNOVATION

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DOI: 10.22163/FTEVAL.2025.702

ABSTRACT

In a knowledge-based economy, understanding local capabilities is essential for identifying regional specialisations and technological trajectories. Recognizing where valuable knowledge resides and how innovation systems evolve is vital for enhancing the European Union's competitiveness and overcoming some of the multifaceted challenges the world is facing today. From a policy perspective, this understanding is a crucial input for research and innovation (R&I) policies. Effective R&I policies require data-driven decisions based on comprehensive analysis. However, traditional indicators tend to miss the necessary nuances of technological progress by focusing on the quantity instead of quality of knowledge output. This has prompted a growing interest in complementary quality-based metrics, including the concepts of complexity and relatedness. Complexity captures the diversity and interdependencies of economic activities, while relatedness measures the connections between different economic activities. This paper explains how incorporating these metrics can enhance the ability of the EU to foster economic growth and address societal challenges through the design of more impactful policies. In particular, the paper focuses on how these metrics can inform three EU policy priorities: safeguarding access to critical technologies, fostering the green transition and promoting greater territorial cohesion.

Keywords: Complexity, relatedness, R&I policy

1. INTRODUCTION

In today's economy, knowledge is a critical resource for long-term economic growth (Romer, 1990). It tends to concentrate in densely populated areas, where geographical proximity facilitates spillovers, rapid idea diffusion, and the recombination of capabilities. Much of this knowledge, however, remains tacit and context-dependent, thereby reinforcing the role of localised learning environments and institutional ecosystems (Polanyi, 1966; Lundvall, 1992; Cooke, 2001). This localised concentration can further be enriched by global knowledge flows through collaborations and networks. Through these processes, economies can obtain a set of capabilities that form the basis for the development of unique technological assets (Storper & Venables, 2004). These unique assets, which are difficult to replicate, become the cornerstone of a sustainable competitive advantage and contribute significantly to long-term economic development.

Consequently, it is important to understand the depth and the breadth of knowledge capabilities within an economy. Traditional innovation indicators often fall short due to their dominant focus on output quantity, which fails to capture the more qualitative aspects underlying knowledge development and application (Balland & Rigby, 2017). Newer quality-based indicators, such as citation-weighted impact and novelty metrics, offer important improvements, but do not assess how knowledge is structured, connected or embedded within the economy. Yet, understanding these patterns is important as they shape an economy's capacity to absorb new ideas, diversify into emerging sectors, and sustain long-term innovation-driven growth. In response to these limitations, the concepts of knowledge complexity and relatedness have been gaining more prominence. Complexity measures an economy's ability to produce a diverse range of sophisticated technologies, thereby emphasizing both, the variety of technologies it produces and their global rarity (Balland et al., 2022). Relatedness measures the degree of similarity between different economic activities based on the shared knowledge and competencies required for their production (Boschma, 2017). Together, these concepts provide a complementary and comprehensive framework for understanding the unique strengths of an economy's existing knowledge base.

Such insights offer valuable guidance for addressing challenges facing the European Union (EU), e.g., increasing sustainability (Santoalha et al., 2021; Sbardella et al., 2022; Mealy and Teytelboym, 2022; European Commission, 2024) and reskilling (Stephany and Teutloff, 2024). The complexity framework can help policymakers assess an economy's current capabilities and growth potential, highlight opportunities for diversification and design more targeted interventions. It also enables continuous monitoring to ensure that policies remain adaptive to changing economic and technological landscapes. This approach is particularly valuable for research and innovation (R&I) policies that aim to move beyond traditional models, which often focus solely on technological innovation and economic growth, to create more holistic policies capable of addressing grand societal challenges (Cavicchi et al., 2023).

This paper is structured as follows: Section 2 provides an overview of the theory and measurement of complexity, while Section 3 discusses how complexity can serve as a tool for R&I policy. Section 4 presents case studies demonstrating the potential of complexity in guiding current EU policy discussions, including the safeguarding of critical technologies, the acceleration of the green transition, and the promotion of territorial cohesion. Through these examples, this paper highlights the value of complexity for innovation policy practitioners.

2. COMPLEXITY: THEORETICAL BACKGROUND

Knowledge plays a key role in shaping economic systems and driving long-term economic growth (Romer, 1990). It accumulates through the exchange of ideas and the combination of diverse expertise, facilitated by interactions between individuals, firms and institutions located in close geographical proximity (Storper & Venables, 2004). This implies that knowledge is not created in isolation but through a systemic and interactive process embedded within networks of economic and institutional actors, where learning occurs through mutual engagement and contextual collaboration (Lundvall, 1992). This learning is rooted in specific places, giving rise to regional innovation systems in which innovation is fostered through local knowledge interactions (Cooke, 2001). Since much of this knowledge is tacit, it remains closely tied to its social and geographical context and cannot be easily codified or transferred (Polanyi, 1958; Polanyi, 1966). However, local knowledge bases can be further enriched by engaging within global knowledge flows through licensing agreements, collaborations or personal networks, which complement and build upon local capabilities (Archibugi & Michie, 1995; Doel & Hubbard, 2002; Bathelt et al., 2004).

As knowledge accumulates and diversifies, it creates a unique set of capabilities (Storper, 1997) essential for technological development. However, not all technologies are equally valuable and have the same growth potential. Advanced technologies, such as the Internet of Things, demand expertise across multiple domains like cloud computing, wireless communication and embedded systems. As a result, their development requires a deeper understanding and seamless integration of these diverse knowledge areas, making them inherently complex and challenging to replicate. These high-value, non-ubiquitous technologies (Nelson & Winter, 1982) offer significant competitive advantages due to their rarity and sophistication (Hidalgo & Hausmann, 2009). Understanding these capabilities is crucial for uncovering a territory's technological trajectory and revealing the geographical patterns of economic growth and development (Schumpeter, 1942; Romer, 1990; Pugliese et al., 2018; Pintar & Sherngell, 2022; Hidalgo & Hausmann, 2009; Hausmann et al., 2014; Tacchella et al., 2018).

The concept of knowledge complexity is central to these ideas. Knowledge complexity relates to economic complexity, which explains an economy's ability to produce and export a wide range of goods (Hidalgo & Hausmann, 2009). Knowledge complexity, however, focuses on an economy's capacity to produce a diverse range of sophisticated technologies. More precisely, it considers both, the variety and ubiquity of knowledge capabilities required for their production (Balland & Rigby, 2017). Since these capabilities are not directly observable, knowledge complexity is inferred using outcome-based approaches, such as analysing patent data (Antonelli et al., 2017; Ivanova et al., 2017).

Among the measures of knowledge complexity[1], the Knowledge Complexity Index (KCI) adapted from the Economic Complexity Index (ECI) (Hidalgo & Hausmann, 2009; Balland & Rigby, 2017), examines patent applications to measure technological diversity (the number of technologies in which an economy specialises) and ubiquity (the number of economies specialising in this technology). Higher values of KCI signify that an economy produces diverse technologies that are less commonly produced globally, thereby revealing a deeper knowledge base. Similarly, the Technology Complexity Index (TCI)[2] captures how complex a specific technology is by assessing how difficult it

1 Like with economic complexity, this literature has proposed different measures of knowledge complexity; the most prominent are Sbardella et al. (2018)'s Technological Fitness and Balland et al. (2019)'s Knowledge Complexity Index (KCI).

2 From a technical standpoint, KCI measures the complexity of a region/country's knowledge base considering how unique and diversified its innovation output is; whereas, TCI measures technological complexity by evaluating how specialised and widely distributed different technologies are across regions/countries (Balland & Rigby, 2017). More in general, the KCI of a location is defined as the average of the TCI of the technological activities (typically proxied by patent activities) that are located in it. Similarly, the TCI of a technology is defined as the average KCI of the locations where that technology is observed (Hidalgo, 2021). For more information see also The Observatory of Economic Complexity.

is to patent in that area. Hence, TCI zooms in on the complexity of individual technologies. Together, KCI and TCI indices can provide an indication of proximity to the technological frontier (Schetter, 2022).

Another closely related concept is technological relatedness, which measures the similarity between technologies based on the knowledge and competencies required to produce them (Boschma, 2017). Two technologies are considered related when they share similar knowledge or require overlapping skills (Hidalgo et al., 2018; Balland et al., 2019; Pugliese et al., 2019). Relatedness is often inferred from the geographic co-location of innovation activities, i.e., technologies that are often produced in the same location are considered similar as their co-location suggests that they leverage the same local capabilities. For example, economies with a strong robotics industry may also excel in the automotive industry due to overlapping expertise. In other words, relatedness provides insights into an economy's proximity to a specific technology, complementing traditional specialisation metrics like the Balassa Index[3] by identifying untapped opportunities for diversification.

Knowledge complexity and relatedness are often used together to provide a comprehensive understanding of an economy's knowledge base. While knowledge complexity reflects an economy's ability to produce sophisticated technologies, relatedness indicates how well it can expand into new, related areas. These concepts reinforce each other dynamically: advancing into related technologies increases knowledge complexity, which in turn facilitates further diversification. This cycle boosts the ability to innovate and adapt, contributing to long-term economic growth and resilience by enabling economies to engage in technological advancements and respond to changing global demand (e.g., Liao, 2015).

3 The Balassa Index, also known as the Revealed Comparative Advantage (RCA) index, is a measure that quantifies a country's comparative advantage in the production and export of specific goods or services. It helps identify sectors in which a country is relatively more competitive in international trade compared to others.

3. USING COMPLEXITY IN RESEARCH AND INNOVATION POLICY

The development of effective policies relies on evidence-based decision-making and clear data analysis. Traditional indicators based on patent counts, scientific publications and similar metrics offer valuable insights by measuring the quantity of innovation outputs making them useful for quick policy assessments, the monitoring of (relative) innovation performance and easy communication to the wider public (Hollanders et al., 2009). However, using the number of patents or publications implicitly assumes that they all have the same value, failing to fully capture all nuances of technological progress (Balland & Rigby, 2017), including potential heterogeneity in terms of underlying know-how and links to pre-existing specialisation patterns. Indeed, the dynamics of technological progress depend not only on output, but also on the sophistication and relationships within an economy's innovation ecosystem.

To address these gaps, policy frameworks are increasingly adopting a layered approach to indicators, combining output metrics with more quality-driven citation-weighted impact measures, novelty detection tools and composite indicators. Citation-weighted indicators (Aksnes et al., 2019) capture the influence of knowledge over time, showing how innovations contribute to future developments. Novelty metrics (Verhoeven et al., 2016), based on textual and structural analysis of patents, identify whether innovations represent incremental improvements or radical shifts. Composite indicators (Nardo et al., 2008), like the European innovation Scoreboard or the Global Innovation Index, go further by offering a broader view of innovation by integrating data on R&D inputs, collaboration and commercialisation.

Complexity metrics offer a distinct yet complementary perspective to the aforementioned indicators by focusing not just on innovation outputs, but also on how they are embedded and connected within the system. These indicators provide structural insight into technology linkages, assess the absorptive capacity, and offer a forward-looking perspective by identifying potential innovation pathways based on existing strengths. Complexity metrics are compiled based on matrix factorization, which help preserve these relational patterns, thereby enabling more nuanced analysis of innovation and growth potential (Hidalgo, 2021; Hidalgo & Hausmann, 2009; Hausmann et al., 2014). This makes the complexity framework particularly well-suited for guiding innovation policies by examining both the current state and future potential of an economy's innovation ecosystem.

The concept of relatedness further enhances this understanding. Relatedness assesses the feasibility of developing new technologies based on existing capabilities and network connections, highlighting that technologies closely linked to current strengths offer more feasible, less risky, and less costly opportunities for diversification (e.g., Frenken et al., 2007; Boschma & Frenken, 2011). These insights allow economies to strengthen their innovation performance by leveraging existing assets and helping to build on current strengths to explore new areas of innovation.

When combined with other factors, such as the social returns to research and innovation investments, these insights enable policymakers to craft tailored interventions that align with regional strengths and development trajectories. Indeed, although complexity indices have been mainly used to identify diversification paths (e.g., Hausmann et al., 2014; Deegan et al., 2021), it can also provide a forward-looking perspective to help create environments that support transitions into new, complex technological areas. This approach encourages policymakers to plan and organise long-term strategies for developing emerging technologies (e.g., Alshamsi et al., 2018; Waniek et al., 2020). By understanding how technologies are interconnected, policymakers can make more informed decisions about resource allocation, investments in skills and infrastructure, and potential collaborations to support the development or adoption of these technologies. Additionally, the complexity toolbox can enable continuous monitoring, allowing strategies to be adapted to evolving technological landscapes and economic conditions.

All these characteristics make complexity a powerful tool in the pursuit of ambitious EU policy objectives. By obtaining a clear understanding of the dynamic capabilities, more tailored interventions can be designed that allow Member States to build on their strengths with the purpose of enhancing overall innovation capacity, while mitigating the risks associated with technological and economic shifts. In addition, tailored advice can also help economies catch up with more advanced ones by identifying opportunities for investment that promote convergence. This approach enhances Europe's competitiveness, improves living standards (European Commission, 2024), reduces regional disparities, and increases cohesion through innovation.
As such, complexity thinking aligns well with the principles of National and Regional Innovation Systems, offering a way to map interdependencies and guide place-based strategies, but may require more adaptive and iterative policy tools than currently standard.

At the same time, the ability to structure and organise for long-term strategic development is particularly relevant for the EU's mission-oriented R&I policies aimed at addressing societal challenges, such as climate change and sustainable development. These challenges require a coordinated approach across various economic areas. Complexity can offer valuable insights to guide the development and coordination of the assets needed to address these challenges. This approach enhances the capacity to deliver innovations that are both technically feasible and socially meaningful, contributing to broader systemic change. However, they may also challenge conventional top-down governance approaches that favour linear planning.

Although promising, complexity's use in R&I policy is relatively recent. Initially, it was applied to national-level phenomena, such as economic growth (e.g., Hidalgo & Hausmann, 2009; Pugliese & Tacchella, 2021), income inequality (e.g., Chu & Hoang, 2020) and sustainability (e.g., Mealy & Teytelboym, 2022; Sbardella et al., 2022). These applications allowed policymakers to capture economic interdependencies and formalise principles of development, such as complementarity (e.g., Rosenstein-Rodan, 1943; Hirschman, 1977). As the limitations of linear innovation models became evident in addressing the complexity of technological systems, complexity theory began to shape R&I policies. Notably, it became a key component of the EU's Smart Specialisation Strategies (S3) under Cohesion Policy, moving away from one-size-fits-all approaches and instead fostering regional innovation by leveraging unique regional strengths.

4. CASE STUDIES: COMPLEXITY FOR A COMPETITIVE EUROPE

This section explores how complexity can be leveraged to address three critical transformations which the EU must navigate to secure its future competitiveness (Draghi, 2024): increasing technological sovereignty and reducing dependencies, advancing the green transition and closing the innovation divide. Case 1 highlights the usefulness of complexity metrics to identify key technologies for future growth and investment decisions while Case 2 explains how the European Green Deal can benefit from the same metrics by identifying regions with the potential for green technology development. Case 3 explores how complexity analysis can inform policy practitioners on how to reduce regional disparities in technological capabilities by fostering cross-border collaboration.[4]

CASE 1: COMPLEXITY AND TECHNOLOGICAL SOVEREIGNTY

In the last decade, political and economic shocks have challenged the standard globalisation growth model and its division of labour (European Commission, 2024). Protectionist policies and a revival of industrial policy are reshaping Global Value Chains (GVCs), aiming to reduce reliance on imports, while boosting national innovation, investments and growth (Aghion et al., 2023). At the same time, the growing securitisation and weaponisation of science and technology policies have intensified debates on how the EU can safeguard access to critical technologies and reduce foreign interferences. While ensuring the availability of critical technologies has always been a priority for policymakers, the approach to securing these technologies is evolving as free international technological cooperation and trade are undergoing significant restructuring (European Commission, 2024).

To address these challenges, complexity metrics provide policymakers with a data-driven lens towards technological sovereignty. As highlighted by Edler et al., (2023), an effective strategy for technological sovereignty begins with identifying which technologies are critical to the functioning of an economic system, followed by an assessment of the system's ability to access and develop them. Yet, this identification and assessment is complicated by the rapid pace of technological change, the expanding set of policy objectives as well as the general lack of data to inform development decisions. To this purpose, complexity measures can offer valuable guidance by identifying technologies with the highest growth potential, thereby providing data-driven insight on where to redirect public resources. For example, as shown in Figure 1, complexity analysis indicates that digital technologies, such as the Internet of Things (IoT), artificial intelligence (AI) and cybersecurity stand out as complex and hard to replicate fields. These are precisely the fields where strategic investment could offer significant growth and competitiveness advantages (Balland & Rigby, 2017; European Commission, 2024).

4 All cases are syntheses of existing studies, performed by the authors, curated to support the policy argument.

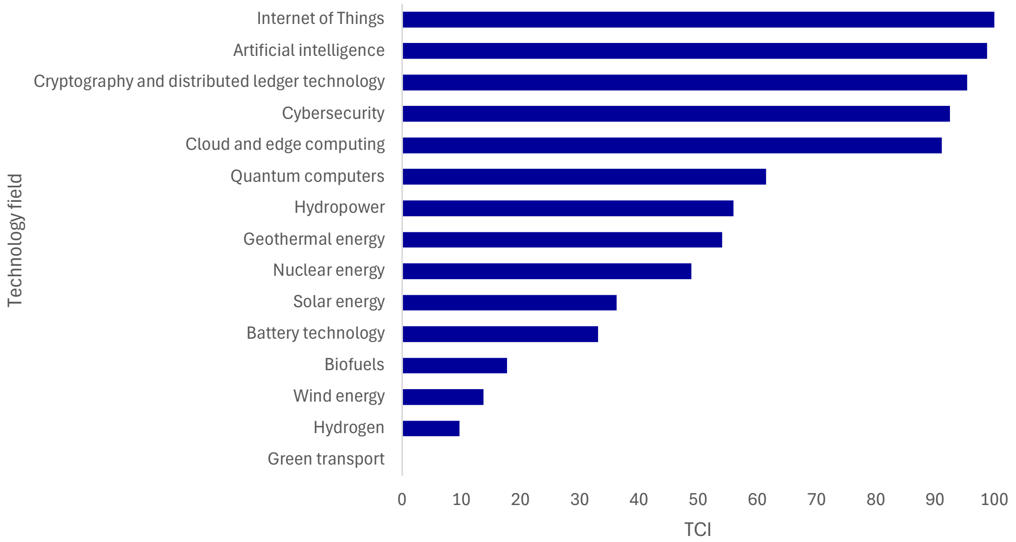

Figure 1. The complexity of key strategic technologies

Note: On the y-axis, technologies are ranked by Technology Complexity Index (TCI), which measures complexity at the technology level, normalised between 0 and 100. Source: The Science Research and Innovation Performance Report (SRIP) 2024.

Once critical technologies are identified, it is key to monitor their development over time and assess both current capacity and future potential. Indicators using patent counts or specialisation indices clearly highlight that the EU's technological performance in digital fields has been weakening thereby broadening the gap with competitors like the US and China (European Commission, 2024). However, these metrics are backward-looking and offer limited insights into the EU's future technological potential. In this context, relatedness indicators offer a more forward-looking lens, identify technological trajectories that a country is more likely to pursue based on current strengths.

As shown in Figure 2, the EU faces a significant technological gap compared to other key players in technologies such as Internet of Things, AI, blockchains, cybersecurity and quantum computers - not only in terms of current specialisation, but also when looking at the diversification potential in these fields (captured by the relatedness density indicator). This implies that the EU's current ability to build up capacity in such technologies is limited (European Commission, 2024). On the contrary, the EU's current specialisation is stronger in technologies such as wind energy, hydrogen, and green transports, whereas a higher potential for technological development is observed in other important green fields (e.g., hydropower, geothermal energy). This is a crucial aspect, as indicators such as relatedness density can be used as a tool to identify the types of strategic technologies in which the EU could better leverage its existing capabilities for further specialisation, thereby helping to optimise investment priorities and improve the efficiency of public support.

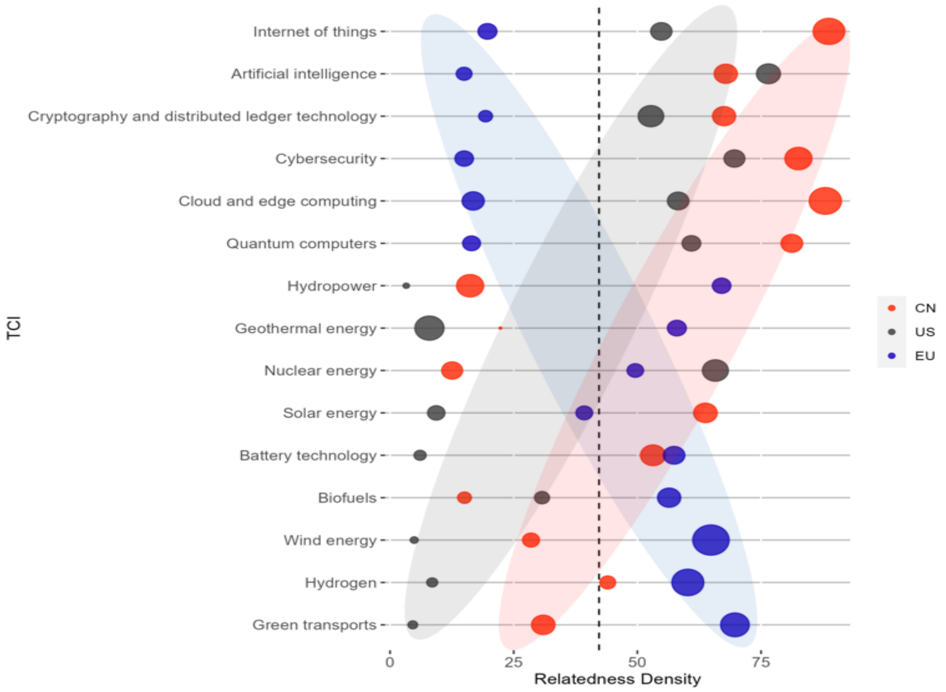

Figure 2. The EU's position in complex technologies versus the US and China, 2019-2022

Note: The x-axis indicates the relatedness density in any of the technology fields considered. On the y-axis, technologies are ranked by complexity levels, normalised between 0 and 100. The size of the bubble captures the degree of specialisation that each country reports in a given technology field, as measured by the revealed comparative advantage (RCA).
Source: The Science Research and Innovation Performance Report (SRIP) 2024.

To further build up technological capacities and to guarantee access to critical technologies, the EU can either deepen its domestic innovation capabilities or rely on international sources of knowledge to acquire new capabilities (e.g., via collaborations) (Boschma, 2005; Edler et al., 2023). While the EU has long prioritised openness and international collaboration in science and technology, there exists a natural tension between the priority of safeguarding the EU's technological sovereignty and fostering international R&I cooperation (European Commission, 2024). This calls for empirical approaches able to support policymakers in identifying potential international partners from which the EU can gain in terms of technological complementarities, helping diversify the EU's partners pool and reduce the risk of exacerbating one-sided dependencies. As showcased by Figure 3, relatedness metrics can be used also to this purpose[5], as they can provide insights on the extent to which non-EU countries can complement the EU's technological deficiencies in different technology fields, especially more complex ones.

5 In this context, the concept of 'relatedness added' can be used to capture technological capabilities around a given technology that are missing in a country and that are available in other countries. For more information, please refer to Balland & Boschma (2021).

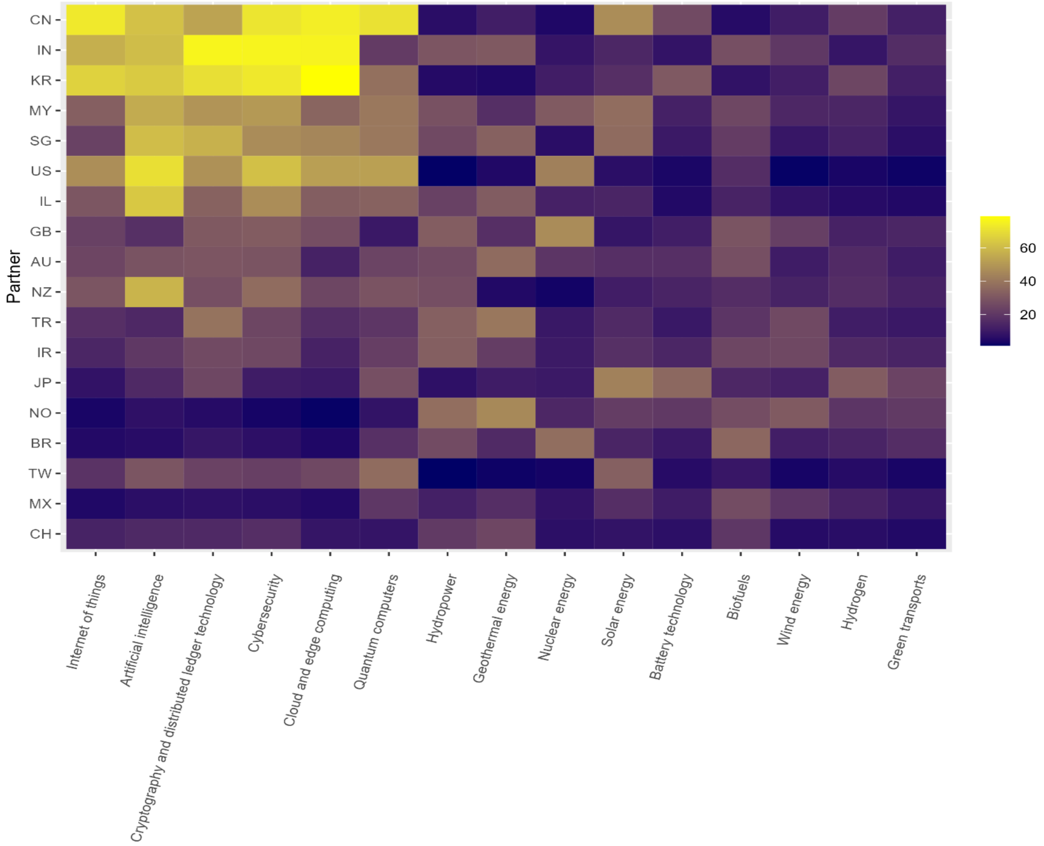

Figure 3. The EU's technological complementarities

Note: On the x-axis, technologies are ordered according to the degree of technology complexity (TCI index). On the y-axis, countries are ranked according to the average relatedness density added. Example of interpretation: South Korea, India and China show strong specialisation in technologies which are closely related to cloud and edge computing, and in which the EU shows weaker specialisation.
Source: The Science Research and Innovation Performance Report (SRIP) 2024.

CASE 2: COMPLEXITY AND FOSTERING THE GREEN TRANSITION

The European Green Deal aims to offset greenhouse gas emissions by 2050 while enhancing economic growth. To meet carbon neutrality goals, the EU will have to accelerate the development of climate-related technologies as climate targets cannot be met by only relying on existing technologies. In this case, complexity and relatedness metrics can provide guidance regarding the direction of policy intervention by evaluating which green technologies have the potential to be developed in the EU and which areas are better placed to do so based on their existing capabilities. This type of analysis can thus provide insights into identifying investment opportunities to develop a particular green technology and on which green technologies the EU should be focusing on.

The literature on economic geography has long argued that regions, often functioning as clusters of knowledge exchange, are the most apt unit of analysis when thinking about capabilities, accumulation of know-how, specialisation, innovation and diversification (Glaeser et al., 1992). It is therefore likely that regional policies will increasingly embed European Green Deal objectives. Vice versa, it is also likely that European Green Deal policies will look towards regions for sources of innovation.

In this context, the framework of Economic Complexity proves particularly relevant. There are already many studies that apply the paradigm of economic complexity to understand the technological evolution towards the green transition. In the academic literature, for instance, Sbardella et al. (2018) calculate the complexity of green technologies. Mealy and Teytelboym (2022), instead, propose indices of green complexity and green potential in traded commodities. Caldarola et al. (2024) review these and other contributions to document the emergence of the economic complexity approach to analyse the sustainable transition. This rise is reflected also in the policy discourse, especially at the regional level. In a JRC policy brief, Sbardella et al. (2022) analyse the green potential of European regions. This report builds a mapping of relatedness between non-green and green technologies to assess the green potential of EU regions, based on their non-green technologies (as illustrated in Figure 4).

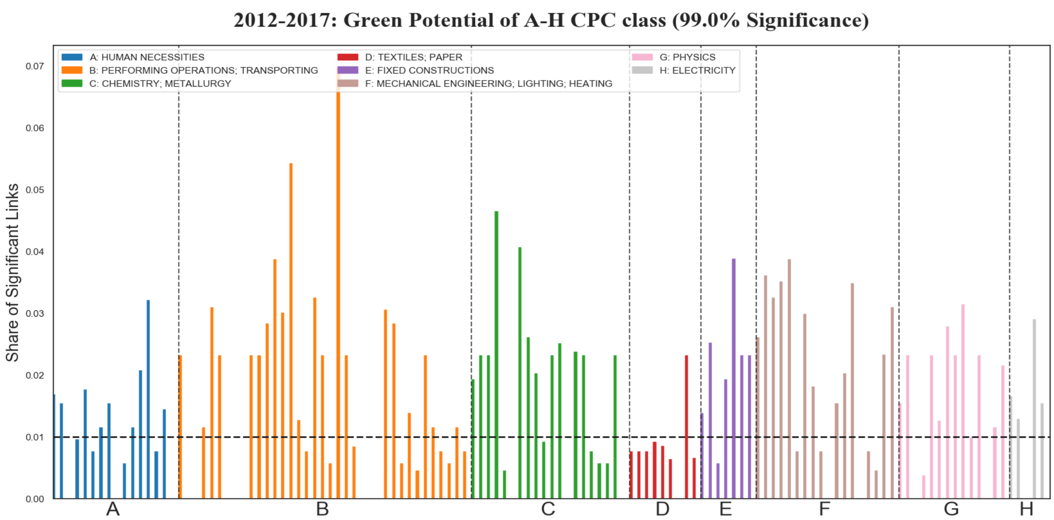

Figure 4. Relatedness between non-green and green technologies

Note: Share of 99% statistically significant links in the non-green—green technology space of each A-H CPC non green technology at 4-digit aggregation to all Y02 green technologies at 8-digit aggregation level. Source: JRC policy brief (Sbardella et al., 2022).

More recently, the Science, Research and Innovation Performance Report (European Commission, 2024; Chapter 9) focuses on specific green technologies. The analysis finds that, for instance, the EU is lagging in climate-change mitigation technologies related to aeronautics. These are technologies such as efficient propulsion systems or drag reduction techniques. The analysis then assesses the capacity of European regions in this domain as well as their potential, again based on the relatedness between the target green technology and the non-green technologies that do exist in EU regions. Both pieces of information are depicted in Figure 5. The regions in light and dark blue already have high patenting activity in green aeronautics. The regions in yellow and orange, instead, currently have no capacity in this technology, but medium to high potential, given their current specialisation in related technologies.

This analysis is useful for national or super-national policies that target technologies of strategic importance. It can, in fact, help identify regions with the greatest potential for development and impact. The analysis is also useful for regional and cohesion policies as it can identify new pathways – or untapped opportunities, which is how these are often refer to in the Smart Specialisation literature – for development in lagging regions.

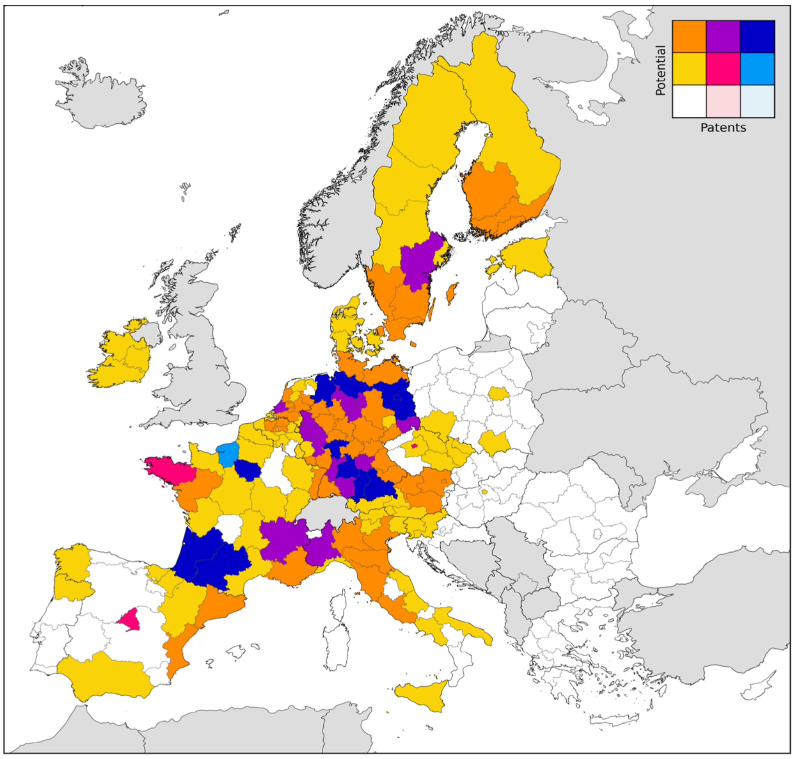

Figure 5. Map for green technology "aeronautics"

Source: The Science Research and Innovation Performance Report (SRIP) 2024.

As a matter of fact, the ideas of Economic Complexity resonate well with Smart Specialisation. Both approaches are place-based, aiming at exploiting local capabilities to foster new technological trajectories; both are vertical, meaning that investments should be targeted to a limited number of economic or technological areas and both are based on the idea that unknown, untapped opportunities exist (Diodato et al, 2023). As Foray (2015) argues, Smart Specialisation is "the capacity of an economic system (a region for example) to generate new specialties through the discovery of new domains of opportunity and the local concentration and agglomeration of resources and competences in these domains."

CASE 3: COMPLEXITY AND R&I CONNECTIVITY NETWORKS

Technological and innovative capabilities vary significantly across the EU, resulting in a concentration of advanced technologies in certain regions. This is especially evident in the development of complex technologies, which require multidisciplinary expertise and cross-border collaborations. Indeed, as technologies become more complex, they increasingly rely on diverse knowledge inputs from multiple regions and sectors, creating a greater need for more interconnected R&I ecosystems (e.g., Balland & Rigby, 2017).

Consequently, regions that can effectively integrate into international collaborative networks gain a clear advantage in developing and scaling complex technologies (Fleming & Sorenson, 2001; Balland & Rigby, 2017). In fact, there is a correlation between the ranking by complexity index of a specific technology category and its level of European inter-country collaborations, with a stronger correlation observed for more complex technologies (see Figure 6). However, cross-border cooperation in the EU remains limited, where the regional co-patenting network is fragmented along national lines (European Commission, 2024), hindering the sharing of knowledge and resources necessary for advancing complex technologies such as IoT, blockchain and cybersecurity. This fragmentation also exacerbates regional disparities, as innovation remains concentrated in leading regions that already possess the necessary expertise and infrastructure, while others struggle to catch up.

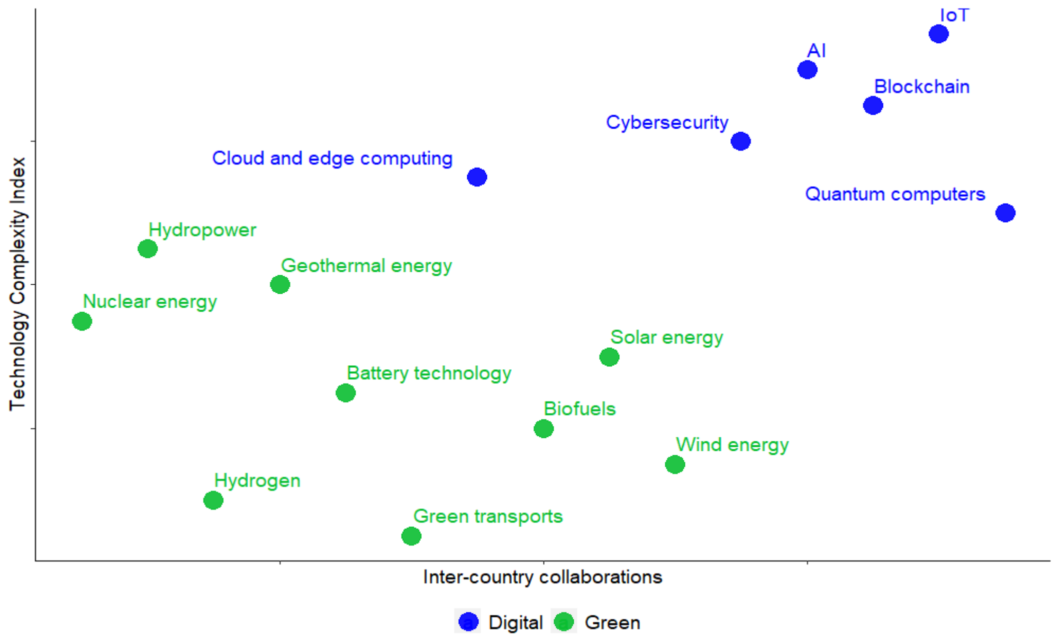

Figure 6. European inter-country collaborations by technology ranked according to complexity index, 2014-2020

Source: The Science Research and Innovation Performance Report (SRIP) 2024.

Bridging these regional gaps and fostering more integrated, cross-border innovation ecosystems is crucial for ensuring that Europe remains competitive in the global technological landscape. R&I policies play an important role in promoting international collaborations and knowledge diffusion across borders (European Commission, 2022), helping to overcome traditional barriers to knowledge exchange and enabling regions to benefit from collective expertise. One example is the initiatives under the Framework Programme for R&I, which aims to align regional strengths with broader European objectives, enabling less-developed regions to contribute to complex technological advancements.

Nevertheless, in practice, the increasing complexity of knowledge that is being produced and the speed at which new technologies are evolving can have a profound impact on achieving truly inclusive collaborations. Indeed, despite the EU's inclusive objectives, Balland et al., (2019b) show that pre-2004 member states are more frequently positioned as central players in high-complexity projects while post-2004 member states tend to participate in lower-complexity projects. This division risks reinforcing a spatial concentration of complex knowledge within pre-2004 member states. Without targeted strategies to support capacity-building in post-2004 member states, this cycle may continue, limiting these regions' ability to engage meaningfully in the EU's broader technological goals.

Complexity analysis can support this capacity-building by identifying regional strengths and weaknesses, revealing synergies between regions with complementary expertise. This can help guide targeted EU interventions to bridge gaps, strengthen knowledge networks and create more inclusive innovation ecosystems. By highlighting regions' relative positions in knowledge networks, complexity metrics can help policymakers create partnerships that ensure all regions can meaningfully engage in high-complexity technological development. This approach enables the EU to strategically allocate resources, promote cross-regional collaborations and support a more resilient and balanced technological landscape.

LIMITATIONS OF COMPLEXITY

To ensure the correct application and interpretation of complexity for policy purposes, it is important to recognise several limitations. First, although the complexity metrics presented in this paper go beyond traditional well-established metrics, they are still largely based on patent data, which may underestimate local capabilities, as not all knowledge is captured in patents. This is a well-known limitation of the use of patent data for analyses related to the measurement of knowledge and innovation. However, standard patent analysis perceives patents simply as an output value, while complexity uses patents as a proxy to identify technological specialisation irrespective of the overall absolute patent production. Complexity should therefore be less affected by this limitation (Diodato et al., 2023). Second, complexity is more effectively analysed when historical data on technologies are abundant and may be less accurate for emerging technologies, where it may struggle to capture rapid changes. Third, the use of patents to assess technological opportunities assumes that the region or country can always enter in the development of a technology if it possesses the necessary know-how. However, even with the required capabilities, territories can choose not to be active in a field for various reasons. Hence, while complexity can be used as an instrument to assess capabilities or technological opportunities, it does not provide direct solutions for the most appropriate strategy based on specific territorial or sector characteristics.

CONCLUSION

In the rapidly evolving global economy, the EU faces multifaceted challenges in ensuring its future competitiveness while encouraging inclusivity and sustainability. Navigating these challenges demands innovative approaches that can complement more traditional innovation metrics. Knowledge complexity and relatedness can be considered pivotal frameworks in this context, offering powerful tools to understand and help improve economic and innovation policies. Both concepts emphasise the dynamic and interconnected nature of knowledge accumulation and technological specialisation. Complexity metrics reveal existing strengths and new opportunities for diversification and growth, while relatedness can identify synergies between current capabilities and new technologies. Therefore, these concepts can contribute to the formation of more tailored, data-driven interventions that align with regional strengths and promote diversification.

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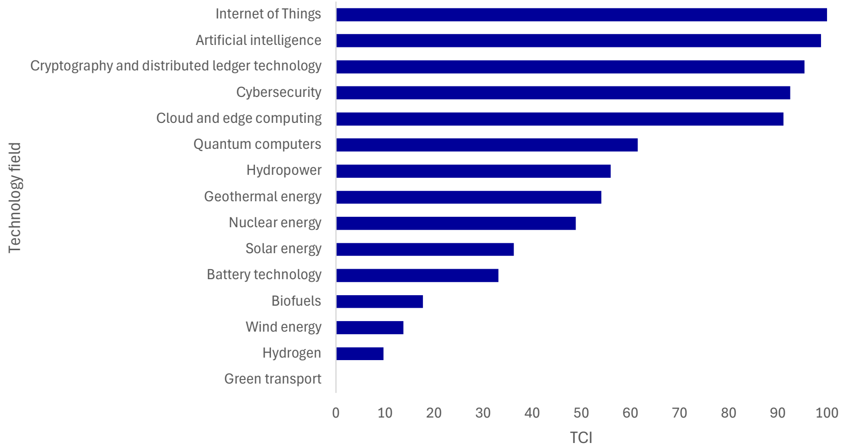
FIGURES

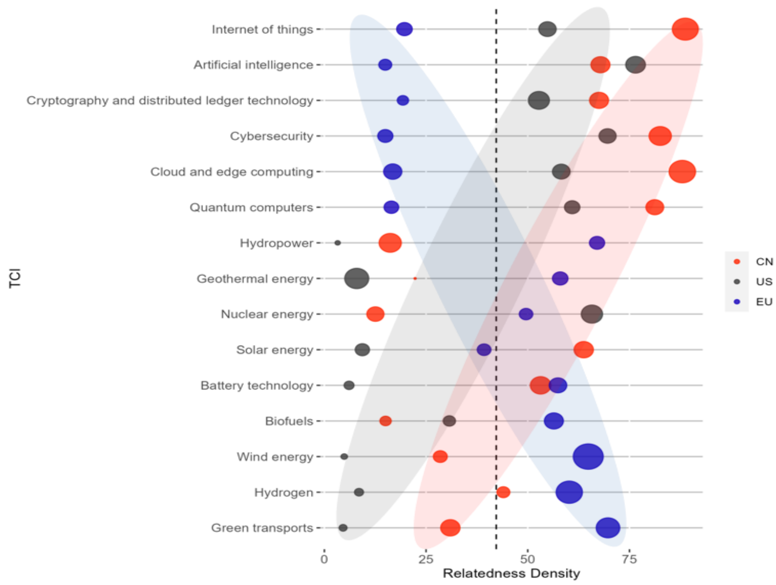
Figure 1. The complexity of key strategic technologies



Note: On the y-axis, technologies are ranked by Technology Complexity Index (TCI), which measures complexity at the technology level, normalised between 0 and 100.

Source: The Science Research and Innovation Performance Report (SRIP) 2024.

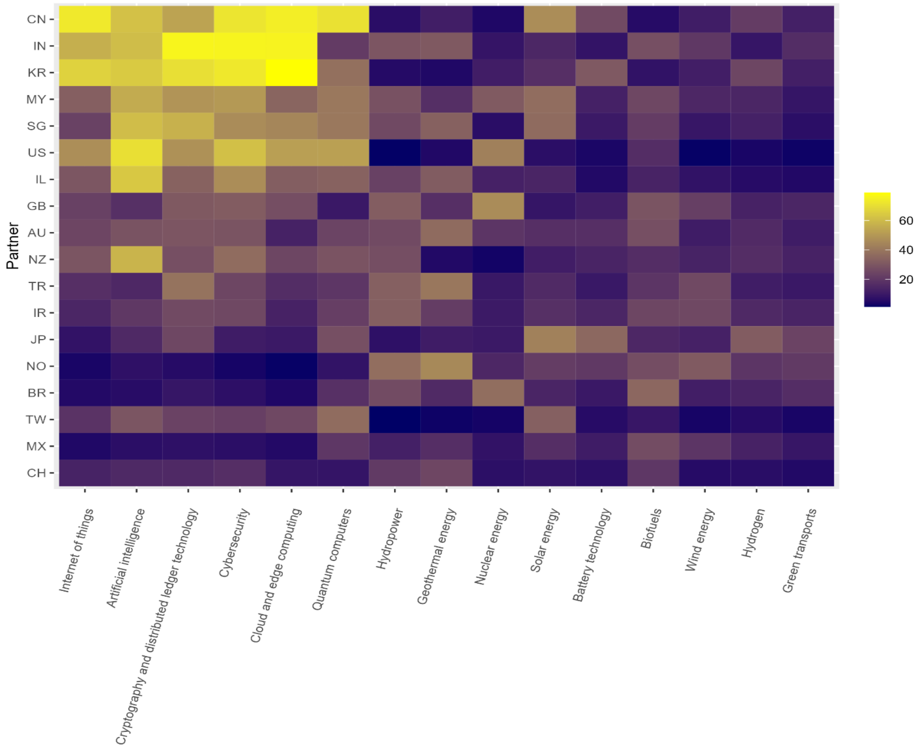
Figure 2. The EU's position in complex technologies versus the US and China, 2019-2022



Note: The x-axis indicates the relatedness density in any of the technology fields considered. On the y-axis, technologies are ranked by complexity levels, normalised between 0 and 100. The size of the bubble captures the degree of specialisation that each country reports in a given technology field, as measured by the revealed comparative advantage (RCA).

Source: The Science Research and Innovation Performance Report (SRIP) 2024.

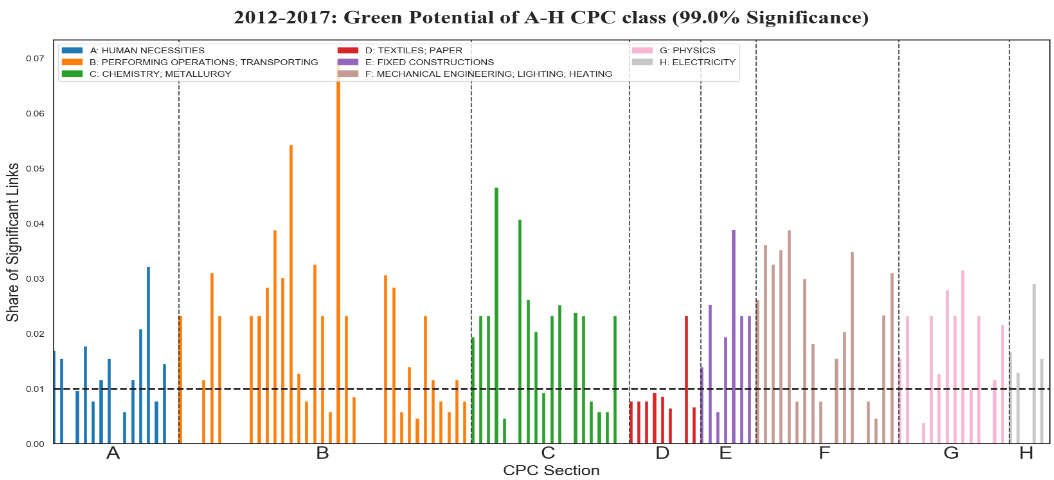
Figure 3. The EU's technological complementarities



Note: On the x-axis, technologies are ordered according to the degree of technology complexity (TCI index). On the y-axis, countries are ranked according to the average relatedness density added. Example of interpretation: South Korea, India and China show strong specialisation in technologies which are closely related to cloud and edge computing, and in which the EU shows weaker specialisation.

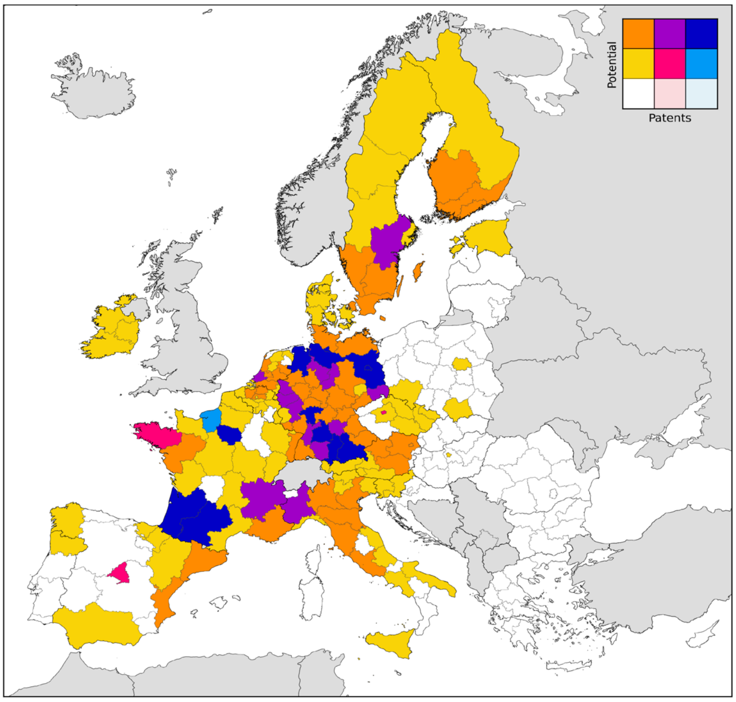
Source: The Science Research and Innovation Performance Report (SRIP) 2024.

Figure 4. Relatedness between non-green and green technologies



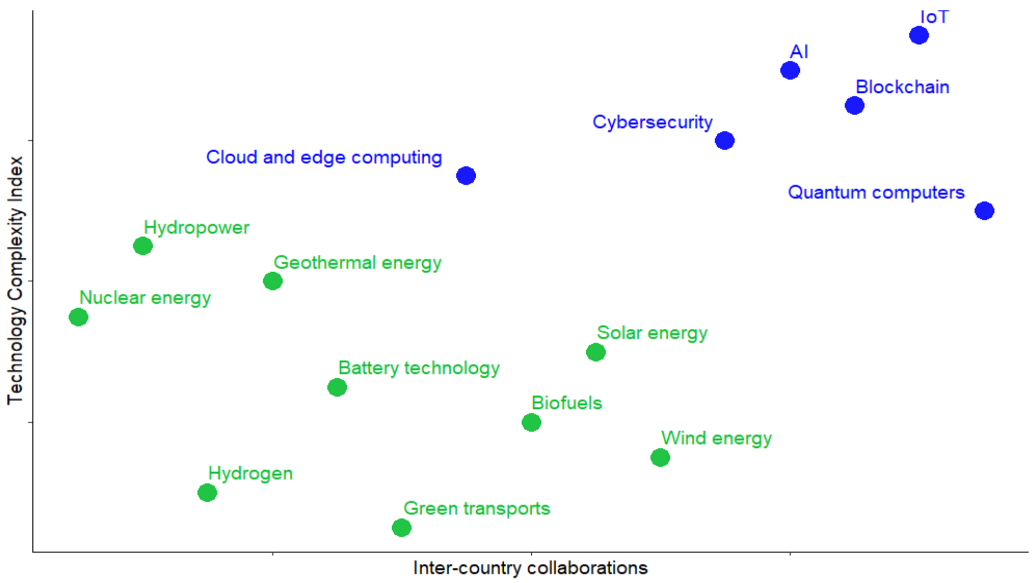
Note: Share of 99% statistically significant links in the non-green—green technology space of each A-H CPC non green technology at 4-digit aggregation to all Y02 green technologies at 8-digit aggregation level. Source: JRC policy brief (Sbardella et al., 2022).

Figure 5. Map for green technology "aeronautics"



Source: The Science Research and Innovation Performance Report (SRIP) 2024.

Figure 6. European inter-country collaborations by technology ranked according to complexity index, 2014-2020



Source: The Science Research and Innovation Performance Report (SRIP) 2024.

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