Breakthrough or break-in? How AI becomes a part of countries' technological paths*

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Abstract: The concept of relatedness has been crucial to understanding the geography of innovation. It explains local specialisations patterns such as the probability that a location develops a given technology. Yet we still lack an understanding of how technological relatedness changes over time, and how these changes affect local technological development. At the example of Artificial Intelligence (AI) we investigate (i) how specialisation patterns linked to AI change over time, (ii) how these changes affect the local exploration of AI at country level, and (iii) how new capabilities related to AI are created by countries. Thereby, we focus on the US, Japan, South Korea, and China as the four countries leading AI development during the observation period (1974 - 2018). Using patent data, we apply a technological space perspective coupled with specialization indices to identify the dynamics occurring at local and technological levels. We find that the technological evolution of AI has little association with how it was locally developed. Instead, the local development of AI relates to countries' existing knowledge bases, even in cases when it was weakly related AI.

Keywords: Artificial Intelligence; technological space; evolutionary economic geography; technological relatedness; knowledge complexity

JEL classification: *O33, O57, O14, D83*

*new provisory title, replacing the former one "The Long-Term Evolution of Artificial Intelligence – Relatedness and complexity perspectives"

1. Introduction

In the late 1990's one uses a cell phone to call a friend to tell about one's first-time access to the internet on a personal computer. Back then both devices had very little in common: the cell phone, maybe produced by the then-popular Finish company Nokia, was used mainly to make phone calls (especially when the internet line was occupied); the personal computer, maybe a PC from the American IBM, was used mainly for computing, word processing and maybe playing games. In the early 2020's, it is hard to differentiate one from the other. If one owns both devices, they may be produced by the same company, which may also produce tablets, smartwatches, smart TVs, and similar devices.

The similarity between these devices is captured through the concept of relatedness, which considers that some elements share commonalities that favour them to be developed in tandem. The concept, translated to a geographical context in Hidalgo et al. (2007), was highly influential, creating what became known as the 'evolutionary turn' in the field of economic geography (Boschma & Martin, 2007). Subsequent research stressed the role of relatedness to predict the activities that a location will enter or exit in the future (Balland, 2016) and also discussed how industrial policy can influence local relatedness so that particular technologies or industries can be developed (Balland et al., 2019). Relatedness-based policies were introduced in several countries including the Smart Specialisation Strategy adopted by the European Union (Hidalgo, 2021).

Despite growing research on the theme, we still know very little about how relatedness emerges and changes over time (Hidalgo, 2021; Juhász et al., 2021). In our illustrative example, this is similar to say that the communalities between cell phones and computers didn't change. This is unlikely. After all, technologies evolve (Arthur, 2009), including the way in which they are combined to create products. The dynamic nature of relatedness is also relevant for industrial policies: should they aim at pushing local knowledge towards the latest technological development, or at strengthening the particularities of existing local technological paths (see for example Marrocu et al. (2020))?

We advance the state-of-the art by analysing i.) how the relatedness of innovations linked to a particular technology changed over time, ii.) how these changes affected the local exploration of this technology in countries leading its development, and iii.) how new capabilities related to this technology were developed in these countries. We do so at the example of Artificial Intelligence (AI), which is modular (Nilsson, 2009) and transversal (Righi et al., 2020) in nature. This makes it a suitable choice, since modularity allows AI to be coupled with other technologies, which indicates a particular potential for recombination. Transversality refers to possible use of AI across a variety of technological sectors, so that distinct technological paths related to AI are likely to emerge locally. Furthermore, our study focuses on the US, Japan, South Korea, and China as the four countries leading AI development during the observation period (1974 - 2018).

Our findings indicate that the technological relatedness of AI evolves, documented by different combination patterns that emerged over time through its development. However, we also document that these combination patterns were not simply replicated by local developments. Instead, countries developed AI following their existing knowledge-bases, i.e., by exploring AI in fields in which they already had some local comparative advantage. This pattern was reinforced the more countries accumulated knowledge about AI. Hence, we argue that AI 'break-in' into local technological paths by being adopted mostly in areas where countries hold an existing comparative advantage. The reverse situation, in which AI would 'breakthrough' existing technological paths by emerging independently in areas particular to AI and decoupled from existing knowledge-bases, is shown to produce comparative advantages in AI that are short-lived.

This paper is structured as follows. Section 2 presents the relevant theory on relatedness and formalizes the research questions. Section 3 describes the data and method, followed by Section 4 in which the empirical findings are presented. Finally, Section 5 discusses the main findings, outlines theoretical contributions, policy implications, and existing limitations of our approach.

2. Theoretical background

2.1. The notion of relatedness

The consideration of how distinct technologies relate to each other has been crucial to explain local technological development (Balland, 2016; Boschma et al., 2014; Petralia et al., 2017; Rigby, 2015) and the emergence of new industries (Colombelli et al., 2014; Feldman et al., 2015; Neffke et al., 2011; Tanner, 2016). The underlying relationship between technologies is captured through the concept of relatedness. The concept is tied to the idea of absorptive capacity (Hidalgo, 2021), which refers to the premise that firms' ability to absorb new knowledge depends on their prior level of related knowledge (Cohen & Levinthal, 1990). Breschi et al. (2003) proposed the concept considering the commonalities between distinct types of knowledge. Hidalgo et al. (2007) extended it by arguing that local factors also affect the creation of commonalities. These local factors include the institutions, infrastructure, physical factors, and technologies existent in a given location. These communalities explain distinct patterns of development seen at the geographical level.

The 'knowledge space'[1] framework proposed in Hidalgo et al. (2007) became popular in subsequent analyses in the Evolutionary Economic Geography (EEG) literature. This framework is commonly depicted as a network, where nodes represent knowledge categories, such as technological or scientific fields, and links between them represent their degree of relatedness (Balland, 2016). For technologies, this network is especially useful to represent visually how they are related, and how local technological paths emerge due to these relations. Empirical evidence shows that these paths are strongly linked to existing local capabilities, including technological paths seen in cities (Boschma et al., 2014; Rigby, 2015), regions (Buarque et al., 2020; Colombelli et al., 2014; Van Den Berge & Weterings, 2014), and countries (Hidalgo & Hausmann, 2009; Petralia et al., 2017).

[1] Although 'knowledge space' in the broader generalization of the framework, the original term used in Hidalgo et al. (2007) was 'product space', once the focus was products exports; later variations like 'technological space' and 'scientific space' were used to refer to technologies and publications, for example, as highlighted in Balland et al. (2016).

The concept seems also able to predict even the emergence of radical technologies. In particular, Tanner (2016) shows that existing knowledge in areas relevant to fuel cell industries explains the local emergence of this disruptive technology. The higher the variety of specialisations of regions in related fields, the more likely it is that they develop this type of industry (ibid).

2.2. Research questions

Despite the central role of relatedness in the EEG literature and in the ‘knowledge space’ framework, there is surprisingly little consideration on how it emerges and changes over time (Hidalgo, 2021). Relatedness has been treated mainly as an independent and almost exogenous factor (Juhász et al., 2021). Only selected recent studies analyse relatedness as being dynamic and endogenously created. For example, Kuusk and Martynovich (2021), find that inter-industry relatedness changes considerably over time and that this change influences regional employment growth. Juhász et al. (2021) focus specifically on technological relatedness. They find that co-location of technologies and relatedness not only change over time but also affect each other: The more two technologies overlap within spatial distributions, the greater is the change in their relatedness. As relatedness between two technologies increases, so does the probability of them being co-located in the same geographical space.

Although geography - in terms of locational specific factors - plays a crucial role, relatedness is also affected by technological changes. In particular, Juhász et al. (2021) find that when two distinct technologies are combined once, the likelihood that they are combined again (and thus become more related) increases. Similarly, the literature on recombinant innovations stresses that previously unrelated technologies may become related due to new technological combinations (Castaldi et al., 2015; Frenken et al., 2012), regardless of geography. The underlying mechanism is that successful technological variations are selected and retained globally through dissemination (Arthur, 2009). In this way, successful new variations are repeated globally, increasing the relatedness between the recombined technologies. Local conditions, in turn, affect how these successful new variations are disseminated, generating distinct geographical patterns of adoption.

Albeit not yet recognising directly the existence of this mechanism, the EEG literature does find evidence of firms leaving locations due to unexplained local technological changes (Boschma et al., 2014; Rigby, 2015). As the possibility of 'foreign' technological development is not yet addressed, these exits are presented without further discussions on why they happen. This effect has alternatively been discussed through the notion of technological lock-in (Arthur, 1989; Cowan, 1990). The basic idea here is that markets may get 'stuck' in an inferior technological alternative due to network effects. In our geographically focused context, this would mean local technological development not moving towards a better technological alternative developed elsewhere. As a result, industries and regions that don't cope with more efficient technological alternatives may lose markets or fail, which would explain the local exit of firms.

In our view, the approach presented in Hidalgo et al. (2007) is particularly suited to address this gap in the literature by comparing location 'unbounded' technological change to local development. One of the arguments in Hidalgo et al. (2007) is that, by focusing on an outcome-based measure (relatedness), the relevant factors that affect the emergence of geographical-related communalities are captured. We argue that the same reasoning applies to technological change: by focusing on the global innovations of a given technology, the communalities related to its use are captured. In the technological case, the communalities refer to which technical combinations are being used to address the typical problems related to the technology. This leads to the emergence of innovation patterns, which reflect the main technical routes taken with the technology. These patterns, in turn, reflect the structure of technological knowledge linked to the technology and tend to be relatively invariant over time (Dosi & Grazzi, 2006).

Therefore, by focusing on the global innovations in a particular technology we aim at identifying how its use changes over time. To that end, a network perspective is particularly suited to understanding dynamic aspects of knowledge and to identify changing structures of technological knowledge (Antonelli et al., 2010). The resulting innovation patterns can then be compared to local exploration of the technology to identify how local patterns are influenced by geographically ‘unbounded’ or general global technological development. In our particular case, we are interested in two research questions:

1. How are the specialisation patterns linked to AI changing over time, and how do these changes affect its local exploration by countries?

As pointed out in Hidalgo (2021), relatedness can anticipate changes in local specialisation patterns. Accordingly, we expect that any changes in the innovation patterns related to AI use are reflected on how AI is explored locally by countries leading its development. This is to say that successful recombinations developed worldwide with AI will be locally adopted by these leading countries. Particularly, we use the term ‘global innovations’ to refer to these successful recombinations that are repeated worldwide.

Our following second research question is:

2. How do AI leading countries create and stablish new capabilities in AI while they explore this technology?

Based on Tanner (2016) we expect that the leading countries considered have capabilities in a variety of fields highly related to AI. This would explain particularly their technological leadership in the considered technology. By analysing the technological trajectory of these countries in AI, we expect that new capabilities developed in this technology emerge in an independent technological path in which new fields are explored according to their relevance to AI development (i.e., AI breakthrough the existing technological paths). This differs from the alternative in which new capabilities in AI would emerge in fields following countries’ existing capabilities (i.e., instead of breaking-in the existing technological paths).

3. Data and method

Following (Balland et al., 2019; Boschma et al., 2014; Feldman et al., 2015; Rigby, 2015; Whittle, 2020), we combine a technological space perspective with specialisation indices to analyse knowledge dynamics and the development of local capabilities. Specialisations indices are used in this literature as a proxy for local capabilities, whereas patents are used as a proxy for innovations. We follow this implementation and further differentiate between dynamics occurring at the local and technological levels. Next, we describe in detail the dataset and method.

3.1. Data collection and identification

We use PATSTAT 2019 (Spring version) to identify all registered priority filings[2] (granted or not). The creation of this patent dataset rests on three main choices: i.) strategy for identifying AI patents, ii.) assignment of patents to countries, and iii.) definition of the period of analysis and the intervals used to identify technological change.

Following Leusin et al. (2020), we use a keyword-based search strategy for (i) identifying as AI-patents all patents mentioning at least one typical AI technique in their title or abstract. These AI techniques are the advanced statistical and mathematical models used to implement AI functions such as computer vision, natural language processing, knowledge representation, etc. They include, for example, keywords related to machine learning (e.g., deep learning, neural networks, classification and regression trees), logic programming (e.g., expert systems, logic programming) and probabilistic reasoning. The selection of these AI-techniques is based on the classification presented in WIPO (2019), which we complement with synonyms collected from Wikipedia. The resulting search strategy has a total of 36 keywords (see Appendix A).

Following De Rassenfosse et al. (2019a), we assign in (ii) patents to countries by using inventors' location. In contrast, to assignees' location, this approach captures the locus of

2 A priority filing is the first patent application filed to protect an invention. If the same patent is registered in other patent offices, the following registrations are called non-priorities, constituting a patent family linked through the priority filing. The terms 'patents' and 'priority filings' are used interchangeably throughout the paper to refer to these registers.

knowledge creation (Squicciarini et al., 2013). We do not use the dataset presented in De Rassenfosse et al. (2019a), since it ends in 2014 and would omit the most recent period, for which we can document a substantial number of AI related inventions. As De Rassenfosse et al. (2019a) use additional sources to increase the location information of inventors and applicants related to their dataset, we perform a cross-check validation with our dataset. Taking the AI patents as reference, we find that 23,983 of our 42,971 AI-priorities are registered between 2015 and 2018. From the remaining 18,988 priorities, 15,355 are also found in the dataset presented by De Rassenfosse et al. (2019b). These patents hold the location information for 28,324 inventors, from which our dataset contains the same information for 27,275 inventors, which suggests a 96.3% correspondence.

Thus, based on this location proxy, we identify that more than 92% of the total number of AI priority filings in our dataset are accounted for by inventors from only four countries. These countries are China, Japan, South Korea, and the US, and are the ones we define as leading AI development. Japan and the US are early leaders in AI development, registering AI patents since as early as 1975. South Korea and China emerge in the second interval, with a particular spike in AI registers seen for China in the third interval. See Appendix B for more information on the registration of AI patents by these countries over time.

Finally, for (iii) we select the term from 1974 to 2018 as period of analysis considering the priority year of the first AI related inventions[3]. This results in 29,935,041 priority filings[4] considered in our patent dataset. We chose to analyse dynamics through three 15-years intervals. A 15-years definition allows us both to create intervals with the same length within the considered period (i.e., 1974-1988, 1989-2003, and 2004-2018), and to separate early AI adopters (Japan & US) from latecomers (South Korea & China). The latter developed their first AI patents in 1989, which coincides with the first year of our second interval. Each interval also

[3] The exceptions are 2 AI patents registered by the US in the year 1961, which were followed by a 13-year global hiatus of no further AI-registers that we chose to ignore; the first AI patent after this hiatus is registered in 1975.

[4] This number includes 72 priority filings for which the applied method of geographical proxying could not find the inventors' location.

represents particular technological developments of AI: the rise of knowledge-based expert systems, which took place from 1980 to 1987 (WIPO, 2019), the fast development of machine learning during the 1990's (Li & Jiang, 2017), and the culmination of machine learning through deep-learning, proposed in Hinton and Salakhutdinov (2006).

3.2. Method

We apply a technological space approach and specialisation indices to analyse the above described patent dataset. The technological space approach, proposed in Hidalgo et al. (2007) and thereafter adapted for patents (Balland, 2016; Boschma et al., 2014), displays technologies in a network visualization according to their particular measures of relatedness. These measures are based on the co-occurrence of two technologies within the same patent. If two technologies co-occur more often than what would be expected by chance under the assumption of statistical independence, we assume that they are more related to each other.

The measure of relatedness, first conceptualized in Breschi et al. (2003), considers the fact that patent examiners assign one or more classification codes to each patent. A symmetrical matrix of co-occurrences 'C' is calculated to account for every possible combination between two distinct technologies (from technology 'k' = 1 until the 'n' last technology considered in the classification scheme considered, for example). The resulting symmetric matrix 'C', which has dimensions 'n' x 'n', is then normalized to avoid the overestimation of knowledge links involving technologies that are largely used. Breschi et al. (2003) propose the use of the cosine index 'S' for this normalization, which is calculated in pairs considering every co-occurrence between two generic 'i' and 'j' technologies, as presented below:

$$S_{ij} = \frac{\sum_{k=1}^{n} C_{ik} C_{jk}}{\sqrt{\sum_{k=1}^{n} C_{ik}^2} \sqrt{\sum_{k=1}^{n} C_{jk}^2}}$$

Hidalgo et al. (2007) extend this idea by representing a normalized symmetric matrix of products exported by countries in a network perspective. Using a network layout that puts densely connected nodes in more centralized positions of the network, Hidalgo et al. (2007)

demonstrate that the most densely connected nodes are also related to more sophisticated products.

We follow the technological space approach proposed by Hidalgo et al. (2007), but use patents as the unit of analysis and the cosine index proposed in Breschi et al. (2003) for normalizing knowledge-relatedness. We use the 3rd version of the IPC technological field classification to differentiate between technologies, which includes a total of 35 technological fields. This classification overcomes some inconsistencies of earlier classifications by i.) considering all existent IPC codes, ii.) balancing the size of the considered fields, and iii.) reducing the overlap between similar technologies (Schmoch, 2008). We build two distinct technological spaces: a ‘global’ one, and one which is ‘AI-specific’. The global technological space considers all priority filings identified in the considered period. It is used to highlight the exploration of AI by the US, Japan, South Korea, and China. The AI-specific technological space, in turn, includes only the AI priority filings. This technological space is dynamic, varying from one interval to the other according to the AI patents registered in each interval, and is used to highlight AI’s development. No stocks of patents are considered from one interval to the other for any of the calculations.

Moreover, we measure the specialization of every considered entity over each interval through the Revealed Comparative Advantage (RCA) index[5], presented in Balassa (1965). If an entity has an RCA[6] equal or higher than one, it has a specialisation, whereas values below this threshold show an absence of specialisation. We use the RCA both to highlight specializations of entities over the considered technological spaces and as an independent indicator. For the latter, we measure the specialization of countries in ten selected IPC subclasses (i.e., 4-digits IPC codes), differentiating between countries ‘general’ specialisations (i.e., based on all priority filings), and AI specialisations (i.e., based only on the AI priority filings). For the former, we

[5] $\mathrm{RCA}_{Technology\ t,\text{entity e}} = \dfrac{\frac{\text{Number of patents in technology t from entity e}}{\text{Total of patents of entity } e}}{\frac{\text{Total number of patents in technology } t \text{ in the larger economy E}}{\text{Total number of patents in the larger economy E}}}$

[6] Technically, we use the Revealed Technological Advantage (RTA) index, which is an extension of the RCA index to technologies, but the principle is the same.

consider the same classification used in the technological spaces, i.e. IPC technological fields. In the global technological space, the RCA is used to highlight countries existing capabilities (i.e., specialisations), whereas in the AI-specific technological space it reflects technologies that are used above their particular relative average in AI patents.

4. Empirical analysis

4.1. Identifying technologies linked to AI in the AI-specific technology space

We first look into how AI-related innovations evolved over the considered intervals. We aim at identifying the main structure of technological knowledge used in AI innovations in each considered interval, which is stable over time.

Accordingly, in Figure 1, we present the technologies linked to AI over the three considered intervals. We use colours and node formats to highlight distinct technological sectors, and node size to emphasize codes connectivity (regarding number of links) to other technologies[7]. Specializations, in turn, are highlighted by depicting the name of the technological field which has a specialization in the respective interval.

[7] Depicted in the label 'Degree', which stands for Degree of Connectivity (i.e., higher values mean more connected technological fields), whereas the label 'weight' stands for the weight of the links (i.e., higher values mean more connections between the two technologies related to the link).

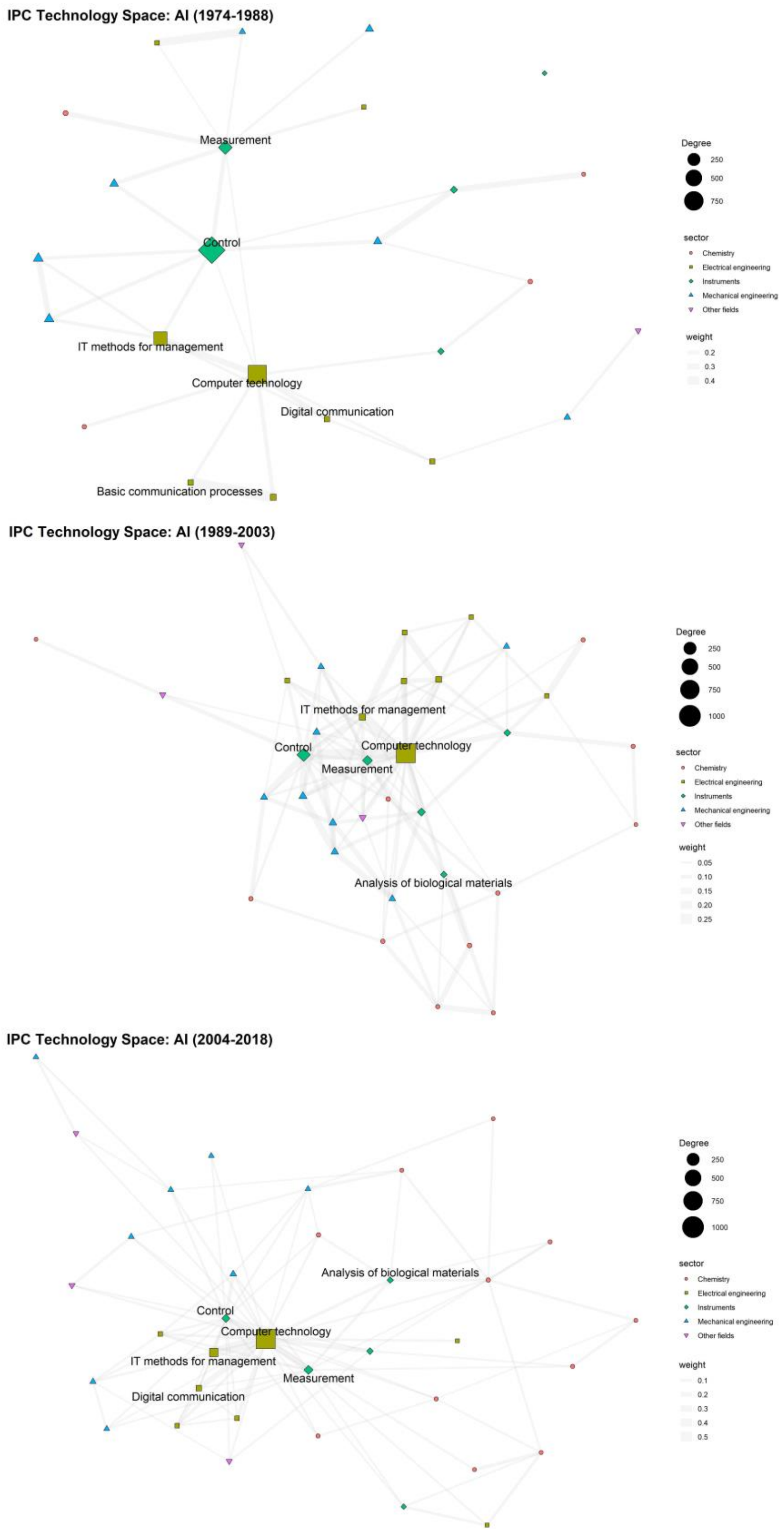


Figure 1. AI relatedness and specialisations over the considered intervals and IPC fields.

AI started as a combination of technologies sparsely distributed in the network, which then evolves to become more densely connected (see Figure 1). The number of technological fields linked to AI innovations is 25 in the first interval, and reaches the maximum of 35 fields in the second and third intervals. Specializations, i.e., the main technological fields related to AI, do not change much over time, as expected. All of them are exclusively within the sectors of 'Electrical engineering' and 'Instruments'. Only three technological fields change specializations over time. The less connected 'Basic communication processes' and 'Digital communication' lose their relevance after the first interval. Although, the latter presents again a specialization in the third interval. The field of 'Analysis of biological materials', in turn, is highlighted with a specialization in the second and third intervals. The 'stable' technological fields, which show a specialisation in every interval, are 'Computer technology', 'Measurement', 'Control' and 'IT methods for management'.

Overall, the technological fields of 'Control' and 'Computer technology' are both essential for AI innovations in the first interval. After this, the latter becomes increasingly important and central in the AI network. In the third interval, 'Computer technology' is indisputably the most connected technological field for AI innovations. The fields of 'Control' and 'Measurement' also play important bridging roles. 'Control' connects AI to technologies related to the sector of 'Mechanical engineering', while 'Measurement' connects AI with technologies from the 'Chemistry' sector.

4.2. Specialisations in AI fields in the technology space at the country level

Next, we focus on all priority fillings registered in the considered period (1974 – 2018), which are used subsequently to analyse the local exploration of AI. This global technology space is presented in Figure 2. Once again, we use node colours and node formats to highlight distinct sectors, and node size to highlight connectivity.

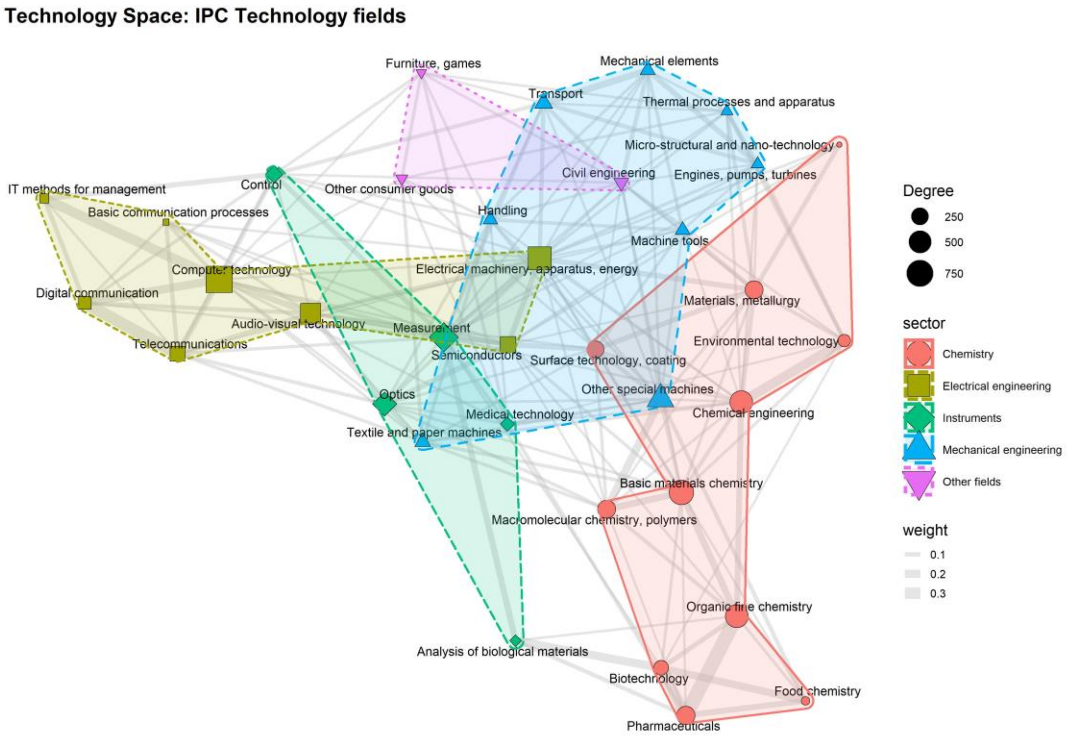


Figure 2. Global Technological Space for IPC fields.

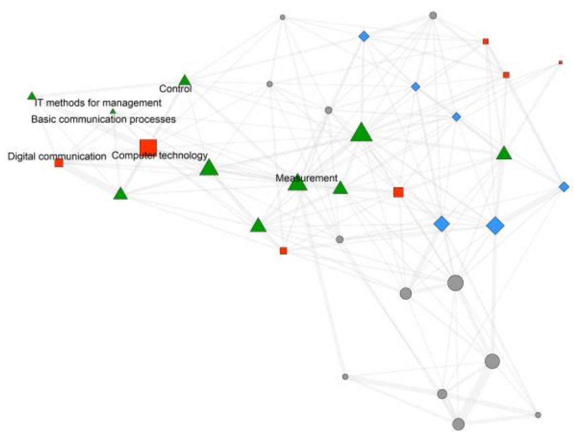
One can see in the global technological space that technological fields from the same sector are often close to each other, highlighting the expected stylized fact that the similarity between technologies within the same sector is higher than the similarity across distinct sectors. 'Electrical engineering'-related fields are mostly placed jointly on the left side of the network, while 'Mechanical engineering' and 'Chemistry'-related ones are placed on the top and right of the figure respectively (see Figure 2). One can also see that the main technological fields linked to AI through specializations (see Figure 1) are placed close to each other on the left side of the network (the only exception being the field of 'Analysis of biological materials', placed at the bottom). The field of 'Computer technology', which was the most connected in the AI network in the third interval, is also the most connected when all priority filings are considered in the Global perspective (see Appendix C for a complete list of the fields' connectivity). Technological fields linked to the sectors 'Mechanical Engineering' and 'Other fields' are relatively less connected, whereas technological fields linked to the sectors 'Electrical engineering' and 'Chemistry' are more connected.

Next, we use this global technological space to highlight the technological trajectory of countries leading AI development.

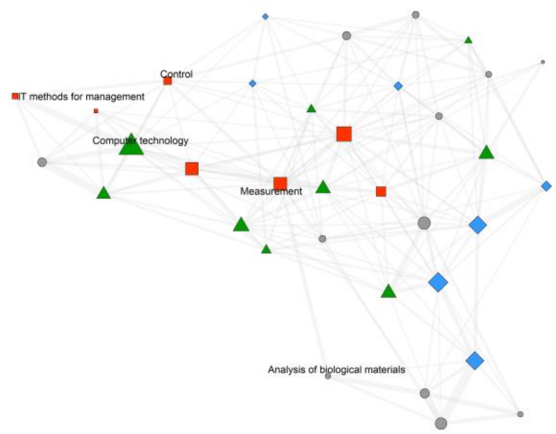
We identify local technological development by outlining the specializations of Japan, the US, South Korea, and China in the global technological space over the three considered intervals. Thereby, we differentiate between two main kinds of specializations: General specializations refer to the performance of a country considering all patents registered[8] in each considered interval. AI-related specializations, in turn, focus on AI patents, measuring the performance of each country according to its registers of AI patents in comparison to all AI patents registered in each considered interval. We use these two kinds of specialisations to create four labels capturing local exploration of AI, as presented in Figure 3. The colours and node formats used for each label are: Grey circles for no specialization of the country in the considered technological field (type 0), red squares for a general specialization (type 1), blue rhombus for an AI-specialization (type 2), and green triangles highlight that the country holds both a general and an AI-specialization in the same field (type 3). Furthermore, we use node size to stress connectivity and fields' names to highlight the technologies at each interval that were previously identified (i.e., in Figure 1) as AI-specialized.

[8] The calculation for both kinds of specializations considers the priority filings registered by all countries, not only the four countries in which the analysis is focused on.

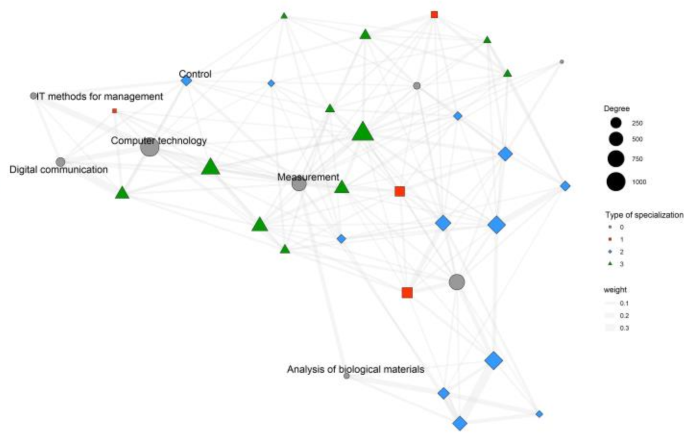
IPC Technology Space: Japan (1974-1988)



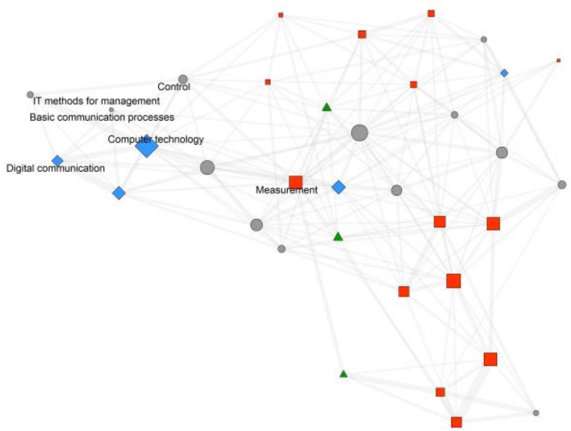
IPC Technology Space: Japan (1989-2003)



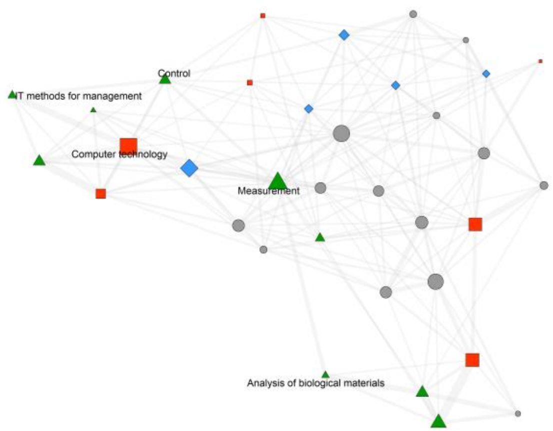
IPC Technology Space: Japan (2004-2018)



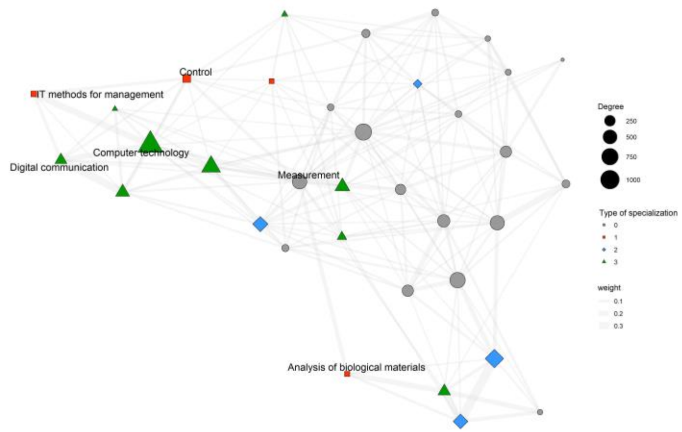
IPC Technology Space: USA (1974-1988)



IPC Technology Space: USA (1989-2003)



IPC Technology Space: USA (2004-2018)



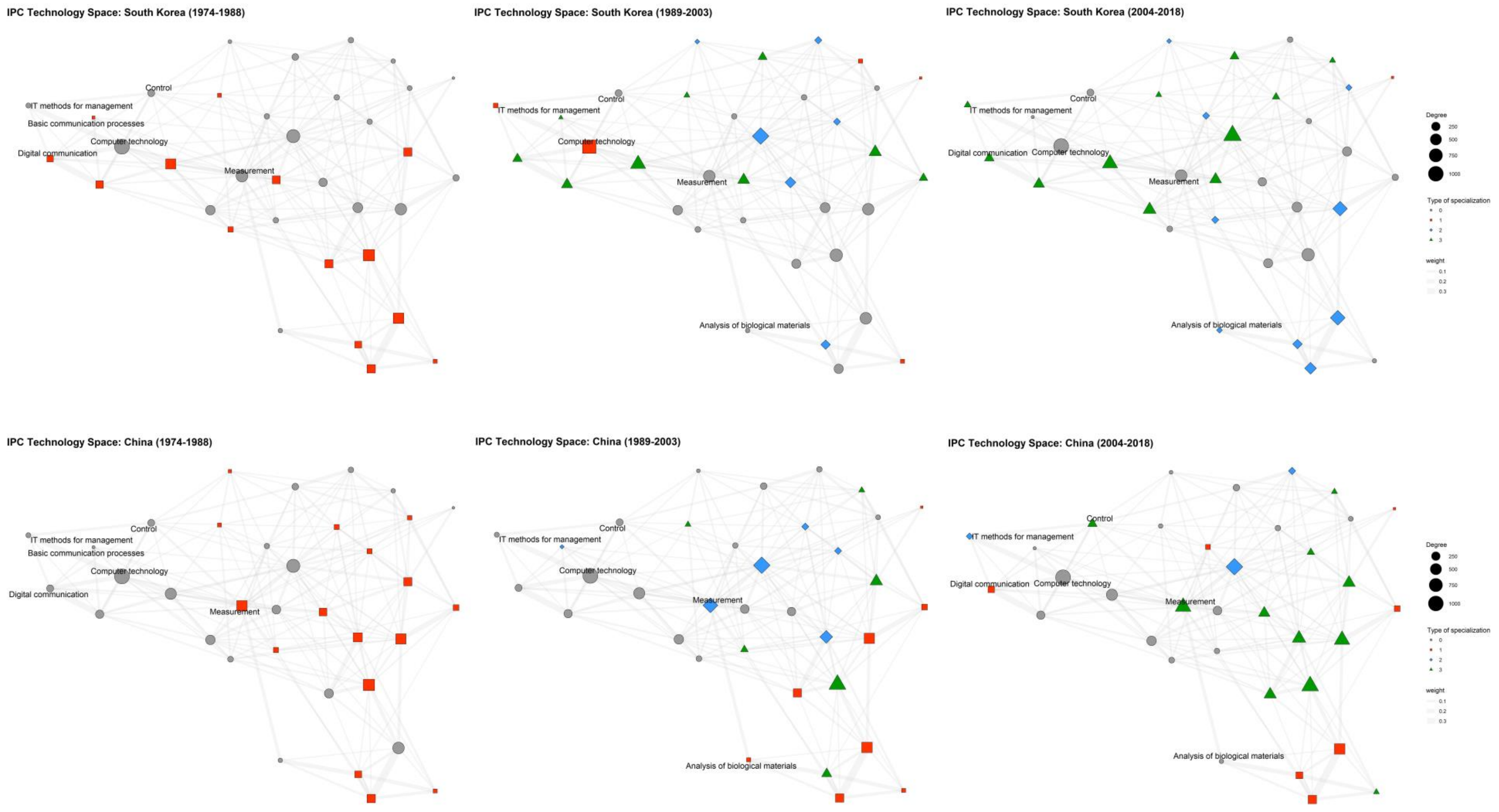


Figure 3. Specialisations in the considered technological fields for Japan (a), United States (b), South Korea (c), and China (d).

We detect a trend in Figure 3, which shows that the share of coinciding specializations (type 3) steadily increases over time in comparison to the number of general specializations (type 1). This indicates that countries increasingly combine their general and AI-specific specializations in the same technological fields. As a result, general-only specializations become less common, whereas coinciding specializations increase (red squares are overtaken by green triangles). Figure 4 quantifies the mentioned trend by displaying the share of coinciding specializations in relation to the total number of general specialisations[9].

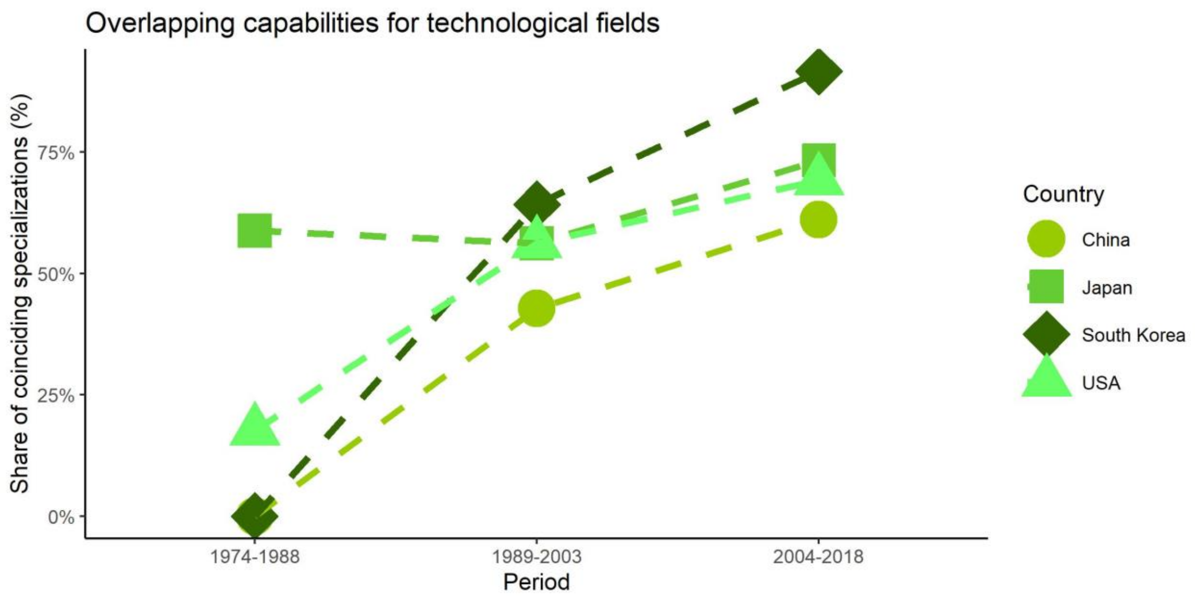


Figure 4. Share between coinciding and general specialisations for the four considered countries at the technological field level.

Surprisingly, specific trends related to AI innovations do not seem to affect how countries develop AI-related specializations (see Figure 3). The latecomers South Korea and China, for example, develop both an AI-specialization in the technological field 'Basic communication processes' when they start exploring AI in the second interval, although this field is not particularly relevant to AI anymore. Notably, China does not develop any kind of specialization (i.e., neither general or AI-specific) in the field of 'Computer technology' over the whole considered period, despite its importance to AI innovations. The country instead is the only

[9] Calculated as: *Share of coinciding specializations* = $\frac{Number\ of\ coinciding\ spec.}{Number\ of\ coinciding\ speci.+Number\ of\ general\ spec.}$

one holding a coinciding specialization in the bridging field of 'Measurement' in the third interval, which might be better suited for China given its particular focus in fields related to the 'Chemistry' sector. South Korea, in comparison, starts exploring AI by developing a general specialization in the 'Computer technology' field, which happens to be close to fields in which the country already had general specializations in the first interval. Conversely to China, South Korea's coinciding specializations remain close to the AI cluster on the left side of the network. The early adopters Japan and the US present different specialization patterns over time. Japan starts out with some type of specialization in every field related to AI, but loses both general and AI-specific specializations in 'Computer technology' and other fields around it in the third interval. The US instead starts exploring the AI-side of the network mainly through AI-specific specializations and doesn't lose its 'Computer technology' general specialization over time.

4.3. Overall and AI specialisation in technological classes at the 4-digits IPC level

We need to interpret our results based on the RCA index cautiously, since it compares the relative share of patents produced by a country to a relative global average. This implies that countries with few patents may present specialisations due to a low total number of patents (see also Soete (1987)). In our particular case, none of the considered countries has a low patent output. Still, an AI-specialisation might be attributed to a country in a given field just because the overall number of AI patents in the field is too small. Therefore, we refine our analysis by considering only the technologies more often used in AI patents. In this way we minimize the risk of having AI-specialisations linked to a country just because the number of AI patents linked to this technology is too low. As we have a limited number of fields strongly linked to AI at the technological field level, we broaden our analysis of specialization indices to the 4-digits IPC level (subclasses). The subclass codes are considerably more specific than the technological field codes, which allows us to better separate the technologies more related to AI. There are 645 subclasses available in the considered 2019 scheme[10], from which 456 are used at least once in one of our identified AI patents. Due to this large number, we avoid

[10] https://www.wipo.int/classifications/ipc/en/ITsupport/Version20190101/transformations/stats.html

the network analysis at this stage (which is reported separately in Appendix D). We focus on the ten IPC subclasses most used in AI patents. These ten codes concentrate 77% of the subclasses used in the AI patents identified. The majority of them are related to the technological field of 'Computer technology' (namely the subclasses 'Electric digital data processing' (G06F), 'Recognition and presentation of data' (G06K), 'Computer Systems' (G06N), 'Image data processing or generation' (G06T), and 'Speech analysis or processing' (G10L))[11].

We focus on the same four countries, and differentiate once again between general (see upper panel Figure 5) and AI-specific specialisations (see lower panel Figure 5). The main focus now is to disentangle if AI-specialisations coincide with general specialisations also for the technologies in which there is a high concentration of AI patents. Moreover, this time we use a non-binary RCA index[12]. By doing so, we can see in detail the small variations in countries' specialisations that precede the consolidation or not of a particular specialisation. Additionally, we use the Log 10 values of the specialisation indexes for better visualization. In this way, a specialisation is present for values above 0 and absent for values below this threshold.

[11] The remaining five subclasses are from the technological fields of: 'Measurement' (G01N), 'Control' (G05B), 'IT methods for management' (G06Q), 'Digital communication' (H04L), and 'Medical technology' (A61B).
[12] Meaning that it can take values between 0 and 1, and also values beyond 1.

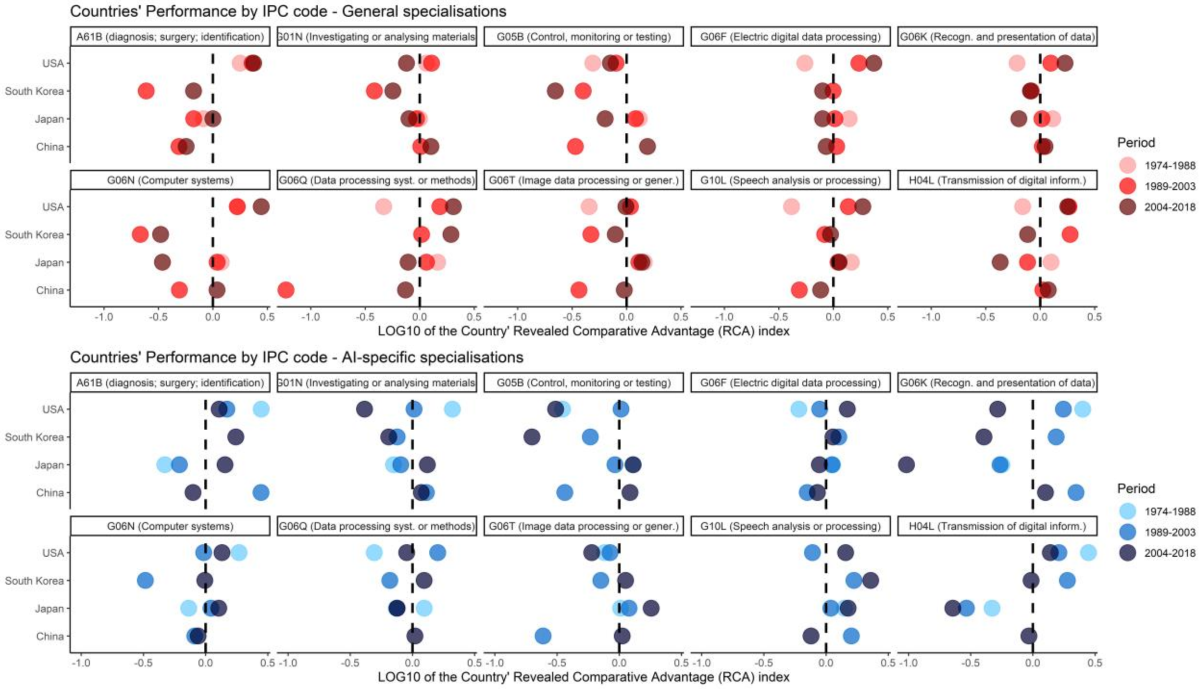


Figure 5. General and AI-specific RCA across AI patent subclasses for Japan, the US, South Korea, and China.

We see again that countries' AI-related specialisations often appear in codes in which they hold a general specialisation (see Figure 5). Conversely, we see that rarely a specialisation in AI precedes a general specialisation in the same subclass. Where this is the case, it does not last. For example, China loses very rapidly its new A61B and G10L AI-specialisations acquired in the second interval, when these subclasses are not yet part of the country's general specialisations. The same holds for the US in the codes G05B, G06K, and H04L, as well as South Korea for G06K. The only exception to this is South Korea's sustained specialisation in the subclass 'Speech analysis or processing' (code G10L). We also find that despite Japan losing several of its specialisations in the AI cluster in the third interval in the network perspective (see Figure 3a), the country maintains specialisation advantages in the main AI subclasses (e.g., leading in the subclasses G05B and G06T as well as relevant in G10L, A61B, G01N, and G06N).

Furthermore, there are specialisation patterns in the considered codes which are not entirely captured by a binary consideration of RCAs as used in the prior analysis. For example, all countries move towards the subclass 'Computer systems' (code G06N) in the AI perspective.

The US, an early AI adopter, is the only country that reduces its level of specialization in this subclass in one interval (i.e., the second interval), precisely when latecomers start developing AI. Japan and the US are the only countries that do develop a specialisation in this subclass, but China and South Korea advance steadily towards it. Conversely, a decrease in the level of specialisation is also seen for the subclass 'Recognition and presentation of data' (code G06K) in the AI perspective. Japan and the US 'move away' from this specialisation in later intervals, followed by South Korea and China. A similar behaviour was seen previously for the latter two countries in the general technological space (see Figure 3), when both developed an AI specialisation in the 'obsolete' technological field of 'Basic communication processes'.

Having confirmed that general and AI-specialisations often coincide for the ten most used AI technologies, we measure the share of coinciding specialisations at the subclass level. We do so for the ten considered subclasses (see Figure 6a), and for all subclasses available (see Figure 6b). The trend is very similar to what was seen previously at the technological field level: Over time, codes with a general specialisation are increasingly likely to show also an AI-specific specialisation. For the ten considered subclasses, leading countries lose some of their coinciding specialisations when latecomers start exploring AI. Countries' coinciding specialisations in all subclasses reach roughly a third of the scale seen previously at the technological field level in the third interval[13].

[13] Note that some staggering shares appear as a result of the limited number taken as reference in Figure 6a. These are shown for Japan and South Korea in the third interval, which appear with a 100% share of coinciding specialisations. These high shares are due to the limited number of general specialisations that these countries hold in this interval in the considered ten subclasses (Japan holds a general specialisation in the codes G06T and G10L, whereas South Korea does it in the code G06Q).

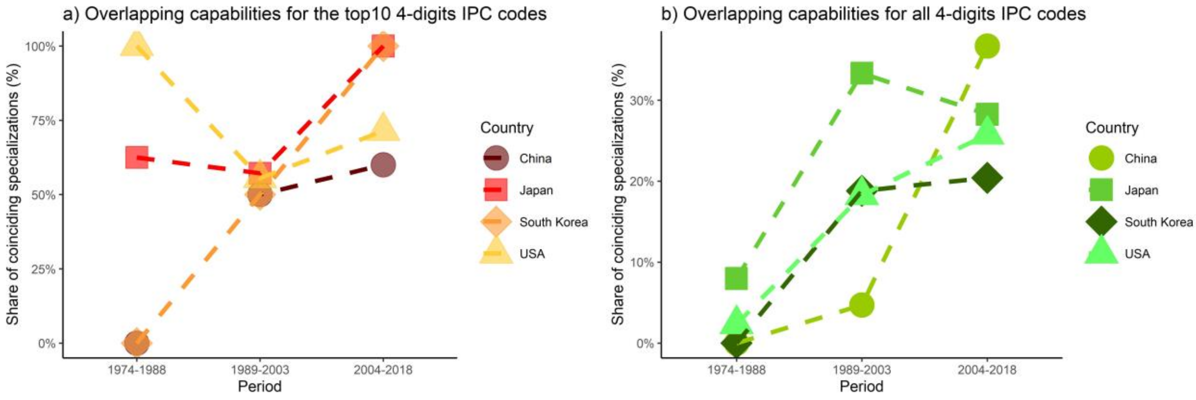


Figure 6. Share between coinciding and general specialisations for the four considered countries at the subclass level for the ten codes (a) and all codes (b).

5. Discussion and concluding remarks

5.1. Summary of the main findings

This paper analysed the technological evolution of AI and compared it to its local exploration by countries leading its development. The purpose was to understand how the innovation patterns linked to AI changed over time, how countries leading AI development explored this technology, and whether AI's changing innovation pattern was reflected on how leading countries explored this technology. Using a technological space framework to visualize the changes in relatedness between technologies linked to AI innovations, we identified a considerable transformation over time. AI evolved from a dispersed network of weakly related technologies to a dense network centred around the field of 'Computer technology'. In this process, some technological fields initially linked to AI lost their importance (e.g., 'Basic communication processes'), whereas others gained relevance (e.g., 'Analysis of biological materials').

Our results indicate that these general changes in the technological development of AI were not uniformly reflected on its local exploration by countries leading AI development. Instead, the existing local knowledge was seemingly more correlated with the development of AI-related capabilities. Interestingly, this local knowledge didn't hinder countries from developing AI specialisations in fields where there was no previous related knowledge, but it acted to 'preserve' the specialisations that were linked to existing general knowledge. As a result, AI specialisations developed in technologies that were not part of the local existing knowledge bases were very likely to vanish. This ‘selection’ process was shown to lead to the emergence of a pattern where local specialisations developed in AI increasingly coincide with existing ‘general’ specialisations.

5.2. Contributions

This paper makes methodological and theoretical contributions. Regarding theoretical contributions, our findings contribute to recent literature considering technological relatedness as being dynamically created. In particular, we add to Juhász et al. (2021) by showing that geographically ‘unbounded’ dynamics also contribute to shaping technological relatedness. This follows the mechanism proposed in Arthur (2009) in which successful innovations that contribute to technological development are repeated. The repetition of these successful innovations creates innovation patterns, which reflect the technical routes taken to solve the problems typical of a technology (Dosi & Grazzi, 2006). The repetition of these technical routes, in turn, leads to an increase in the relatedness between the technologies linked to them.

In this way, combinations that improve a technology’s performance significantly are expected to be (eventually) adopted and repeated in local innovations. The fact that this technological progress is weakly reflected on local technological exploration offers an explanation to why some local industries, once-promising and successful, eventually decline and fail. The stronger role of path dependency over geographically ‘unbounded’ technological development may lead such industries to get stuck in local versions of a technology. In this case, if a relevant development with the technology occurs abroad and is not successfully translated to the local context, existing industries may become less competitive and decline. This finding allows linking the idea of technological lock-in (Arthur, 1989; Cowan, 1990) to the EEG literature, offering an explanation to the not-yet addressed phenomena of firms leaving specific locations (Boschma et al., 2014; Rigby, 2015). Particularly, we documented that these dynamic innovation patterns occur for a particular technology over time. These dynamics are to be even greater when the evolution of all technologies is considered simultaneously.

Our findings also show that leveraging local knowledge is likely to even open new unrelated technological opportunities. Despite counterintuitive in the sense that this kind of leverage is expected to create only related technological variety, we show that the recombinatorial process allows new technologies to break-in locally. This happens through the recombination of a novel technology with the existing local knowledge-base, which may lead to the creation of a new technological path.

Regarding methodology, we propose a way of 'disentangling' local innovations made with a particular technology from 'global' innovations. This was done by analysing these innovations separately. Global innovations refer to all patents registered worldwide for a given technology, and reflect unbounded innovation patterns. Local innovations refer to patent registers related to a technology proxied by location. By using the RCA index to highlight specialisation patterns of these distinct datasets over technological spaces, one can compare global 'unbounded' development to local development. Although based on a simple idea and implementation, we find no similar approach in the literature. This disentanglement allows measuring distinct kinds of specialisations (i.e., technological-specific and general ones), which is crucial to understand how new technologies are incorporated into local knowledge-bases. In this regard, we think our methodological approach is more intuitive than the one presented in Buarque et al. (2020), for example. Put simply, the authors examine how AI is integrated into the knowledge spaces of regions by looking at how these networks change when AI patents are excluded from them. In our opinion, this kind of exclusion is problematic. For one, it takes the assumption that technological efforts made towards developing AI wouldn't be used to develop other technologies in the case that AI wouldn't exist. Besides, a bias may be created towards regions with an overall low number of patents, making AI appear to be more important than it actually may be.

Regarding the AI literature specifically, our investigation contributes to the identification of technological fields related to AI innovations in distinct intervals of time. In contrast to earlier studies (Buarque et al., 2020; Fujii & Managi, 2018; Klinger et al., 2018; Righi et al., 2020), we manage to capture the dynamic development of AI, including the use of distinct main technologies over time to generate AI innovations. The consideration of this distinct set of technologies contrasts to findings presented in Buarque et al. (2020). The authors point out that developing computing-related technologies is potentially a necessary condition to develop AI. Our findings, stressed most clearly by the case of China, highlight that this condition doesn't seem to apply to the national development of AI. The existing specialisations of China when it started exploring AI stress the absence of general capabilities in technological fields apparently central to AI development, like 'Computer technology', 'Measurement' and 'Control'. Nevertheless, China managed to develop specialisations in AI through its existing knowledge in fields mostly related to the 'Chemistry' sector.

5.3. Policy implications

Our empirical findings are relevant to the design of policies aimed at inducing technological development. The concept of Smart specialisation (Foray et al., 2009) has been recently stressed in the EEG literature as particularly appropriate to that aim (Balland et al., 2019; Hidalgo, 2021; Montresor & Quatraro, 2020; Whittle, 2020). This concept proposes leveraging existing local capabilities to achieve economic and technological development. Our empirical evidence shows that local specialisations developed in fields where there are general local ones are likely to last longer than technological-specific specialisations developed in fields disconnected from local knowledge. This finding supports policies that argue for the leveraging of local capabilities as a way to induce further technological development, as the ones related to Smart specialisation. This should partially address criticisms towards Smart specialisation for being a 'policy running ahead of theory' (Foray et al., 2011). Our findings can also be linked to the 'diversification dilemma' highlighted in Balland et al. (2019). The authors associate this dilemma to the implementation of Smart specialisation, in which policies must consider between favouring the emergence of less related but more profitable (a.k.a. complex) capabilities, or the further developing of local existing capabilities. Balland et al. (2019) find that high relatedness leads to the local emergence of more profitable technologies, solving the dilemma in favour of the further development of existing capabilities. Our findings complement this by showing that this leveraging of local knowledge possibly favours the emergence of new technological paths. These new paths are created through the recombination of a novel technology with the existing local knowledge-base. Hence, highly connected sectors may be the most efficient to induce this creation, as highlighted in Alshamsi et al. (2018).

Finally, our findings also have implications for policies being created globally towards AI development in the so-called ‘AI global race’ (Klinger et al., 2018). They highlight the multiple ‘entry points’ possible for AI development, which should impact policy-making towards leveraging the deployment of AI in combination with existing local capabilities. This strategy seems appropriate even for technologies not very related to AI, which was notably seen in the case of China through its exploration of AI in technologies related to the Chemistry sector. These multiple entry points may be linked due to the particular transversal nature of AI (Righi et al., 2020).

5.4. Limitations and future research directions

We need to acknowledge the limitations of our approach, of which the most explicit ones are linked to the data. Firstly, we identify AI innovations by just considering patents, although many innovations in this field are not patented. This might constitute a particular issue for AI innovations based on software and even more to open source software development. Hence, in a strict sense, our results refer to AI ‘inventions’ (with proprietary characteristics) rather than ‘innovations’. Secondly, we consider both granted and non-granted patents, which possibly introduce a quality bias on our dataset. Thirdly, we develop a keyword-based search to identify AI, which we prefer in our case over strategies based on classification codes. However, such an approach is inherently subjective and sensitive to the choice of keywords. Finally, we also kept the ‘global technological space’ static, conversely to what we considered in the AI technological space. This was done to simplify the analysis and justified by our main focus on technological dynamics and how they interact with local knowledge. Discussions regarding the latter are already extensively addressed in the literature (see for example Hidalgo et al. (2007) and Hidalgo (2021)).

We also highlight that the adopted methods do not allow conclusions regarding causality. In particular, this applies to the emergence and failure of the different types of specialisations identified. We can't argue that the short-lived aspect of AI specialisations that didn't match the local knowledge-base was caused by this mismatch. These aspects are subject to further inspection, which would need to apply causal inference strategies to test, whether the indicative findings revealed in this study are robust and beyond reasonable econometric doubt. This might also require a larger set of countries under investigation during the observation period. Our study focused on four countries, which account for the lion's share of AI patents during the observation. Obviously, this choice limits our ability to generalize our findings. The exclusive focus on AI adds to this generalization aspect.

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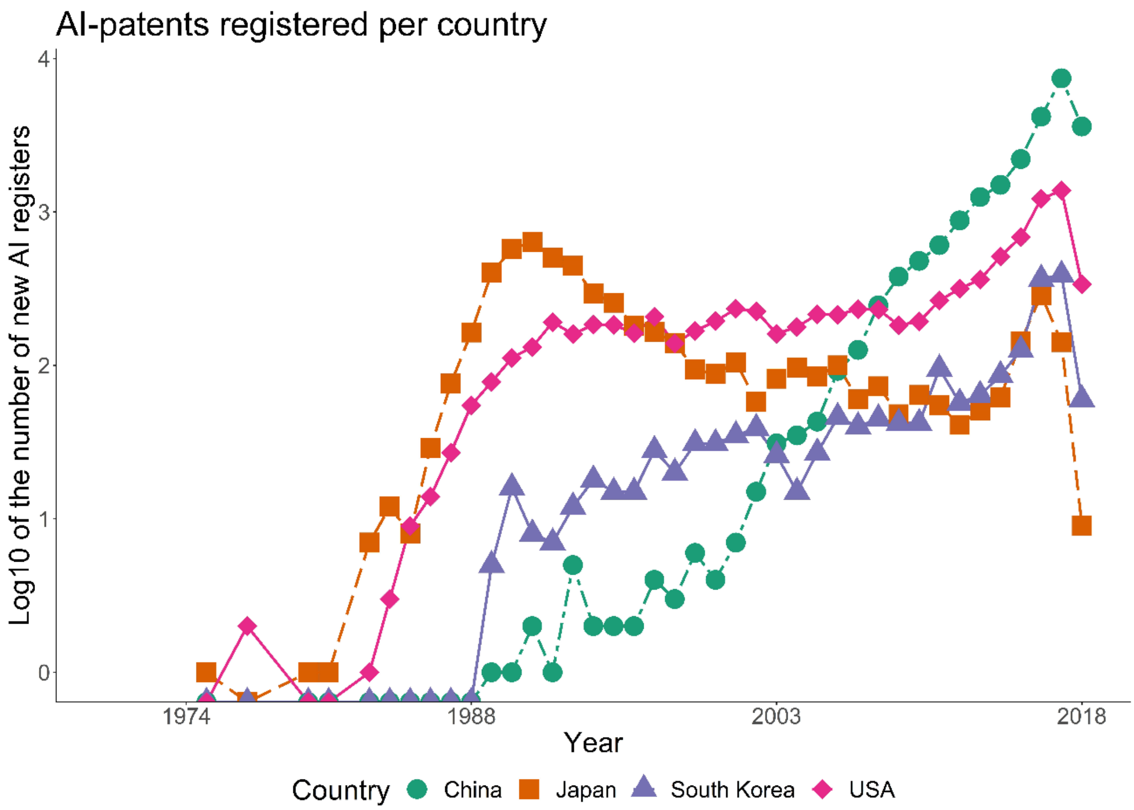
Appendix A. Search strategy applied in PATSTAT 2019 spring version for identifying AI patents.

The SQL query presented below comprehends all keywords used to identify AI patents. This search strategy is similar to the one presented and discussed in *Leusin, M. E., Günther, J., Jindra, B., & Moehrle, M. G. (2020). Patenting patterns in Artificial Intelligence: Identifying national and international breeding grounds. World Patent Information, 62, 101988*, with the exception that we exclude the generic keyword 'Artificial Intelligence' and its related Wikipedia synonym 'Machine Intelligence', which are not included in the list of AI-techniques presented in WIPO (2019). For more details on each keyword and synonym, see Leusin et al (2020), Tables 1 and 2 (pg. 3 and 4, respectively).

Select appln_id from tls202_appln_title
Where *appln_title* like '%machine learn%' OR *appln_title* like '%Probabilistic reason%' OR *appln_title* like '%Fuzzy logic%' OR *appln_title* like '%Logic Programming%' OR *appln_title* like '%Ontology engineer%' OR *appln_title* like '%pervised learn%' OR *appln_title* like '%reinforced learn%' OR *appln_title* like '%task learn%' OR *appln_title* like '%neural network%' OR *appln_title* like '%deep learn%' OR *appln_title* like '%expert system%' OR *appln_title* like '%support vector machin%' OR *appln_title* like '%description logistic%' OR *appln_title* like '%classification tree%' OR *appln_title* like '%regression tree%' OR *appln_title* like '%logical learn%' OR *appln_title* like '%relational learn%' OR *appln_title* like '%probabilistic graphical model%' OR *appln_title* like '%rule learn%' OR *appln_title* like '%instance-based learn%' OR *appln_title* like '%latent represent%' OR *appln_title* like '%bio-inspired approach%' OR *appln_title* like '%probability logic%' OR *appln_title* like '%probabilistic logic%' OR *appln_title* like '%reinforcement learn%' OR *appln_title* like '%multitask learn%' OR *appln_title* like '%Decision tree learn%' OR *appln_title* like '%support vector network%' OR *appln_title* like '%deep structured learn%' OR *appln_title* like '%hierarchical learn%' OR *appln_title* like '%graphical model%' OR *appln_title* like '%structured probabilistic model%' OR *appln_title* like '%Rule induction%' OR *appln_title* like '%memory-based learn%' OR *appln_title* like '%bio-inspired comput%' OR *appln_title* like '%biologically inspired comput%'

UNION
Select appln_id from tls203_appln_abstr
Where *appln_abstract* like '%machine learn%' OR *appln_abstract* like '%Probabilistic reason%' OR *appln_abstract* like '%Fuzzy logic%' OR *appln_abstract* like '%Logic Programming%' OR *appln_abstract* like '%Ontology engineer%' OR *appln_abstract* like '%pervised learn%' OR *appln_abstract* like '%reinforced learn%' OR *appln_abstract* like '%task learn%' OR *appln_abstract* like '%neural network%' OR *appln_abstract* like '%deep learn%' OR *appln_abstract* like '%expert system%' OR *appln_abstract* like '%support vector machin%' OR *appln_abstract* like '%description logistic%' OR *appln_abstract* like '%classification tree%' OR *appln_abstract* like '%regression tree%' OR *appln_abstract* like '%logical learn%' OR *appln_abstract* like '%relational learn%' OR *appln_abstract* like '%probabilistic graphical model%' OR *appln_abstract* like '%rule learn%' OR *appln_abstract* like '%instance-based learn%' OR *appln_abstract* like '%latent represent%' OR *appln_abstract* like '%bio-inspired approach%' OR *appln_abstract* like '%probability logic%' OR *appln_abstract* like '%probabilistic logic%' OR *appln_abstract* like '%reinforcement learn%' OR *appln_abstract* like '%multitask learn%' OR *appln_abstract* like '%Decision tree learn%' OR *appln_abstract* like '%support vector network%' OR *appln_abstract* like '%deep structured learn%' OR *appln_abstract* like '%hierarchical learn%' OR *appln_abstract* like '%graphical model%' OR *appln_abstract* like '%structured probabilistic model%' OR *appln_abstract* like '%Rule induction%' OR *appln_abstract* like '%memory-based learn%' OR *appln_abstract* like '%bio-inspired comput%' OR *appln_abstract* like '%biologically inspired comput%'

Appendix B. Log 10 of number of AI-priority filings by Japan, the US, South Korea, and China.

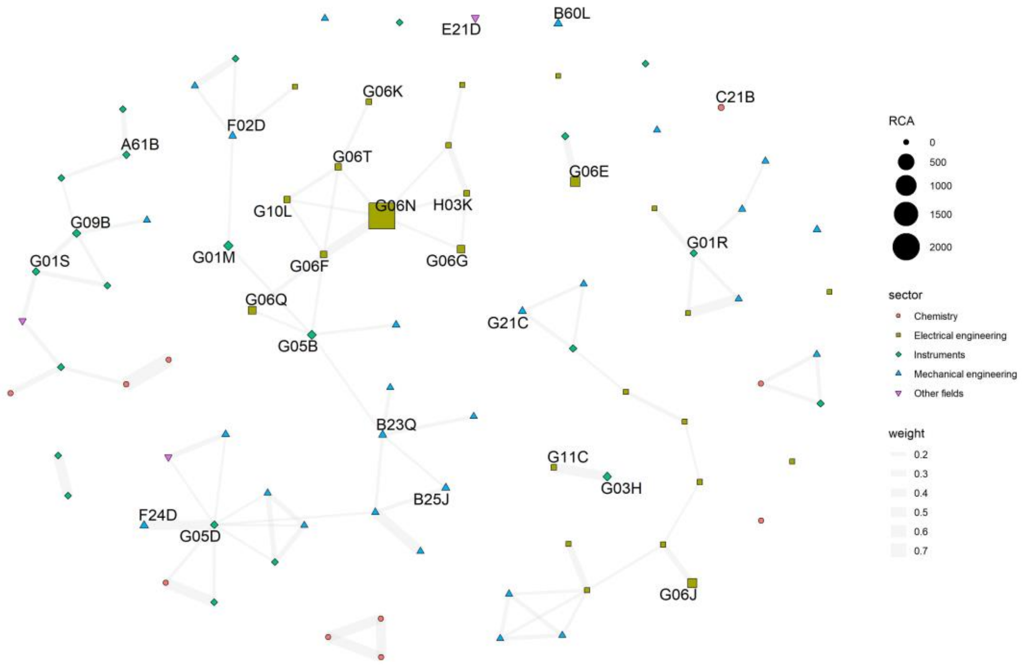


Appendix C. Technological fields connectivity considered in the global technological space network.

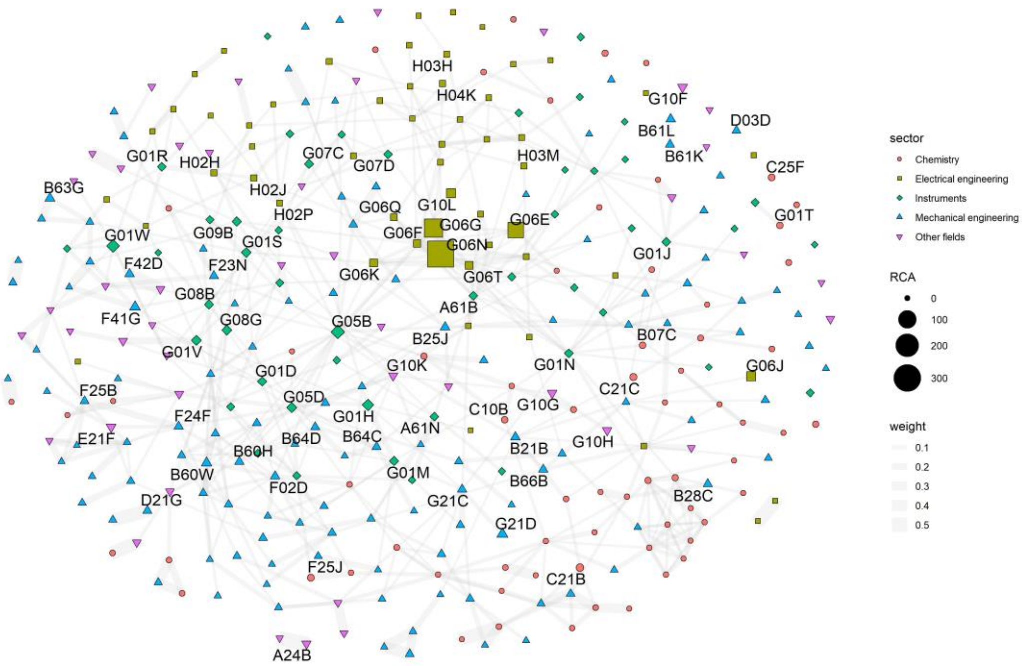
Field name	Sector	Degree of connectivity
Computer technology	Electrical engineering	1,000
Electrical machinery, apparatus, energy	Electrical engineering	0,955
Basic materials chemistry	Chemistry	0,938
Organic fine chemistry	Chemistry	0,913
Measurement	Instruments	0,912
Chemical engineering	Chemistry	0,906
Audio-visual technology	Electrical engineering	0,901
Other special machines	Mechanical engineering	0,856
Optics	Instruments	0,839
Pharmaceuticals	Chemistry	0,825
Materials, metallurgy	Chemistry	0,822
Macromolecular chemistry, polymers	Chemistry	0,820
Semiconductors	Electrical engineering	0,804
Surface technology, coating	Chemistry	0,790
Telecommunications	Electrical engineering	0,782
Biotechnology	Chemistry	0,738
Digital communication	Electrical engineering	0,719
Control	Instruments	0,708
Transport	Mechanical engineering	0,688
Environmental technology	Chemistry	0,670
Textile and paper machines	Mechanical engineering	0,631
Mechanical elements	Mechanical engineering	0,615
Medical technology	Instruments	0,611
Civil engineering	Other fields	0,607
Machine tools	Mechanical engineering	0,602
Handling	Mechanical engineering	0,601
IT methods for management	Electrical engineering	0,566
Engines, pumps, turbines	Mechanical engineering	0,545
Analysis of biological materials	Instruments	0,510
Thermal processes and apparatus	Mechanical engineering	0,508
Other consumer goods	Other fields	0,499
Food chemistry	Chemistry	0,491
Furniture, games	Other fields	0,427
Basic communication processes	Electrical engineering	0,376
Micro-structural and nano-technology	Chemistry	0,346

Appendix D. AI relatedness and specialisations over the considered intervals for IPC subclasses.

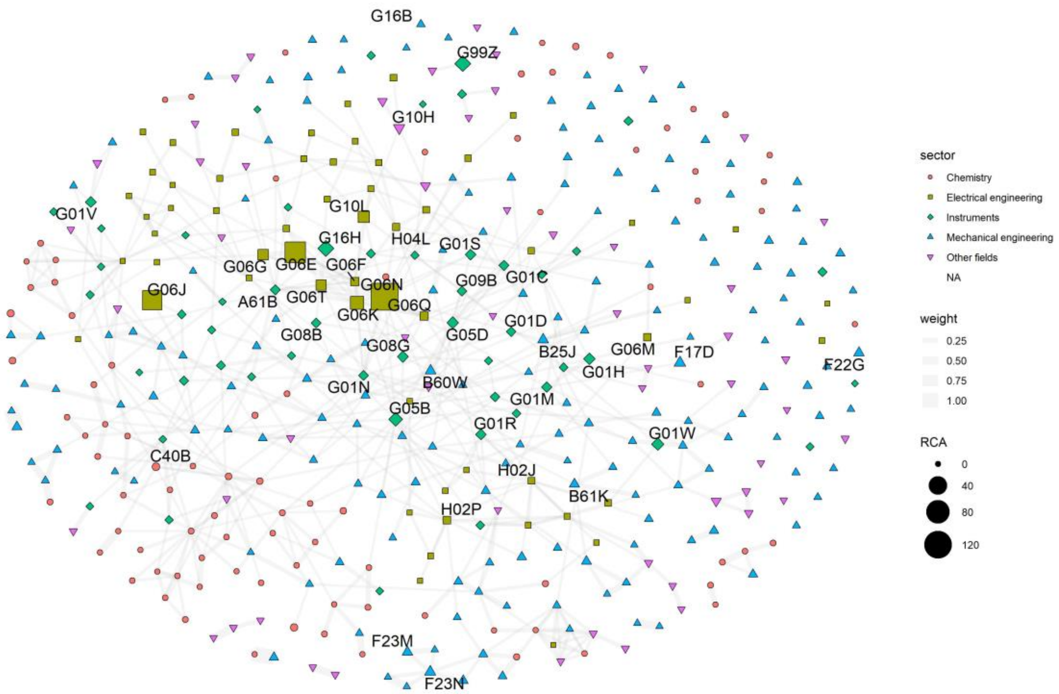
IPC Technology Space: AI (1974-1988)



IPC Technology Space: AI (1989-2003)



IPC Technology Space: AI (2004-2018)



Note that, similarly to Figure 1, AI starts as a narrow network that evolves to a densely connected one centred around a code linked to computer technologies. Here, the central code is G06N, which refers to 'Computer systems based on specific computational models'. Note that all ten main subclasses highlighted previously in Figure 5 also appear as central here in the third interval (i.e., with a positive specialisation). Subclasses related to the sectors 'Chemistry' and 'Other fields' are shown mainly on the periphery of the network, whereas subclasses related to the sectors 'Electrical engineering' and 'Instruments' occupy again central positions.