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FULL ARTICLE

Mapping regional strengths in a key enabling technology: The distribution of Internet of Things competences across European regions

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Abstract

The Internet of Things (IoT) can trigger innovation processes across all sectors of the economy. However, this potential is not available to all regions. As with other enabling technologies, the competences required to develop IoT solutions are numerous and varied, ranging from hardware to software and related services, and are often provided by different companies. To map the application potential of these technologies across European regions, we use textual analysis to identify the NACE codes associated with five main IoT domains. We identify clusters of regions characterized by different mixes of competences in IoT technologies and we discuss the policy implications of our findings at both European and regional levels.

KEYWORDS
cluster analysis, enabling technologies, Internet of Things, regional competences, text-mining

JEL CLASSIFICATION
O33, O32, O14, R12, C38, C80

1 | INTRODUCTION

New digital technologies associated with Industry 4.0 (I4.0) —Internet of Things (IoT), cloud services, big data and analytics (Frank et al., 2019; GTAI, 2014; Hermann et al., 2016)—are transforming sectors, value chains and production systems (Capello & Lenzi, 2021a, 2021b; De Propris & Bailey, 2020). These technologies are expected to shape the geography of innovation and knowledge production (Balland & Boschma, 2021; Consoli et al., 2021) and create a range of opportunities for those regional economies that are able to exploit them. In this study, we focus on IoT, which includes a set of technologies that enable the collection and transmission of data between devices; as a result, interconnected and integrated objects can be identified, located, tracked, monitored, and made to communicate with each other (de Sousa Jabbour et al., 2018; Li et al., 2017).

According to many scholars and experts, IoT – like other I4.0 technologies—qualifies as a key enabling technology (Martinelli et al., 2021; McKinsey Global Institute, 2013; Rong et al., 2015). The latter are knowledge-intensive technologies associated with intensive R&D, rapid innovation cycles, significant investment costs and highly qualified labour (Teece, 2018). Thanks to their novelty and pervasiveness, enabling technologies are capable of driving innovation in products, processes and services across all sectors of the economy, and, finally, promote economic development (Adner & Levinthal, 2002).

Leveraging the potential of key enabling technologies such as the IoT to drive economic growth and job creation is an important development strategy for regions, particularly in high-income economies (Capello & Lenzi, 2021a; European Commission, 2009; Evangelista et al., 2018; Laursen, 2000; Montresor & Quatraro, 2017). To exploit such potential, however, regional economies need to possess the required competences (Consoli et al., 2021). Because these technologies are usually complex and require the integration of many different competences, often provided by different firms (Teece, 2018), the presence of a sizeable set of firms providing core elements of the technology, or parts of the value chain, is crucial for a region to be "on the map" of technological and industrial development. Moreover, given the specific systemic characteristics of IoT, a combination of very different competences is needed to be able to produce workable solutions. Gathering a critical mass of competences in the core elements of the technology is important: it has been shown that regions with relevant expertise in enabling technologies are able to grow more than the regions that do not host such competences, and can more easily embark on radical innovation paths (Antonietti & Montresor, 2021; Evangelista et al., 2018; Montresor & Quatraro, 2017). This is because technological competences in core elements of the enabling technology act as building blocks for further technological developments in several directions, both along the same technological trajectory and into related technologies (Boschma & Frenken, 2011; Heimeriks & Boschma, 2013). In turn, these developments can lead to the growth of related industries and even to the inception of new industries (Capello & Lenzi, 2018).

In order to understand the extent to which European regions possess the technological competences that may drive further technological developments and consequent growth of related and new industries in the region, in this study we propose an original methodology to map the regional distribution of IoT competences in Europe. While research has suggested that the competences needed to leverage I4.0 technologies are unevenly spread across European regions (Martinelli et al., 2021; Muscio & Ciffolilli, 2020), few attempts have been made to develop a regional mapping of competences of IoT (Capello & Lenzi, 2021a, 2021b).

A crucial factor that makes it difficult to map the geographical distribution of competences in IoT is that it does not fit existing industry classifications, a problem that is common to most emerging technologies (Feldman & Lendel, 2010). Some scholars have approached this problem by relying on patent data, and have constructed maps of the inventive competences of the regions (Balland & Boschma, 2021; Capello & Lenzi, 2021b; Martinelli et al., 2021; Metallo et al., 2018). Others have focused on sectoral data, in order to map the production competences of firms in the regions in the broad area of I4.0 (Capello & Lenzi, 2021a, 2022). Although both approaches have limitations and advantages, we believe that the production competences approach is particularly interesting in order to derive a comprehensive mapping in the field of IoT, since in this field some of the key activities and artefacts—such as the production of software, the processing of data, and the combination of known software and hardware into new architectures—are hardly ever subject to patenting (Trappey et al., 2017).

Our approach involves identifying firms' production competences in different activities related to IoT, and mapping their presence in 18 European countries, at regional (NUTS 3) level.[1] The originality in our approach lies in the identification of groups of NACE codes that are associated with specific IoT-related activities (which we call 'IoT domains'), where the association between IoT domains and corresponding NACE codes builds upon the automated text analysis of firms' textual descriptions of their activities. In addition to being important in its own right, geographic mapping allows us to identify regions where the full IoT value chain is present, and regions where substantial manufacturing or software and telecommunication components of the IoT value chain are present, but not the full value chain. Drawing on such mapping, and on the analysis of regional socio-economic conditions, we can discuss policy implications for the development of IoT in Europe.

The paper is structured as follows. In Sections 2, 3 and 4, we discuss strands in literature that provide, respectively, a background for our research on regional mapping, IoT and its key components (layers, functions and players), and the classifications of regions according to their technological potential. In Section 5 we describe the data and the methodology of our research and discuss the extent to which our methodology complements and extends current approaches. In Section 6, we present the outcomes of the mapping exercise and propose a typology of regions based on the variety of IoT competences they feature and their socio-economic conditions. Finally, in Section 7, we draw some conclusions and suggest avenues for future research. The Appendix presents supplementary material with tables and figures. A selection of figures in the text and in the Appendix (marked with the symbol) can be browsed online using the Tableau Public navigation tool available at https://www.poliinnovazione.unimore.it/iot-competences-across-european-regions/.

2 | REGIONAL MAPPING OF ENABLING TECHNOLOGIES

Enabling technologies include radical technologies that emerge from new discoveries, or incremental technologies that arise from the convergence of existing technologies; they have the potential to create new industries or transform existing ones (Day & Schoemaker, 2000). Thus, by definition, enabling technologies offer a rich source of market opportunities for some firms and challenges for others, in some cases destroying incumbent firms (Srinivasan, 2008).

Although many key enabling technologies are highly complex and characterized by a high degree of uncertainty—in terms of the nature of the key players, the products and processes that build on them, the viable marketing strategies and profitable business models (Srinivasan, 2008)—they are very important for regional development (Adner & Levinthal, 2002; Laffi & Boschma, 2022). In fact, having a strong knowledge base in key enabling technologies is linked to a greater regional economic performance (Evangelista et al., 2018; Laursen, 2000) and a greater number of new technological specializations (Montresor & Quatraro, 2017), which facilitates the branching out of the regional economy into new directions (Antonietti & Montresor, 2021).

Mapping the competences in key enabling technologies, and especially in I4.0 technologies, has received growing attention in recent years (Balland & Boschma, 2021; Capello & Lenzi, 2021b). Focusing on Europe, scholars have found that research and innovative competences are unevenly distributed, and that the most active regions are those that already possessed relevant research and technological competences prior to the emergence of the current key enabling technology (Balland & Boschma, 2021; Ciffolilli & Muscio, 2018; Ménière et al., 2017). Large urban areas with the biggest research and technology transfer infrastructures such as London, Paris, Berlin and Madrid have emerged as leaders in artificial intelligence, quantum computers and other IT-related technologies. Technologies such as 3D printing have developed in the old manufacturing world's most innovative regions. On the other hand, Capello and Lenzi (2021b, 2022) identified a large number of regions involved in patenting applications of technologies using I4.0 core and enabling technologies within specific application contexts, including some unexpected islands of competences in regions that, in the past, had not been at the forefront of IT-related technologies.

Taking a "demand-side" perspective, Capello and Lenzi (2021c) identified the regions where I4.0 technologies are applied. Bringing together quantitative evidence and findings from case studies in six European countries, they focused on the following broad domains: technology invention, technology adoption in manufacturing sectors, technology adoption in services, and the ways in which I4.0 transforms regions.

Other approaches to mapping technological competences have relied on "big data." For example, NIESR (2013) and Nathan and Rosso (2015) mapped the UK's digital economy by extracting information from company websites about their products and services (using a set of predefined keywords), developing new categories of digital products and services, and reclassifying NACE sectors based on this new information, thereby uncovering a large number of digital companies. By scraping product directories and fan websites, Mateos-Garcia et al. (2014) created a more comprehensive list of UK video games companies than would have been possible by simply relying on NACE codes.

The "big data" approach overcomes the limitation of relying solely on outdated codes of economic activity. Additionally, it provides an up-to-the-minute picture of company activities, as it builds on up-dated information obtained online. On the other hand, this approach is probably insufficient to develop comprehensive mapping when the technology under scrutiny is complex and identification of individual keywords is insufficient to subsume all the relevant companies. In such cases, it might be reasonable to combine several sources (e.g., web scraping, text mining, sectoral codes), including expert judgement, to make sense of the spatial and organizational features of the new technology. With a focus on IoT, our methodology complements and extends current approaches in providing the identification of IoT domains associated with combinations of selected NACE codes, and the regional mapping of companies engaged in those domains.

3 | THE INTERNET OF THINGS

The IoT is a system that involves several complementary technologies, including software applications, connectivity and hardware components and devices, which rely on sensors, information-processing, communication and networking technologies to provide solutions for specific applications (Zhang & Chen, 2020). IoT technologies and applications emphasize strong connectivity, strong reliability, security, privacy, extremely low latency and the capacity to cope with a huge amount of data (Jiang et al., 2021; Kim, 2021; Sisinni et al., 2018). Like many other key enabling technologies, IoT solutions can be considered as a platform-based ecosystem (Teece, 2018; Tiwana et al., 2010), specifically targeting various types of applications. While each IoT solution is delivered through a complex set of devices and interconnected systems, and the specific features of each solution tend to be unique, IoT solutions architecture is made up of several conceptually distinct elements, or layers, that are present in all IoT solutions. The three key layers are software, connectivity and hardware. Adapted from Romeo (2016), a view of the elements needed to implement specific IoT applications, their functions and the various categories of players, by layer, is presented in Figure 1. This view is widely accepted in the examination of the IoT (Atzori et al., 2010; Chou, 2017; Navani et al., 2017; Razzaque et al., 2016; Sethi & Sarangi, 2017).

The software layers (in light grey, in Figure 1) include IoT middleware software—platform and data—service providers. The IoT platform embeds five essential layers: application enablement, data analytics, data management, device management, and connectivity management. The connectivity layer (in black) embraces wireless, wired, short-range, and long-range connectivity. The hardware layer (in grey) is the set of sensors, actuators, gateways, and computer and peripheral devices. The vertical functions of integration and security apply to all layers in specific ways.

IoT solution architectures usually rely on complex value chains, which involve different competences across different domains, including software engineering, telecommunications engineering, information networks management, and the manufacturing of hardware devices, among others (Romeo, 2020; Scully & Lueth, 2016). The implementation of IoT solutions depends on IoT software developers that are specialized in various fields and are

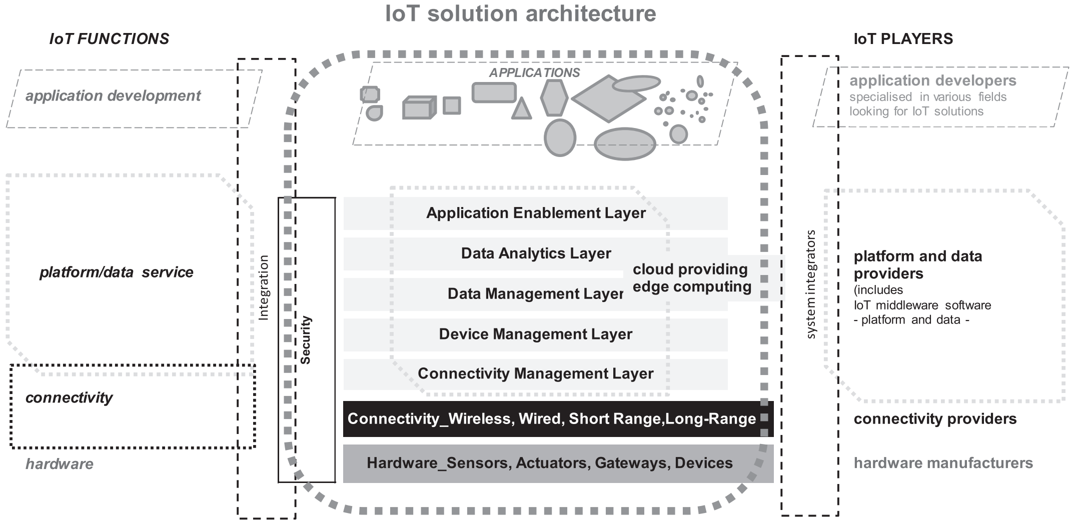

FIGURE 1 IoT solution architecture: functions and players, by layer
Source: Authors—Adapted from Romeo (2016)

not totally bound within the IoT solutions architecture. IoT solutions are, in fact, provided by an array of business organizations (hardware and service providers), each performing different but complementary functions that are kept together by system integrators to produce complex projects (Ibarra et al., 2018; Ikävalko et al., 2018).

4 | CLASSIFYING REGIONS ACCORDING TO THEIR IOT PRODUCTION COMPETENCIES

In the domain of emerging digital technologies such as IoT, the complexity and interdependence of tasks, skills and competences have frequently been put forward. Indeed, complex technological solutions often require an array of competences (Metallo et al., 2018). As discussed above, building an IoT solution requires expertise in both hardware and software and in all the services (e.g., cloud, security) that revolve around them. These competences can be dispersed in space and reorganized by leading companies acting as system integrators (e.g., Amazon; Jacobides, 2019). Alternatively, they may be present in the same territorial context—country or region. In the former case, generally thanks to the activity of system integrators, the region's companies will be involved within IoT value chains that develop on a larger scale while, in the latter case, the entire IoT value chain will be present within the region.

The two situations—the presence of a value chain concentrated on the same territory or dispersed among different territorial contexts—can have different outcomes for the growth of a region. Because enabling technologies can be applied in many sectors, their presence in the region can facilitate innovation and promote growth at the level of the entire regional system (European Commission, 2009; Evangelista et al., 2018). Moreover, thanks to the strong complementarities between inventions and applications in the development of the enabling technologies (Breshanan, 2010), innovations can be developed in many different directions, both along the same technological trajectory, into related technologies, as well as into unrelated technologies (Montresor & Quatraro, 2017).

For these regional development processes to be triggered, the enabling technologies present in the region must exceed a certain threshold (Evangelista et al., 2018). Moreover, the presence of only one type of competence (e.g., producers of a specific type of hardware used in the IoT systems) is unlikely to trigger innovation processes both in related and in unrelated industries (Antonietti & Montresor, 2021; Boschma & Frenken, 2011). The presence of only some parts of an IoT value chain can, however, be considered by policy-makers as a starting point to promote a more articulated system around this enabling technology.

In our empirical analysis, we will distinguish between regions that host complete IoT systems, in which all the macro-components highlighted in Figure 1 are present and, in particular, both hardware and software components, and regions that specialize in the production of some specific components (whether hardware or software).

5 | DATA AND METHODOLOGY

5.1 | Data source

To perform our mapping exercise on IoT competences in European regions, we started from the Bureau van Dijk (BvD) Amadeus database because, in addition to the usual companies' balance sheet data, the database also provides not only the company NACE primary code, but also textual information on the companies' activities, which is included in the field "full overview."[2] We chose this data source exactly to leverage the opportunities offered by this descriptive field. In fact, the description of a company's activity, provided by the company itself on its own website, is potentially a very interesting source: we assume that a company pays attention to this channel of communication with potential customers, in order to showcase what it can do and what its strengths are, and that it will ensure that this information is accurate and current. In general, this information is much more detailed than the one that is associated with each NACE code (Eurostat, 2008). Hence, the companies' full overview fields provide up-to-date information that we can analyse using text mining techniques in order to detect specific information regarding IoT-related activities. While this information is not available for all the companies, it is sufficient in order to identify the IoT-related activities associated to the various four-digit NACE codes, as we will describe in detail below.

5.2 | Expert pre-selection: Four-digit NACE codes, 18 European countries

To extract data from the Amadeus dataset, we pre-selected a number of four-digit NACE Rev.2 codes within the following divisions: 26-Manufacture of computer, electronic and optical products; 27-Manufacture of electrical equipment; 61-Telecommunications; 62-Computer programming, consultancy and related activities; and 63-Information service activities. Since there are no specific codes linked to the many diverse IoT-related activities in the NACE classification of economic activities, for this pre-selection we relied on the opinion of an expert[3] in IoT, who is also one of the authors of this paper. We identified a set of 28 codes listed in Table A1 (Supplementary material). With respect to those codes, we identified a group of 18 countries in Europe that host a significant presence of companies for which information exists in the Amadeus database (Table A2).

In these countries, the number of companies operating in the 28 preselected NACE codes is 205,651. The field "full overview" is available for 17,008 companies. Although the availability of full overview fields varies by NACE code and company size, overall the information provided in these fields allows us to obtain an adequate variety of descriptions for each NACE code. We used the full overview in order to gain an understanding of the companies' activities in various IoT-related domains,[4] and to identify the NACE codes corresponding to these IoT domains, as outlined in the methodology below.

Our multi-step methodology is schematically represented in Figure 2 and described in detail below, to highlight issues, research strategies, hypotheses, data and the specific five-step procedure we adopted to address the research questions at the core of this paper.

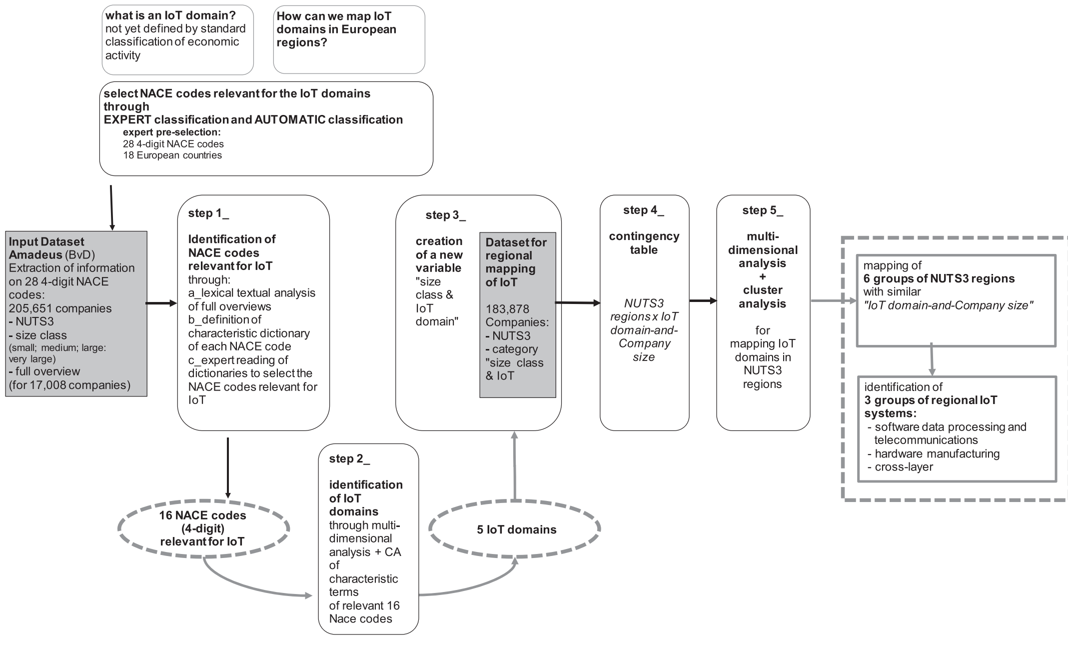

FIGURE 2 Methodology: multi-step procedure adopted to map IoT domains in European regions

5.2.1 | Step 1: text analysis of full overview to identify the characteristic dictionaries of NACE codes and to select those relevant to IoT

We created a *corpus* (collection of texts) of full overviews (available for 17,008 companies). The *corpus* included 54,518 different terms (vocabulary of the *corpus*) for a total of 2,128,018 occurrences (size of the *corpus*). The lexical-textual analysis allowed us to extract 7,611 different active terms[5] (nouns and adjectives, including 3,781 multi-word expressions[6]) for a total of 635,384 occurrences (i.e., number of times in which active terms occur in the text). We then created a matrix <*Active terms* × *NACE codes*> (7,611 × 28) in which we identified the characteristic dictionaries of the 28 pre-selected NACE codes by calculating the test-value[7] (Lebart et al., 1998) of each active term within each NACE code (hence, the "characteristic terms," included in the characteristic dictionaries, are the active terms with the highest test values for each NACE code).

The expert reading of the characteristic dictionary of each NACE code allowed us to refine the initial list of codes and select 16 NACE codes (out of 28 identified previously) that are relevant to the IoT (list available in Table A4, Supplementary material).

The main objective of the textual analysis is to group the selected NACE codes based on the similarity between the activities described by the companies.[8] This unsupervised clustering allows us, at the same time, to define the semantic category at the basis of each cluster. Alternatively, a classification based on the details provided by each NACE code would not have allowed us to group the NACE codes except through a subjective and possibly questionable choice made by experts.

5.2.2 | Step 2: identification of IoT domains

In order to identify specific IoT layers and components in the IoT solution architecture (summarized in Figure 1), we again used a text-mining approach. We classified the 16 NACE codes with regard to their similarity in terms of IoT content, based on the characteristic terms emerging from the analysis of the corpus created with the full overviews. This classification was obtained through a correspondence analysis[9] of the matrix <*NACE Codes Relevant to IoT* × *Characteristic Terms*> (16 × 7,440). Through a cluster analysis applied to the first 10 factors resulting from the correspondence analysis, we were able to group the NACE codes into clusters based on the similarity of distribution of terms.[10] This clustering phase constituted an unsupervised and unambiguous classification of the NACE codes, reflecting the semantic similarity between them, which could then be summarized in a category that was not defined *a priori* but was derived from the analysis.

TABLE 1 First 50 characteristic terms of each IoT domain

For each IoT domain: IoT domain identification number—*expert label*; list of characteristic terms sorted by decreasing order of test-value (see footnote 6)
IoT domain 1– Software & data processing
software, computer, data processing, information technology, provision of computer, computer programming service, consulting service, management, computer hardware, modifying, advice, consulting, solution, supporting software, writing, provision, expertise, computer system, programming, designing computer system, software development, data processing facility, operation of clients, planning, technical, communication technology, exceptional domain knowledge, computer programming, information, financial service, service, training, computer system design, provision of information, support, finance, computer software design, streaming service, application hosting, mainframe facility, professional, modification of custom, hosting, technology solution, insurance, custom software, application service provisioning, variety of additional service, business intelligence, consultancy.
IoT domain 2—Telecommunication
provision of telecommunication, voice, telecommunication service, satellite, transmission facility, broadband, radar station operation, satellite tracking, communication telemetry, network, data communication, satellite system, facility, communication service, internet, communication, telecommunication, fixed, data service, internet access, microwave, service, mobile, carrier, provision of communication, transmitting telecommunication, broadband internet, receiving telecommunication, call, internet service, transmission of voice, mobile phone, landline, terrestrial communication system, wireless broadband, distance, single technology, telecommunication applications, worldwide telecom, internet network, local phone, satellite broadband internet, satellite terminal station, reselling, maintaining switching, traditional local telephone service, competitive local telephone service, digital tv, provision of telephone, combination of technology.
IoT domain 3—Manufacturing of telecom equipment
mechanical accessory, coaxial, gearbox, manufacture, antenna, equipment, radio, product, data communication equipment, loudspeaker, accessory, manufacture of communication, cordless telephone, receiving antenna, system, router, telephone answering machine, receiver, switching equipment, amplifier, transmitter, television, cable television equipment, wire telephone, television studio, broadcasting equipment, audio, mobile communication equipment, transmitting, communication equipment, telephone, pager, gateway, cellular phone, production, alarm, bridge, wireless communication equipment, component, intercom, television broadcast, speaker, mast, telecommunication product, fire, military, lan modem, sale of communication, detector, device.
IoT domain 4—Manufacturing of electronic components
convenience, seal, strict, terminal block, trunking, fibre optics, aluminium, cable, connectors, switch, manufacture, electrical, wiring device, conductor, copper, lamp, electric, plug, socket, cord, product, voltage, relay, insulated, insulated wire, power cable, power, transformer, electrical equipment, component, cable product, outlet, lighting, coaxial cable, fuse, voltage cable, circuit breaker, rubber, production, cutout, connector, telecommunication cable, instrumentation cable, bare, panel, cabinet, accessory, control cable, electric wire, cable assembly.
IoT domain 5—Manufacturing of measure instruments
nautical system, measuring, manufacture, instrument, sensor, measurement, equipment, product, temperature, gauge, meters, navigation, pressure, water, laboratory, control, valve, instrumentation, gas, manufacture of instrument, system, detection, production, measuring instrument, appliance, precision, calibration, analyzer, industrial, controlling device, navigational, electromedical, control instrument, component, thermometer, tester, probe, laser, heating, navigating, machine, weighing, physical property testing equipment, mechanical, aeronautical, meter, vibration, metrology, analytical instrument, test equipment.

This process allowed us to define five clusters of NACE codes that singled out specific IoT-related activities, which we called "IoT domains." Table 1 summarizes the key characteristics of these domains, which we have labelled on the basis of the main activities they encompass. Table 2 presents the number of companies belonging to the 16 identified NACE codes, by IoT domain and company size.

IoT domain 1 revolves around *software and data processing*; it includes competences relative to computer programming, designing computer systems, software development and software design, among others. These activities correspond to the "IoT platform" layers in Figure 1 (highlighted in light grey). IoT domain 2's focus is on *telecommunications*. It includes know-how related to the provision of telecommunications services, satellites, broadband, radar station operations, satellite tracking, networks, and different types of communication-related activities. These activities correspond to the connectivity layer (in black) in Figure 1. The next three domains correspond to different elements of the hardware layer (in grey) in Figure 1. In particular: IoT domain 3 includes competences related to *manufacturing of telecom equipment*, such as antennas, radio equipment, loudspeakers, cordless telephones, receivers and others; IoT domain 4 covers competences in *manufacturing of electronic components*, such as cables, fibre optics, connectors, wiring devices and others; lastly, IoT domain 5 comprises expertise in *manufacturing of measurement instruments*, such as control instruments, sensors, precision tools, calibration, etc.

Each company in the dataset is associated with one of the five IoT domains based on its NACE code.[11] The total number of companies under analysis is 183,878 (Table 2).

5.2.3 | Step 3: creation of a new variable for the analysis

In step 3 we created a variable capturing, for each company, its relevant IoT domain and its size. Combining each of the five IoT domains (identified in step 2) with each of the four company class sizes (small, medium-sized, large, very large), we obtained a variable for the 183,878 companies in the dataset, namely, *IoT domain-and-Company size*, with 20 categories. Including information about company class size in the analysis allows us to specify what kind of enterprises possess the production competences we are observing—whether large enterprises with a wide umbrella of activities and market power or small specialized enterprises.

5.2.4 | Step 4: construction of contingency table

Based on the new variable, we constructed a contingency table *NUTS3* $\times$ *IoT domain-and-Company size* (1,105 $\times$ 20): this allows us to count, for each of the 20 categories, the number of companies in each of the 1,105 NUTS 3 regions.[12]

5.2.5 | Step 5: clustering of NUTS 3 regions according to the classes IoT domain-and-company size

In the last step, we implement a cluster analysis to group the NUTS 3 regions based on their similarities. Grouping is obtained through hierarchical cluster analysis on the matrix <*NUTS3* $\times$ *IoT domain-and-Company size*> (1,105 $\times$ 20) created in step 4.[13]

The optimal number of clusters is two (see Calinski-Harabasz index in Figure A1 and factorial map in Figure A2). This cut basically highlights the two main features of the database in analysis, namely the very large presence of small companies (83.1%) and the very large number of companies in the IoT domains "Software and Data Processing" (85.7%); the figures are in Table 2. This cut splits NUTS 3 regions into two groups: one group of 348 NUTS 3 regions (on the left in the dendrogram in Figure 3) that is characterized by small enterprises in software

TABLE 2 Number of companies belonging to the 16 identified NACE codes, by IoT domain and company size

	‘NACE		n. of companies		company size			
Cluster IoT domains	**code**	**Description**		**Very Large**		**Large**	**Medium sized**	**Small**
1 Software and Data Processing	2,620	Manuf. of computers and peripheral equipment	157,682 (85.7%)	3,872	62	197	812	2,801
	6,201	Computer programming activities		66,514	343	1,552	6,166	58,453
	6,202	Computer consultancy activities		48,575	307	1,531	4,448	42,289
	6,203	Computer facilities management activities		4,886	72	228	510	4,076
	6,209	Other inform. techn. and computer service activities		24,720	278	1,169	2,753	20,520
	6,311	Data processing, hosting and related activities		9,115	107	530	991	7,487
2 Telecommunication	6,110	Wired telecommunications activities	12,040 (6.5%)	3,135	101	298	497	2,239
	6,120	Wireless telecommunications activities		2,075	104	196	289	1,486
	6,130	Satellite telecommunications activities		252	27	55	40	130
	6,190	Other telecommunications activities		6,578	249	679	1,039	4,611
3 Manufacturing of Telecom Equipment	2,630	Manuf. of communication equipment	4,880 (2.6%)	2,831	62	231	732	1,806
	2,640	Manuf. of consumer electronics		2,049	23	67	265	1,694
4 Manufacturing of Electronic Components	2,731	Manuf. of fibre optic cables	1,202 (0.6%)	52		9	11	32
	2,732	Manuf. of other electr. and electric wires and cables		350	25	55	124	146
	2,733	Manuf. of wiring devices		800	9	95	295	401
5 Manufacturing of Measure Instruments	2,651	Manuf. of instruments and appliances for measuring, testing and navigation	8,074 (4.4%)	8,074	156	638	2,625	4,655
Total			183,878 (100.0%)		1,925 (1.0%)	7,530 (4.1%)	21,597 (11.7%)	152,826 (83.1%)

Note: Figure in brackets is the share of companies by IoT domain (first column) and size (last row).

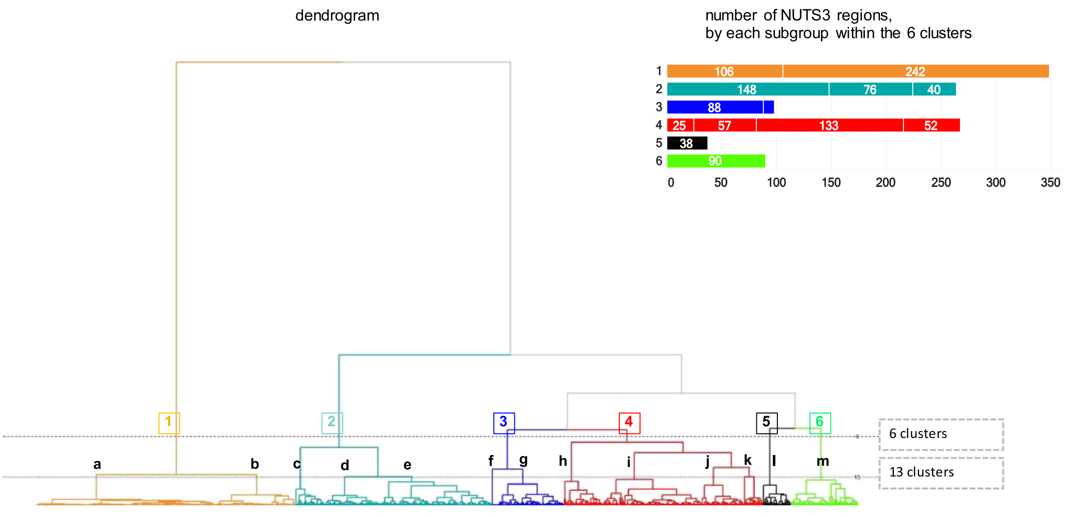

FIGURE 3 Dendrogram and number of NUTS 3 regions by cluster (main cut at six groups and 13 subgroups)

and telecommunication activities. The remaining group of NUTS 3 regions includes mainly manufacturing activities, with a mix of software and telecommunications, of different companies' size. We prefer the six-cluster cut (a relative optimum observed in Figure A1), which allows us to obtain a finer-grained definition of groups of NUTS 3 regions, in terms of their specialisations in one of the identified IoT domains and their company size. We also implement an analysis at 13-clusters cut, because these subgroups allow a better focus on groups of NUTS 3 regions with distinct characteristics (see the factorial map in Figure A3). Results are presented in the following section.

6 | RESULTS AND DISCUSSION

6.1 | NUTS 3 regions mapping

We have labelled the six clusters by considering the most characteristic categories (ranked according to their test-value), among the 20 categories of the *IoT domain-and-Company size* variable. In each label, we mention the most characteristic activities and company sizes—or combinations—in each cluster (details in Dashboards A1–A6, Supplementary material). Then, each label does not exclude that other activities might be present in the cluster to a lesser degree. The first cluster includes *software data processing and telecommunications, in small companies*; the second includes a combination of companies in *manufacturing of measurement instruments, of small and medium size*; the third cluster includes mainly *small companies in the manufacturing of measurement instruments and telecommunications*; the fourth cluster includes, together with companies in the *manufacturing of measurement instruments and telecommunications equipment, of small size, companies in software and data processing and telecommunications, of large and very large size*; the fifth cluster includes a combination of *companies, medium and small sizes, in manufacturing of telecommunications equipment and of measurement instruments*; the sixth and final cluster includes *companies, of all sizes, in the manufacturing of electronics components*.

Table 3 summarizes the characteristics of the six clusters with respect to the companies' size class (details by country available in Figure A4 and in Tables A6 and A7). Figure 4 presents the geography of IoT specializations, at NUTS 3 level, in the 18 European countries under analysis, while the emergent patterns at country level will be explored in subsection 6.2). The exploration of the clustering at 13 subgroups makes possible to identify specific characteristics within four of the main six clusters of regions,[14] as will be discussed, below, with respect to the

TABLE 3 Number of NUTS 3 regions and number of companies by cluster of NUTS 3 regions, according to *IoT domain-and-Company size* variable, and by company class size

Label 6 with size	NUTS 3	Company size: Small	Medium sized	Large	Very Large	Total
Null		3,650	253	52	36	3,991
cl-1 Soft. Data Proc. & Telecom. _Small	348	140,682	14,874	2,707	708	158,971
cl-2 Manuf. Meas. Instr. _MSEs & Small	264	2036	2,245	666	168	5,115
cl-3 Manuf. Meas. Instr. & Telec.Eq._Small	98	1,085	276	197	36	1,594
cl-4 Manuf. Meas. Instr. & Telec.Eq._all size + Soft. Data Proc. & Telecom._L & VL	267	4,360	3,091	3,565	927	11,943
cl-5 Manuf. Telec. Eq. & Meas. Instr._Small & MSEs	38	87	104	22	4	217
cl-6 Manuf. Elect. Comp._all size	90	926	754	321	46	2,047
Total	1,105	152,826	21,597	7,530	1,925	183,878

Note: Null values are due to missing information on company's NUTS 3 level, hence no information for the cluster analysis on the matrix <*NUTS3* × *IoT domain-and-Company size* >.

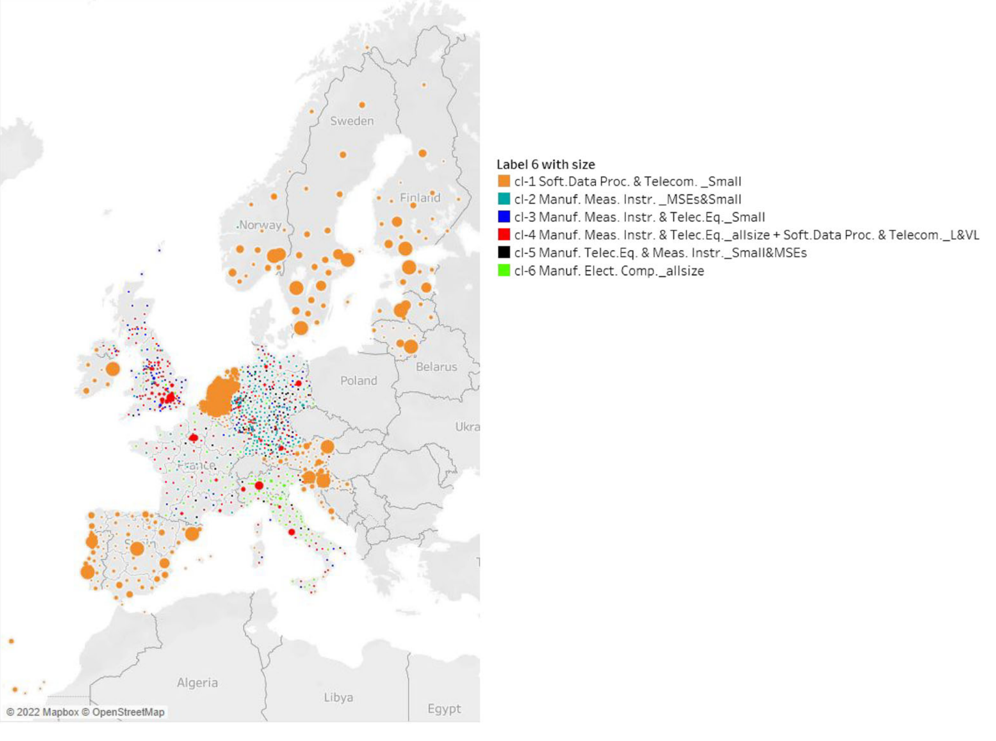

FIGURE 4 Map: Clusters of NUTS 3 regions according to the *IoT domain-and-Company size* variable

distribution of companies by class size in the IoT domains (see Table 4 and detailed information in the factorial maps at six clusters and 13 subgroups, respectively, in Figures A3 and A4).

The six clusters characterize three main groups of NUTS 3 regions, with different degrees of presence of the IoT value chains and specific composition of companies' size classes (details in Table 4 and in Dashboards A1–A6).

TABLE 4 NUTS 3 regions by cluster and share of companies, by company size, in each of the six clusters and 13 subgroups

Label 6 with size	subgroups 13	NUTS 3 regions number	NUTS 3 regions share	Share of companies Small	Medium sized	Large	Very large	Total
cl-1 Soft. Data Proc. & Telecom. _Small	cl.a	242	21.9%	89.9%	8.3%	1.5%	0.4%	100.0%
	cl.b	106	9.6%	81.1%	15.3%	2.9%	0.7%	100.0%
	Total	348	31.5%	88.5%	9.4%	1.7%	0.4%	100.0%
cl-2 Manuf. Meas. Instr. _MSEs & Small	cl.c	40	3.6%	28.3%	62.9%	7.2%	1.7%	100.0%
	cl.d	76	6.9%	34.6%	43.2%	17.3%	4.9%	100.0%
	cl.e	148	13.4%	46.2%	42.8%	9.3%	1.7%	100.0%
	Total	264	23.9%	39.8%	43.9%	13.0%	3.3%	100.0%
cl-3 Manuf. Meas. Instr. & Telec.Eq._Small	cl.f	10	0.9%	100.0%				100.0%
	cl.g	88	8.0%	67.8%	17.4%	12.5%	2.3%	100.0%
	Total	98	8.9%	68.1%	17.3%	12.4%	2.3%	100.0%
cl-4 Manuf. Meas. Instr. & Telec.Eq._all size + Soft. Data Proc. & Telecom._L & VL	cl.h	52	4.7%	45.7%	25.8%	25.8%	2.6%	100.0%
	cl.i	133	12.0%	33.6%	25.9%	32.1%	8.4%	100.0%
	cl.j	57	5.2%	60.2%	25.1%	12.4%	2.3%	100.0%
	cl.k	25	2.3%	42.5%	26.0%	17.7%	13.8%	100.0%
	Total	267	24.2%	36.5%	25.9%	29.9%	7.8%	100.0%
cl-5 Manuf. Telec.Eq. & Meas. Instr._Small & MSEs	cl.l	38	3.4%	40.1%	47.9%	10.1%	1.8%	100.0%
	Total	38	3.4%	40.1%	47.9%	10.1%	1.8%	100.0%
cl-6 Manuf. Elect. Comp. _all size	cl.m	90	8.1%	45.2%	36.8%	15.7%	2.2%	100.0%
	Total	90	8.1%	45.2%	36.8%	15.7%	2.2%	100.0%
Overall database		1,105	100.0%	82.9%	11.9%	4.2%	1.1%	10.00%

A first group of regions is the one classified in cl-1: it is characterized by "specialized IoT competences in software and data processing, and telecommunications". In this group of 348 NUTS 3 regions, the large majority of companies is small (88.5% of all companies in the cluster, and in particular in *cl.a*, with almost 90% of companies).

A second group of regions—encompassing cl-2, cl-3, cl-5, cl-6—is characterized by "specialized IoT competences in hardware manufacturing," along the three IoT domains that we have identified: manufacturing of measuring instruments (cl-2), measurement and telecommunication equipment (cl-3 and cl-5), and manufacturing of electronic components (cl-6). NUTS 3 regions classified in cl-2 have a large presence of both small and a larger share of medium sized manufacturing companies (respectively, 39.8% and 43.9%; with a larger share of medium sized companies in *cl.c*, 62.9%, that is the highest share among the 13 subgroups); in cl-3, small companies prevail (68.1%, with 100% in the very small group of NUTS 3 regions of *cl.f*), in cl-5, 47.9% of companies are medium sized enterprises and 40.1% are small companies; in cl-6, large companies have a significant presence (15.7%, the highest share among the six clusters), alongside small and a significant share of medium sized companies (respectively, 45.2% and 36.8%).

A third group of regions—classified in cl-4—has "cross-layer IoT competences," as they include a combination of all the main components of IoT value chains, as defined in Section 3. Together with companies of all sizes, specialized in four IoT domains, we observe that: "Measurement instruments" and "Telecommunications equipment" have mainly small companies and also all other sizes; "Software and Data Processing" and "Telecommunications," have large and very large companies (see Dashboard A4). The diversified IoT competences in this cluster of 267 NUTS 3 regions have different mixes in the various subgroups of regions. In particular, subgroup *cl.i*—encompassing 133 regions—shows the largest presence of large and very large companies (respectively 32.1% and 8.4%) in "Software and Data Processing" and "Telecommunications", while the smallest subgroup of 25 NUTS 3 regions, *cl.k*, has a significant presence of large and very large companies (respectively 17.7% and 13.8%) in software and data processing and in manufacturing of telecommunication equipment, and of small companies (42.5%) in manufacturing of telecommunication equipment and of measurement instruments.

6.2 | Focus on countries: selectivity and homogeneity in the cluster of NUTS 3

The country pattern emerging from Figure 4 is now explored with respect to two indices, the selectivity and homogeneity indices, for the 18 countries in our database. The selectivity index measures the extent to which a country is represented in the NUTS 3 regions of each cluster, that is, the specialization of the country in the cluster: this is the percentage of companies in the country classified in the cluster. The homogeneity index indicates the weight of the country within the cluster: this is the percentage of companies in the cluster that belong to the country. Both indexes are reported in Figure 5, with details for the 13 subgroups of regions. The different details impact on both indices and highlight, at country level, some peculiar features of IoT specialisations of NUTS 3 regions discussed above.

The specialized IoT competences in "software and data processing, and telecommunication" (cluster cl-1) are present in most countries. All regions of the Netherlands, Belgium, Norway and Estonia, and almost all regions in Sweden, Finland, Portugal, Austria, Latvia, Hungary, Lithuania are specialized in software and data processing realized by small companies (*cl.a*); while almost all regions in Spain and Ireland are specialized in telecommunication, in small and in medium sized companies (*cl.b*). The map in Figure 4 shows that these NUTS 3 regions are located in specific cities or areas within the regions under analysis. Some cities on the Iberian Peninsula (e.g., Barcelona, Madrid, Lisbon and Porto), Dublin in Ireland, as well as some cities in the Netherlands, Belgium, Scandinavian and the Baltic countries exhibit large agglomerations of companies in these clusters.

The specialized IoT competences in "hardware manufacturing" (cl-2, cl-3, cl-5, cl-6) are essentially embedded in the most advanced manufacturing countries: mainly in Germany, and also in Italy, France and the UK, with the

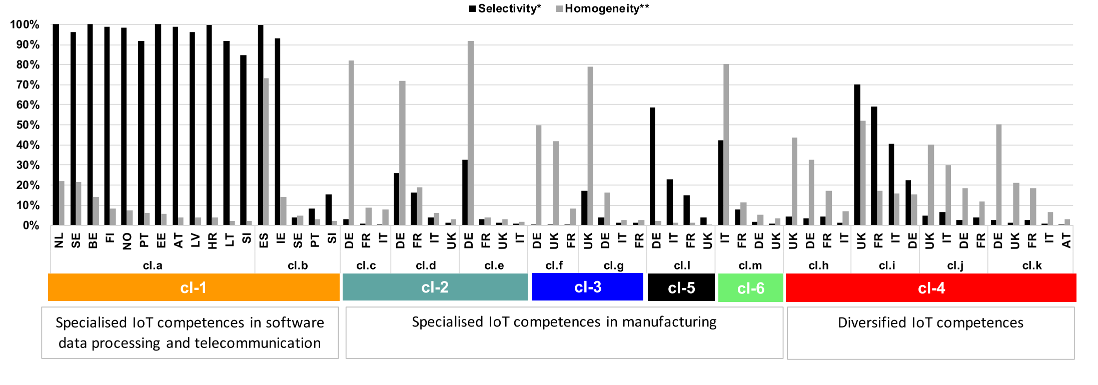

FIGURE 5 Focus on countries: selectivity and homogeneity in the clusters of NUTS 3 regions, subgroups *cl.a-cl.m* within the six clusters.
Notes: *Selectivity indicates the percentage of companies in the NUTS 3 regions classified in the cluster.
**Homogeneity indicates the relative importance of the share of the country within the cluster.
Source: Authors' elaboration based on data from Amadeus, downloaded on 30.09.2019.

manufacturing of measuring instruments in medium sized companies (*cl.e*) in Italy and, to a lesser extent in France, with electronic components in companies of a variety of sizes (*cl.m*).

Regions with “cross-layer” IoT competences (cl-4) can be found in the United Kingdom, France, Italy and Germany, and those in *cl.i* are the capital city regions (London, Paris, Rome, Berlin) and other large urban regions (such as, Milan, Hauts-de-Seine, Westminster, Berkshire, Turin, Cambridgeshire, Hamburg).

We previously argued that, while NUTS 3 regions may have different combinations of IoT competences, and regions that concentrate on specific IoT layers potentially being highly competitive in their own area of specialisation, when it comes to the capacity to exploit technological opportunities created by the IoT, it is the regions that include the entire IoT value chains, that exhibit the greatest potential. Table 5 provides a means to classify NUTS 3 regions in terms of their potential for leveraging further technological opportunities in the IoT.

In the case of “cross-layer” IoT competences, it is the capital cities and the large cities that benefit from the presence of system integrators.[15] They are able to integrate a variety of hardware manufacturing and software and telecommunications present within the regions with competences missing in the regions but available in other regions or countries. This gives these regions a very high potential to capture technological opportunities when companies invest in the continuous innovation process of very rapid technological changes in all IoT domains.

The regions hosting specialized IoT competences in either “hardware manufacturing” or “software and data processing, and telecommunication” need to collaborate with firms in other regions to provide complete IoT solutions, as complementarity cannot be achieved within the region, completing the IoT supply chains being another strategic issue for regional innovation development in IoT. The two types of regions have nonetheless different potential developments, relying also on different types of policy interventions.

Companies with hardware IoT competences can leverage the presence of a potential nearby market in which they are embedded, where proximity with users is a powerful lever to enhance virtuous circles of users-producers' interaction in enhancing innovation and expansion, also, to new IoT applications. The regional and country level of specialisation is of importance: the variety of companies' sizes contribute to covering the variety of specialisations that are needed in manufacturing and application, thus fuelling innovation that supports the development of other innovation chains in the region. In addition to a market advantage, in these regions there is a need for the development of competences in software and data processing. These competences can be acquired with relatively less intensive capital investments, within the companies specialized in hardware manufacturing, but regional innovation policies become essential in supporting the creation of software hubs for the creation of complementary software competences in the region.

Companies specialized in software and data processing, and telecommunications need to rely on extra-regional connections in order to participate in the provision of IoT solutions. Such regions can rely on critical mass of competences in the very specific fields of middleware software—platform and data—service providers, but they hardly master the overall IoT architecture and their potential is strongly dependent on system integrators (located outside these regions, as discussed above) and on companies networking over regions and countries. In these regions, the development of the complementary supply chains with hardware competences is more difficult because it requires a variety of a complex set of competences and large investments, but regional policies can leverage the attraction of investments of companies acting as system integrators and there might be the case for developing complementarities between regions with competences in software and data processing and telecommunications, and those with competencies in hardware manufacturing.

6.3 | Socio-economic conditions of clusters of NUTS 3 regions

In order to analyse how the clusters of IoT competences relate to their underpinning economic structure, we have cross-tabulated the clusters of NUTS 3 regions with the classification of socio-economic conditions of their NUTS 2 regions. The classification of socio-economic conditions is based on the open access data set created by Pagliacci

TABLE 5 Classification of NUTS 3 regions according to the presence of IoT-related activities

IoT competence clusters	Description	Clusters and countries (homogeneity index) based on NUTS 3 regions classification
Cross-layer IoT competences	The entire IoT value chain is present in the regions. Very high potential for further development of companies able to target continuous innovation processes in the context of very rapid technological changes in all IoT domains. Country-level policies are important for supporting such developments encompassing strategic infrastructures such as telecommunications and connectivity.	cl-4 UK (44.2); DE (23.5); FR (17.2); IT (15.0)
Specialized IoT competences in hardware manufacturing	Substantial part of the manufacturing layers of IoT manufacturing value chain is present in the region. It exploits technological manufacturing complementarities in other sectors within the region. Potential for growth of the enabling technology, within the region and the country. Software and data processing and telecommunications competences are needed to complete IoT supply chains. Their development can occur within the hardware manufacturing companies. Regional policies can support hub of competences in software	cl-2 DE (81.8); FR (11.3); IT (4.0) cl-3 UK (78.7); DE (16.4); IT (2.6); FR(2.4) cl-5 DE (58.5); IT (23.0); FR (14.7); UK (3.7) cl-6 IT (80.4); FR (11.2); DE(5.2); UK (3.2)
Specialized IoT competences in software and data processing, and telecommunications	Substantial part of the IoT middleware software—platform and data—and telecommunications service value chains are present in the region. Potential for growth of IoT-enabling technologies relies on networks with other regions. Regional development policies could leverage interregional cooperation across different complementary competences and on the attraction of investments by hardware manufacturers with competences in system integration that could exploit the dense presence of software and telecommunication competencies in the attracting/hosting regions.	cl-1 SE (18.8); NL (18.6); BE (11.7); ES (11.5); FI (6.8); NO (6.3); PT (5.4); EE (4.6); AT (3.4); LV (3.3); HR (3.1); IE (2.4); SI (2.0); LT (2.0)

Notes: Results built on the relative importance of countries in the clusters of NUTS 3 regions (based on the number of companies, homogeneity). In grey: countries with a homogeneity index below 18%.
Source: Authors elaboration based on data from Amadeus, downloaded on 30.09.2019.

et al. (2020). In their analysis, structural similarities of EU NUTS 2 regions refer to population, labour market, and the sectoral composition of the economy; a hierarchical clustering on the top nine principal components[16] returns 19 - different types of EU regions (grouped in three macro groups and nine subgroups).

We first classified NUTS 3 regions according to the socio-economic category of their NUTS 2 region,[17] then, we cross tabulated each NUTS 3 region according the IoT competences cluster and regional socio-economic conditions cluster they belong to. Aggregated results about the share of companies are presented in Table 6. Details with information of NUTS 3 regions, by each of the six cluster and the 13 subgroups, can be found in Table A8 and in Figure A5.

The largest share of IoT companies (83.5%) is in North-West European regions. In particular, most of the IoT competences—regardless of specialisation—are located in North-West European regions with medium-to-high income and a high level of employment. However, areas emerge that resemble the islands of innovation already identified by Capello and Lenzi (2021b, 2022), which are located in Mediterranean traditional economy regions and—although to a much lesser extent—in Eastern European manufacturing regions.

Among the companies "Specialized IoT competences in software and data processing, and telecommunication": 74.5% of companies are in subgroup *cl.a* and the remaining in *cl.b*. With regard to the larger subgroup, *cl.a*, the majority of companies, mainly small and specialized software and data processing, are located in North-West European regions. In particular, 24% of all companies are located in medium and high income regions with "High-income; high-employment; low-manufacturing; services & public sector", in Belgium, the Netherlands and Sweden;[18] and in High-income low-population density regions, in Estonia, Finland, Latvia, and Sweden.[19] Almost 21.5% are located in other urban regions with high and very high income, in Austria, Finland, the Netherlands, Portugal and Slovenia.[20] The remaining 10.1% of companies of this IoT system are located, respectively 4.1% and 1.8%, in Eastern European countries, and in particular in very low-income regions with a highly educated population,[21] and in Mediterranean regions with traditional economy and employment unbalances.[22] Regions in the subgroup *cl.b*, with a specialisation of large companies—both in data processing and in telecommunication—are those of Mediterranean traditional economy regions (with low-income; high-density; high unemployment; agriculture; food & drinks; very-low educated), such as Valencia and Seville, in Spain, and more typical "Urban regions; high-income; poorer employment conditions; touristic", such as Madrid and Barcelona in Spain, and "Very-high income; large urban regions; high-employment; highly educated" as in Dublin, Ireland.

The regions in the group of "Specialized IoT competences in hardware" (c2, c3, c5 and c6) are also primarily located in North-West Europe, although they span a broader set of socio-economic clusters of regions, with the exception of Eastern European manufacturing regions and very high income capital regions and touristic regions.

For the remaining 6.6% of all companies, those with "cross-layer IoT competences" (cl-4), there is a strong association between having diversified IoT competences and being located in North-West Europe with high-employment, advanced services and in regions with a very high or medium-high income.

We also note that, in Germany, companies in *cl.i* are located in regions with "very-high income; manufacturing; population imbalances"[23] and in other urban regions with "very-high income; high-density city-regions; high-employment; highly educated; touristic" (as are the city-regions of Berlin, Hamburg); and similarly in Italy (Rome); while in France companies in *cl-i* are in other urban regions with "Very-high income; high-density city-regions; high-employment; highly educated; touristic" (Hauts-de-Seine, Paris); but also in regions with "high-income; poorer employment conditions; touristic" (Val-de-Marne; Seine-Saint-Denis). In the UK, the largest share of companies of *cl.i* is in "Very-high income; capital city-regions; diversified services" (Greater London area).

6.4 | Discussion: the IoT divide within and across European countries and regions

Our mapping exercise points out that IoT competences are spread across European regions, such that most regions feature some types of IoT competences. At first glance, this might indicate that European regions have invested in

TABLE 6 Share of companies of NUTS 3 regions, by cluster of IoT domain-and-company size (columns) and socio-economic groups of NUTS 2 regions (rows)

Cl 3 Label	Cl 9 Label	Cl 19 Label	cl-1 Soft. Data Proc. & Telecom.	cl-2 Manuf. Meas. Instr.	cl-3 Manuf. Meas. Instr. & Telec.Eq.
null			5.875	0.002	
Eastern manufacturing regions	Eastern manufacturing regions	Low-income; high-employment; manufacturing; no foreigners; very highly educated	0.535		
		Very low-income; manufacturing; no foreigners; highly educated	3.818		
Mediterranean traditional-economy regions	Regions with traditional economy & empl. Imbalances	Low-income; high-density; high unemployment; agriculture; food & drinks; very-low educated	2.071		0.020
		Medium-income; employment & population imbalances; manufacturing: textile, basic metal, transport; very-low educated	2.903	0.006	0.003
		Very-low income; agriculture; sparsely populated; very high unemployment; traditional services (G-I)	0.483		
	Touristic areas; traditional-economy	Low-income; high-unemployment; touristic; food & drinks; traditional services (G-I); very-low educated	0.327		
North West European regions	High-employment, with advanced services	Medium-income; high-employment; highly educated; manufacturing: mining & quarrying	0.475		0.061
		Medium-income; high-employment; manufacturing & private services	0.001	0.067	0.637
	High-income low-population density regions	High-income; low-population density; tourism	9.627	0.023	
		High-income; sparsely populated; public sector; highly educated	6.154		
	Medium-high income regions, services & public sector	High-income; high-employment; low-manufacturing; services & public sector	22.097	0.653	0.081
		Medium-income; employment imbalances; low-manufacturing; services & public sector	2.071	0.049	0.004
	Other urban regions	Urban regions; high-income; poorer employment conditions; touristic	8.325	0.017	0.013
		Very-high income; high-density city-regions; high-employment; highly educated; touristic	0.962	0.025	
		Very-high income; large urban regions; high-employment; highly educated	20.045	0.157	
	Very-high income capital city-regions	Very-high income; capital city-regions; diversified services	1.774	0.013	
	Very-high income manuf. Regions	Very-high income; manufacturing; population imbalances	0.831	1.832	0.068
Total			88.373	2.843	0.886

TABLE 6 (Continued)

Cl 3 Label	cl-6 Manuf. Elect. Comp.	cl-4 Manuf. Meas. Instr. & Telec.Eq. + Soft. Data Proc. & Telecom.	cl-5 Manuf. Telec.Eq. & Meas. Instr.	Total
null		0.011		5.888
Eastern manufacturing regions				0.535
				3.818
Mediterranean traditional-economy regions	0.070	0.122	0.003	2.286
	0.147	0.083	0.008	3.151
				0.483
				0.327
North West European regions		0.101		0.637
	0.036	1.983	0.004	2.727
		0.032	0.003	9.684
	0.006	0.001		6.162
	0.097	0.236	0.053	23.216
	0.034	0.251	0.013	2.422
	0.020	0.375	0.002	8.751
		0.311		1.298
		0.640		20.842
		1.216		3.003
	0.728	1.279	0.033	4.770
Total	1.138	6.639	0.121	100.000

acquiring and/or developing IoT technologies, which are an essential part of I4.0 (Capello & Lenzi, 2021a, 2021b; De Propris & Bailey, 2020). However, when we take a deeper look at our findings and, in particular, when we look into the results of the IoT regional mapping, the country specialisation, and regional socio-economic conditions, we provide a picture that tells the story of a sort of "IoT-divide" between parts of Europe. Given that the IoT is a fundamental block of digital transformation (Balland & Boschma, 2021; Ciffolilli & Muscio, 2018; Ménière et al., 2017), this result indicates a "digital transformation-divide" between parts of Europe. On one side, there are North -West Europe, city capitals, and some hubs scattered in some locations in manufacturing regions. These areas, we argue, exhibit the greatest potential to exploit the multiple benefits of the IoT as a key enabling technology and, as we argued above, they are more prone to fostering knowledge production (Consoli et al., 2021). The remainder of European regions is on the other side. For example, Eastern European regions are not entirely part of the world of IoT competencies; they, indeed, focus on software data processing and telecommunications, without the ability to provide cross-layer IoT value chains. A similar situation is found in the Mediterranean touristic regions characterized by traditional economies. Such disparities between the regions in terms of their readiness to fully embrace IoT and leverage it for growth reflect the imbalances and different levels of technological competences, as in complex technologies, building blocks of specific technologies are needed to grow further in related technologies (Boschma & Frenken, 2011; Heimeriks & Boschma, 2013).

Bringing to light the IoT divide leads to significant implications for Europe-wide policy. At the moment, the European IoT/Digital Transformation Space is divided in two sets of regions: those that have (a full range of) IoT competences and those that do not. Yet, the complexity of IoT and similar enabling technologies requires that all regions scale up in order to fully exploit their technological potential. Therefore, the divide needs to be bridged and this is a policy implication for Europe, and the EU in particular, in its entirety. Country level policies are also important for supporting such developments, enhancing the creation of strategic infrastructures, such as telecommunications and connectivity, while the NUTS 2 and NUTS 3 levels are relevant for consolidation of appropriate competences needed for the development of IoT supply chains.

7 | CONCLUSION

Our study deploys an original mapping methodology combining NACE codes and text mining of descriptions of company activities to propose a more accurate identification of the NACE codes that are relevant in the analysis of companies operating in one or more layers characterising the IoT architecture. In this way we are able to classify companies by using their four-digit NACE code and to classify NUTS 3 regions according to their specialization in the various IoT domains that have been identified through semantic analysis. The depiction of regional strengths in individual IoT domains as well as in more complete value chains of IoT competences have been highlighted.

While other mapping exercises have been published in recent years, scholars have tended to focus on activities related to I4.0 more broadly, without conducting extensive and precise mapping of IoT in particular. Our study also differs from prior work insofar as we deployed an original methodology to respond to the challenges that arise when mapping new technologies, which are difficult to grasp within the existing classification of economic activities that are not usually suited to respond to new needs and cannot be significantly identified by using patent data. The use of text mining is not new, but previous studies use expert knowledge to select a limited number of terms to create corpora from web scraping (Mateos-Garcia et al., 2014; Nathan & Rosso, 2015). In our study, we rely on expert knowledge to support the initial selection of the many potential codes in which companies in the various IoT layers can be engaged, and then we analyse their broad descriptions to further focus on the most relevant codes.

The study contributes to theory by showing how the competence base of regions underpins their potential to develop and extend their technological bases in emerging digital technologies. Our study indicates that potential performance outcomes of regions might depend on the mix of competences in the IoT that are embedded in the companies working in this area. In particular, we identify three main groups of regions that, referring to the layers described in Section 3 with respect to the IoT solution architecture, encompass, respectively, cross-layer IoT competences, specialized IoT competences in hardware manufacturing, specialized IoT competences in software and data processing, and telecommunication.

NUTS 3 regions in the three groups are characterized with different networks of competences and innovation processes that can be endogenously supported by the companies in the region or that need policy support for their development. In the case of regions with cross-layer competences, where the most important system integrators are located, the challenge for companies is to maintain the pace of the rapid changes in the IoT technologies. In the case of regions with specialized competences, policy interventions should orient the opportunities for completing the IoT supply chains, as in the case of IoT regions that have specialized IoT competences in hardware manufacturing, and that could be supported by the creation of hubs enhancing software competences in the region. In the case of regions that have specialized IoT competences in software and data processing, and telecommunication, development policies should leverage the attraction of investments of hardware manufacturers with system integration competences and in connection their policies with the one of regions with hardware manufacturing competences.

In this interregional perspective about policy implications, our findings provide regional policy-makers with a very operational support, thanks to the identification of which regions should be fostered as full IoT value-chain providers and which need to specialize further or, alternatively, diversify into new, related, complementary domains and networks across regions and countries. In terms of regional policies, this calls for new perspectives towards different units of policy interventions, as is the case of macro-regional strategies (Pavone et al., 2020; Radosevic et al., 2017; Russo et al., 2019).

In addition, our results highlight the need for strong orientation at the EU level, that is essential to reduce the gap that clearly emerges across regions and countries in Europe, which does not appear specifically targeted by the Next Generation EU Programme.

Our study also has some limitations, which open up avenues for further research. The present analysis is limited to 18 European countries, but IoT competences are found worldwide. Future research could expand the geographical scope of the analysis and additional sources of company information could also be explored since the Amadeus database presents some limitations. Moreover, our analysis relies on the use of NACE codes, which pre-date the IoT. To overcome the limitations of NACE codes, we have relied on the opinion of an expert in the IoT to select 16 NACE codes that are the most relevant to the IoT, and we have developed an original reclassification of NACE codes according to IoT domains. Although we believe that this was the right approach to choose for our mapping exercise, we acknowledge that it is possible that some companies are omitted from our map due to the fact that we include only those companies that correspond to the 16 NACE codes. Another limitation of our study is its use of company descriptions of their activities, which do not necessarily capture the full range of knowledge that underpins these activities. Future research could combine different types of data (patents, competences, activities) to produce a more complete picture of the IoT landscape in European regions.

Finally, this paper mainly focused on IoT systems on the "supply side," mapping IoT competences at the regional level, but the system also consists of the demand side, with IoT solutions tailored to customers' needs. Future studies might focus on the demand side to gain a deeper understanding of the IoT area as a whole. Moreover, we may guess that the "emergence" of competences in IoT domains stems from related competences already found in the region, and that these rely on demand from other regions. The system is thus made up of all these varying interconnections. While a preliminary analysis recently conducted by the European Commission (2019) outlined the spatial distribution of demand for IoT solutions in European regions, as far as we know there has been no systematic investigation of all the entities in the system (which companies are present on the demand and the supply side, which regulatory agencies and policy actors) to date, nor of the relations between these entities.

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ENDNOTES

1 The focus on the NUTS 3 level of analysis allows for a more precise identification of territorial specificities than it would be possible by focusing on NUTS 2 regions, which exhibit a high degree of industrial heterogeneity; indeed, the NUTS 3 level is often preferred in analyses of regional development and regional convergence at EU level.

2 As described by BvD, this field is filled through a 'supervised' web scraping procedure on the firms' websites. The supervision consists of the assistance of one of the BvD consultants who indicates which fields of the websites are relevant and helps to classify the retrieved information (e.g., main products, main customers, company history).

3 The expert has extensive industry experience in the IoT domain and is working with the largest consulting firms in the area of emerging technologies.

4 Details of full overviews are available in Table A3 (Supplementary material).

5 By active terms we mean all lexical forms (words) selected for the purpose of the analysis and thus contrasted with the terms we can call supplementary. In order to identify the semantic contents of the texts and to obtain groups of NACE codes on the basis of semantic contents, we therefore consider as active forms all words grammatically recognized as adjectives and nouns. The latter in particular represent the objects and subjects of texts and are therefore the central element of the message conveyed by a text. Moreover, in order to disambiguate the potentially ambiguous meaning of some words, we proceeded with a multiword expressions recognition which, by linking the simple form to its qualification, allows both to improve the clustering process and to facilitate the interpretation process of the results.

6 Multiword-Expressions (MWEs) represent all idiomatic nouns and technical-specialist terms, therefore representing the specialized terminology of a sector. The recognition of MWEs was performed by applying an information extraction model based on grammatical annotations and the search for recurrent syntactic structures (Pavone, 2018). The 20 most recurring MWEs we have found are: *information technology*, *data processing*, *consulting service*, *provision of computer*, *computer programming service*, *communication technology*, *financial service*, *computer hardware*, *software development*, *supporting software*, *computer system*, *system integration*, *designing computer system*, *domestic market*, *project management*, *technology solution*, *data processing facility*, *provision of information*, *operation of clients*, *exceptional domain knowledge*.

7 Test-value is a statistical criterion associated with the comparison of two portions (considered context and all the other contexts) within the framework of a hypergeometric law.

8 A similar analysis of the different active terms in the NACE descriptions produced a list of 505 terms. The comparison between the sizes of the active terms in the two *corpora*—one with the NACE codes' details and the other based on the companies' full overviews—which are, respectively, 505 and 7,651, suggests that the full overview contains a larger amount of information that is not included in the NACE codes description.

9 The correspondence analysis (Benzecri, 1973, 1992; Greenacre, 1984, 2016) is a factorial technique that can be used to obtain a reduced number of variables (or factors) on which to measure the similarity of a matrix, by examining row and column profiles.

10 We applied mixed clustering (Lebart et al., 1998, p. 95) based on Ward's aggregation method (1963), with Euclidean distance.

11 Each company is associated with only one NACE code, corresponding to its main activity.

12 Information on NUTS 3 is present for 179,887 companies out of the 183,878 in the database.

13 Hierarchical clustering was implemented by applying the Ward method (Greenacre, 2016, p.120; Murtagh & Legendre, 2014; Ward, 1963) and chi-square distance.

14 With a cut at 13 clusters, two of the main six clusters (cl-5 and cl-6) do not split in subgroups.

15 Among the most relevant system integrators feature Capgemini, Accenture, Atos, Cognizant, TechMahindra, Altran, Infosys, EY, HCL, KPMG, DXC, BearingPoint, McKinsey & Company, Wipro, PWC, NTT Data, SAIC, CGI.

[16] In Pagliacci et al. (2020), Principal Component Analysis is performed on 31 input variables; the top nine principal components (PC) are characterized as follows. PC1: variables referring to urbanization and share of service employment; PC2: share of manufacturing employment (B-E industries) and higher education; PC3: touristic arrivals and tiny population; PC4: population imbalances; PC5: share of agricultural gross value added and share of employment in public services (O-Q industries); PC6: share of employment in real estate activities (L industry); PC7: lower share of employment in textile and wood industries (13–15 & 16–18 industries, respectively); PC8: share of employment in mining and quarrying industries (05–09 industries); PC9: share of employment in construction industry (F industry).

[17] Classification of Norway's NUTS 2 regions is not available in the dataset provided by Pagliacci et al. (2020), but is included in our results on IoT specialisations of NUTS 3 regions.

[18] The NUTS 3 regions with more than 500 companies in Belgium are: BE211-Arr. Antwerp; BE310-Arr. Nivelles; BE242-Arr. Leuven; BE241-Arr. Halle-Vilvoorde; BE234-Arr. Gent; BE221-Arr. Hasselt; BE212-Arr. Mechelen; BE213-Arr. Turnhout. In the Netherlands are: NL33C-Groot-Rijnmond; NL332-Agglomeratie ‘s-Gravenhage; NL414-Zuidoost-Noord-Brabant; NL221-Veluwe; NL226-Arnhem/Nijmegen; NL411-West-Noord-Brabant; NL413-Noordoost-Noord-Brabant; NL213-Twente; NL230-Flevoland; NL327-Het Gooi en Vechtstreek; NL337-Agglomeratie Leiden en Bollenstreek; NL113-Overig Groningen; NL423-Zuid-Limburg; NL33B-Oost-Zuid-Holland; NL412-Midden-Noord-Brabant; NL333-Delft en Westland; NL33A-Zuidoost-Zuid-Holland- In Sweden are: SE232-Västra Götalands län; SE224-Skåne län; SE121-Uppsala län; SE123-Östergötlands län; SE331-Västerbottens län; SE125-Västmanlands län; SE125-Västmanlands län.

[19] In these countries, the NUTS 3 regions with more than 500 companies are in Estonia: EE001-Põhja-Eesti; EE008-Lõuna-Eesti; in Finland: FI197-Pirkanmaa; FI1C1-Varsinais-Suomi; FI1D9-Pohjois-Pohjanmaa; in Latvia: LV006-Rīga; LV007-Pierīga; in Sweden: SE121-Uppsala län; SE123-Östergötlands län.

[20] In these countries, the NUTS 3 regions with more than 500 companies are in Austria: AT130-Wien [a very-high income; high-density city-region; high-employment; highly educated; touristic]; in Finland: FI1B1-Helsinki-Uusimaa; in the Netherlands: NL329-Groot-Amsterdam; NL310-Utrecht; NL327-Het Gooi en Vechtstreek; in Slovenia: SI041-Osrednjeslovenska. (Very-high income; large urban regions; high-employment; highly educated]; in Portugal: PT170-Área Metropolitana de Lisboa [an Urban region; high-income; poorer employment conditions; touristic).

[21] Such as HR041-Grad Zagreb; IE061-Dublin, LT011-Vilniaus apskritis; LT022-Kauno apskritis, that are the NUTS 3 regions with more than 500 companies.

[22] As in the region PT11A-Área Metropolitana do Porto.

[23] Mainly in the following NUTS 3 regions: DE212-München, Kreisfreie Stadt; DE21H-München, Landkreis; DEA23-Köln, Kreisfreie Stadt; DE712-Frankfurt am Main, Kreisfreie Stadt; DEA11-Düsseldorf, Kreisfreie Stadt; DE111-Stuttgart, Stadtkreis.

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