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Mapping capabilities for Smart Specialisation: an LLM-based approach

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Abstract

Smart Specialisation Strategies have become a cornerstone of EU Cohesion Policy, yet prioritising investment areas remains a challenge. This paper introduces a methodology for capability mapping to support strategic priority setting, integrating data from patents, scientific publications, and R&D projects, classified using Large Language Models (LLMs). Unlike approaches that focus narrowly on technologies or industries, the method maps the intersection of technological domains and fields of application, as envisaged in the foundational literature on Smart Specialisation. This intersectional perspective aims to support a more precise and policy-relevant identification of areas with transformative potential. An empirical application to the Portuguese case illustrates the potential of the methodology to inform decision-making. The method grounds the analysis in local capabilities and contexts, supporting the exploration of place-based, distinctive pathways for structural transformation.

Keywords: Smart Specialisation Strategies, innovation policy, capability mapping, Large Language Models (LLMs); EU cohesion policy

1. Introduction

Smart Specialisation Strategies (S3) have acquired a central role in policymaking in the European Union (EU) in recent years. Since 2014, S3 have been a prerequisite for Member States to access European Structural and Investment Funds in the field of research, development and innovation (R&D&I).

The core premise of S3 is that, to maximise their economic potential, regions should identify, prioritise and strategically build upon existing capacities to cultivate context-sensitive pathways for structural renewal. This principle of leveraging established regional strengths resonates with insights from evolutionary economic geography, particularly the concept of relatedness. Relatedness literature posits that diversification into new economic activities is most likely to succeed when these activities are cognitively proximate to local capabilities (Frenken *et al.*, 2007; Boschma & Frenken, 2011). This path-dependent perspective suggests regions typically "discover" their future comparative advantages through the recombination or adaptation of current competencies, rather than pursuing radical leaps into unrelated domains (Hidalgo *et al.*, 2007; Neffke *et al.*, 2011). S3 thus represent a deliberate departure from the "one-size-fits-all" model embodied in the Lisbon Strategy, whose application to places with differing institutional, technological and productive capabilities had rendered earlier approaches to EU regional development ineffective (Barca, 2009; Tödtling & Trippl, 2005).

Despite the centrality of S3 in EU regional policy, implementation has not been straightforward. Many national and regional strategies have been criticised for being overly broad in scope (Gianelle *et al.*, 2019; Prognos and CSIL, 2021) and not sufficiently aligned with existing capabilities (Marrocu *et al.*, 2022; Prognos and CSIL, 2021). In this paper, we argue that one reason for these difficulties relates to limitations in the methods commonly used to map research and innovation capacities. Dominant approaches rely on indicators of either economic structure or patenting activity, operationalised at the level of industries or technological classes. While informative, these measures tend to provide only a partial view of R&D&I capacities and overlook more specific areas where "transformative activities" are expected to emerge.

This paper explores one possible way of addressing this gap. We describe and illustrate a methodology to map R&D&I capabilities at the intersection between technological domains and fields of application, using Large Language Models (LLMs) to classify different types of R&D&I outputs. We propose an intermediate, "mid-grained" level of analysis that is neither as coarse as broad sectors or technologies, nor as narrow as individual projects, and that can therefore serve as a practical unit of analysis for S3 design. Concretely, we address three interrelated questions: how can transformative activities be empirically identified and mapped at the technology–application interface in a way that is consistent with the conceptual foundations of S3? To what extent can an LLM-based, multi-source classification of R&D&I activities provide a richer and more policy-relevant picture of capabilities than existing technology- or industry-based approaches? And what does such an approach reveal about the configuration of capabilities at the national (or subnational) level, and about areas with apparent transformative potential?

Methodologically, we put forward a capability-mapping framework that combines three types of evidence: descriptions of funded business R&D projects, titles of patent applications filed under the Patent Cooperation Treaty (PCT), and abstracts of scientific publications. These documents are classified using LLMs according to a purpose-built taxonomy comprising 8 technological domains and 24 fields of application, yielding 192 potential areas of specialisation. To illustrate the potential of this approach, we apply it to the case of Portugal. We construct comparative indicators that benchmark Portuguese activity against international reference populations, thereby identifying technology–application combinations in which Portugal appears to exhibit relatively strong and distinctive capabilities. The analysis has practical implications for national and regional authorities, innovation agencies and other actors involved in S3 governance, by providing evidence that can support strategic planning, help structure Entrepreneurial Discovery Processes, and inform debates on how to align innovation policy with societal challenges.

The remainder of the paper is organised as follows. Section 2 revisits the conceptual foundations of Smart Specialisation and critically examines the limitations of existing approaches to capability mapping. Section 3 sets out our LLM-based capability-mapping framework, detailing the construction and validation of the taxonomy, the data sources and classification procedures, and illustrating its application through a map of Portuguese R&D&I capabilities. Section 4 discusses the implications of these findings for the governance of S3, with particular attention to the diversification–specialisation tension, the alignment of priorities with societal challenges, and the main methodological limitations of the proposed approach. Section 5 concludes by summarising the core contributions of the framework and outlining promising avenues for further research and policy experimentation.

2. Smart Specialisation Strategies as a new policy framework

As a meta-governance principle, S3 rests on the combination of two complementary design principles: an initial top-down “strategic planning” stage, followed by a bottom-up process of “entrepreneurial discovery”, that elicits, articulates, and reorients existing capacities towards new development paths (Foray, 2019). Policymakers are expected to rely on solid evidence about regional strengths to select a limited number of priority areas where regions can build distinctive development trajectories, rather than dispersing resources across many unrelated activities. This creates an evidence-based foundation that supports the subsequent discovery process by anchoring transformation in established regional capabilities (Foray *et al.*, 2021). From this perspective, structural change should build on what regions already do well, while still allowing room for experimentation, diversification and learning (Foray, 2015; Foray *et al.*, 2021). Smart Specialisation therefore represents a move away from generic "one-size-fits-all" policy approaches towards strategies that take the specific characteristics of each territory seriously.

Translating these principles into practice has proved challenging. Many activities that may be critical for future diversification cut across traditional sectoral boundaries, rely on complex combinations of technologies, and involve new articulations between private and public actors. As a result, standard indicators of economic specialisation or scientific and technological performance, which were developed primarily for analysing sectors or technologies in isolation, are often ill-suited for S3 purposes.

Against this background, the remainder of this section outlines the conceptual basis for S3 capability mapping, focusing on the notion of transformative activities, and discusses the main limitations of existing methods to identify them.

2.1 Transformative activities as the relevant unit of analysis in S3

In the context of S3, decision-makers are encouraged to identify and support "transformative activities" rather than simply selecting sectors or technologies. Foray (2018, p. 818) defines transformative activities as "a collection of innovation capacities and actions (...) that is oriented toward a certain structural change". They are not isolated projects, but bundles of interrelated efforts that, over time, can reorient the economic and innovation structure of a region.

A key attribute of transformative activities is their embeddedness in existing regional capacities. They build on the stock of competences, infrastructures, organisational routines and institutional arrangements that characterise a place, including both tangible and intangible assets. In this sense, transformative activities constitute the operational expression of S3's ambition to combine structural change with an explicit focus on place-based capabilities (Foray, 2015, 2018; Jacobsen *et al.*, 2024).

Following Foray (2015; 2018; see also Gianelle *et al.*, 2016), transformative activities are thus defined at the intersection of industries and technologies – such as in the application of materials technology to textiles or biotechnology to agrifood. The same broad sector (for example, "agri-food") may therefore host very different transformative activities, depending on whether it involves, say, digital technologies for precision farming, biotechnology for crop resilience, or new organisational models for short supply chains.

This interpretation is consistent with the broader literature on innovation systems, which emphasises that innovation emerges from interactions among heterogeneous actors rather than from individual organisations acting in isolation (Freeman, 1987; Lundvall, 1985, 1992; Nelson, 1993). Firms, universities, research organisations, and public agencies participate in networks where knowledge circulates, is adapted to local conditions and becomes embedded in specific productive and institutional contexts (Malerba, 2002; Carlsson and Stankiewicz, 1991).

A key insight from the literature on systems of innovation particularly relevant to the concept of transformative activities within S3 is the significance of vertical linkages in driving innovation. Lundvall's (1985) seminal work on user-producer interactions underscores how innovation often arises from the interplay between technology producers and their users in downstream industries. Pavitt's (1984) influential taxonomy of sectoral patterns of innovation further emphasises the crucial role of technology suppliers in driving technological change across various industries. From a related, though analytically distinct, perspective, Porter's (1990) exploration of industrial clusters highlights the competitive advantages that emerge from geographically proximate, vertically related industries. In summary, the transformation of production systems frequently occurs through activities that transcend industry boundaries, a consideration that should be integral to the operationalisation of S3 capability mapping.

From this systemic perspective, the relevant "unit" for S3 is not a sector or a technology in the abstract, but a concrete configuration of activities located at the intersection of technological domains and fields of application, and embedded in particular actor constellations and institutional settings. Transformative activities are thus simultaneously technological, sectoral and territorial phenomena. Making them visible requires analytical approaches that go beyond sector- or technology-based categories and are sensitive to the ways in which technologies are actually deployed in specific fields of application. This has direct implications for capability mapping in S3: if methods are to provide information that is both consistent with the conceptual foundations of Smart Specialisation and useful for informing priority setting, they need to capture these intermediate, technology–application combinations.

2.2 Limitations of current methods to identify transformative activities

The framework proposed by Balland *et al.* (2019) has provided a widely adopted methodological reference for the prioritisation process in S3 (e.g., Santoalha, 2019; Balland and Boschma, 2020; Panori *et al.*, 2022; Kim *et al.*, 2024), addressing a long-standing gap in the literature. Grounded in the notions of technological relatedness and knowledge complexity (Hidalgo *et al.*, 2007; Neffke *et al.*, 2011; Hidalgo & Hausmann, 2009; see Stojkoski & Hidalgo, 2025 and Pinheiro, 2025 for recent critiques), it draws on earlier attempts to mobilise the logic of relatedness in the context of S3 (Boschma, 2014; Boschma & Gianelle, 2014). At its core lies the proposition that regional diversification is more likely to succeed when new activities are cognitively close to pre-existing knowledge domains.

This approach has generated a large empirical literature on regional diversification, resilience and development, and has informed practical tools for policy makers interested in identifying ‘nearby’ opportunities (see Boschma, 2025, and references therein). However, several shortcomings limit the extent to which these approaches can support the identification of transformative activities as understood in the Smart Specialisation literature. These limitations can be grouped into three broad categories: data-related constraints, limitations of mapping instruments, and tensions with the normative and analytical foundations of S3.

Firstly, these studies rely heavily on patent data, which, while a valuable indicator of innovative activity, are subject to notable biases and blind spots. As Griliches (1990) highlights, not all inventions can be patented, nor are all patent-eligible inventions actually pursued through the patenting process. Additionally, the propensity to patent varies significantly across different industries and technologies (Arundel and Kabla, 1998), meaning that an overreliance on patent data may lead to the neglect of innovative activities in industries characterised by low patenting rates but with high potential for regional development.

A second limitation arises from the way technological and productive activities are connected through classification systems and concordance tables. Patent data prioritise information about the underlying technology rather than its field of application, making it difficult to identify the specific application domains or market opportunities to which innovations may be suited. For example, a patent for a “computational method and system for improved identification of breast lesions” is mapped exclusively to the G06 class (Computing, Calculating, Counting) of the International Patent Classification (IPC), despite its evident relevance for the health sector. This reflects generic digital capabilities but fails to capture the productive activities that the innovation may ultimately transform. Similar problems affect studies relying on patent–industry concordance tables (e.g. Panori *et al.*, 2022; Kim *et al.*, 2024), which are inherently constrained by the industry-neutral structure of the IPC. Moreover, existing concordances (e.g. Eurostat, 2014; Lybbert and Zolas, 2014) typically link patents to the industries of patent holders rather than to the sectors that are most likely to adopt or benefit from the underlying innovations. Consequently, they privilege the perspective of producers over that of users, limiting their suitability for identifying application-driven transformative activities.

Finally, relatedness-based approaches sit uneasily with a core rationale of Smart Specialisation, which places strong emphasis on the pursuit of place-specific and distinctive pathways of structural transformation. The standard logic of relatedness is grounded in patterns of co-occurrence: when two activities frequently appear together across multiple economies, they are inferred to be related and, therefore, more likely to branch into one another. When used for policy guidance, this inference may encourage regions to emulate widely observed diversification trajectories, rather than to identify opportunities that are specific to their own contexts and capability endowments. Moreover, co-occurrence alone does not necessarily imply a meaningful or actionable connection between activities. Correlational patterns may point to potential links, but they do not establish the existence of concrete complementarities, knowledge flows or absorptive capacities. As a result, an uncritical application of this logic risks downplaying the contextual and institutional specificities that are central to the S3 approach and may inadvertently reintroduce a 'one-size-fits-all' perspective on regional development – the very mindset that Smart Specialisation was designed to challenge (Gong & Hassink, 2020).

A growing strand of the recent S3 literature focuses on the development of indicators to capture the capacity of countries and regions to address societal challenges and sustainability transitions (e.g. Krlev & Terstriep, 2022; Cappellano *et al.*, 2022). These contributions represent an important step in broadening the scope of Smart Specialisation towards mission-oriented and sustainability-oriented policy objectives (McCann and Soete, 2020; Molica *et al.*, 2025), typically through the use of composite indicators and macro-level readiness measures. However, their high level of aggregation makes it difficult to identify the specific technological and productive activities through which regions may effectively contribute to such transitions. This highlights the need for complementary approaches capable of linking societal challenges to concrete transformative activities embedded in specific innovation systems.

Taken together, existing approaches either focus on technologies or industries, or rely on highly aggregated indicators of regional readiness. What remains missing is an operational way to map capabilities at the intermediate level of specific combinations between technological domains and fields of application, in a way that is both empirically tractable and directly usable for Smart Specialisation.

3. An alternative approach and illustration

We propose a methodology for mapping capabilities to support strategic priority setting in the context of S3 that enables a more precise and policy-relevant identification of areas with transformative potential. Our approach addresses two main limitations of existing methods.

First it complements information derived from patents with rich yet underutilised data on research and innovation capabilities drawn from business R&D projects and scientific publications. As mentioned in Section 2.2, it is well known that patents underrepresent the innovative potential of economically relevant business domains with structurally low patenting activity; therefore, we combine patents with other, richer sources of information in order to achieve a wider coverage of R&D&I capabilities. Business R&D projects provide especially valuable evidence to fill in patents' informational gap in this respect.

Second, our method systematically extracts relevant insights from all three sources – patents, R&D projects, and scientific papers – regarding both the technological domains and the fields of application involved. This dual-level classification enhances the precision with which areas of transformative potential can be identified, addressing the limitations of existing taxonomies that were originally designed for other purposes.

To classify large numbers of diverse types of documents using a coherent and purpose-built taxonomy, our method capitalizes on recent advances in artificial intelligence. Building on the documented applications of generative AI models in economic research (Korinek, 2023; Chen *et al.*, 2024; Weber *et al.*, 2025), we employ LLMs as pre-trained classification agents, instructed to categorise documents in accordance with a structured taxonomy of technology domains and fields of application. The model is provided with a carefully crafted prompt that encompasses: (i) contextual information and guidelines for the task at hand; (ii) a precise definition of the document to be classified; and (iii) the taxonomy itself, outlining the defined application fields and technological domains.[1]

We illustrate this approach with an application to the case of Portugal. This country's S3 for the 2014–2020 period has been characterised by a relatively broad and undifferentiated set of priorities, often with limited alignment to regionally embedded capabilities. Indeed, the comparative analysis by Prognos and CSIL (2021) ranked Portugal's strategy as the least selective among EU member states.

By applying our LLM-based capability mapping methodology to Portugal, we show how the intersectional perspective on R&D&I capabilities emerging from our classification contrasts with one-dimensional assessments. Our method's richer evidence base produces a more informative input for the critical strategic planning phase of S3, revealing potential misalignments or areas for refinement in existing strategies, and offering concrete starting points for the subsequent Entrepreneurial Discovery Processes and for more targeted policy interventions.

3.1 Establishing the taxonomy for capability mapping

To define a taxonomy for the assessment of existing R&D&I capabilities based on technological domains and fields of application, we began by drafting an initial version drawing as much as possible on established official classification schemes. For technological domains, we used the Fields of Science and Technology in OECD's Frascati Manual and WIPO's International Patent Classification (IPC) system, thus ensuring coverage of standard technical categories and international comparability. For fields of application, we considered the established NACE (Rev. 2) classification, the industrial ecosystems defined by the

[1] In the appendix, we present an example of a prompt used to classify R&D projects (the prompts used to classify other types of documents were similar), as well as the auxiliary descriptions that were fed into the model. The model's temperature parameter, which controls the randomness of the model's output, was set to its minimum level to ensure reproducibility. Testing also revealed that this setting maximised classification accuracy.

European Commission, and, to guarantee the inclusion of key domestic strategic priorities, the Clusters of Competitiveness accredited by the Portuguese Ministry of Economic Affairs.

To ensure the relevance, coherence, and comprehensiveness of the proposed taxonomy, we requested an independent assessment from a team of experts designated by the board of the Portuguese National Innovation Agency. For this purpose, the board appointed three senior evaluators with extensive experience in assessing business R&D project applications submitted for public funding. These experts are routinely involved in identifying the technologies underpinning such projects and assessing their relevance to specific fields of application. Their feedback was instrumental in validating and refining the taxonomy. The validation process involved written assessments and follow-up discussions to clarify points of divergence and reach consensus where needed.

Having completed this step, we randomly selected 75 R&D projects and used GPT-4o to classify them according to the revised taxonomy, providing the model with concise descriptions for each category. Several iterations were undertaken to refine both the taxonomy and the category descriptions. The outcome of this iterative exercise was the identification of a total of 192 potential areas of specialisation, resulting from the intersection of 8 technological domains with 24 fields of application (see tables in the Appendix).

Once the final taxonomy was validated, the same team of experts manually classified the 75 projects according to that taxonomy, and their results were used as a "ground truth" benchmark to evaluate the performance of the LLM-based classifications. This benchmark allowed us to identify the best-performing model for our approach.

As shown in Table 1, the results demonstrated that all LLM models exhibited high levels of precision (i.e., few incorrect classifications) and recall (i.e., few missed cases that should have been classified).

Table 1. Average performance of LLMs in the classification of projects

LLM	Precision	Recall
Opus	0.87	0.76
GPT4o	0.87	0.75
Sonnet	0.83	0.75
Haiku	0.77	0.80

3.2 Data

In applying our method to Portugal's S3, we analysed the short descriptions of 23,936 business R&D projects. This dataset, provided by the Portuguese National Innovation Agency, encompasses all projects supported by the country's main direct and indirect support schemes (grants and tax credits) aimed at fostering business R&D between 2015 and 2021, as well as projects funded by Horizon 2020 (the EU's research and innovation funding programme from 2014-2020). We also examined 2,142 patent applications filed under the Patent Cooperation Treaty (PCT) by Portuguese residents between 2014 and 2024, drawn from the WIPO database. Additionally, we analysed 73,060 abstracts of scientific papers authored by researchers based in Portugal, published between 2020 and 2023, all of which had been cited more than once.[2,3]

To compare the share of national R&D&I activity within specific domains with the corresponding share in international reference populations, we constructed suitable benchmark datasets based on global random samples of Horizon 2020 projects, PCT patents, and cited academic publications.[4] A rigorous assessment of capabilities requires such comparative analysis, as absolute counts of projects, patents, or papers may merely mirror global trends rather than indicate unique domestic strengths. Comparing national activity shares against these international baselines allows us to identify domains where Portugal's R&D&I efforts are comparatively more focused.

3.3 Classifying R&D projects, patent applications, and scientific papers

The next step involved applying the final taxonomy to classify the R&D projects, patent applications, and scientific papers, using LLMs as outlined above. Each document was associated with one or more technological domains and fields of application.

Table 2 illustrates the advantage of our method to infer the fields of application compared with the traditional approach of converting IPC codes to NACE classifications (adopted in Panori *et al.*, 2022). NACE codes inferred from IPC codes often associate each patent application with industries that typically produce the relevant technology, instead of linking

[2] Abstracts of scientific papers were obtained from the OpenAlex catalogue (openalex.org). Since not all this knowledge has relevant applications to productive activity, and to manage costs, we opted to exclude publications in the fields of social sciences, arts, humanities, economics, management, psychology, and mathematics, focusing the analysis on the domains of science, technology, and healthcare.

[3] The use of partially overlapping time windows across data sources reflects both substantive and practical considerations. Since patent applications and scientific publications typically materialise with a lag relative to the underlying R&D activities, their observation windows are extended beyond the end date of the R&D projects. For patents, a longer horizon (2014–2024) was required to ensure sufficient volume and technological coverage. For scientific publications, the very large volume of data and the associated computational cost constraints led us to focus on the most recent period (2020–2023), which nonetheless remains well aligned with the later stages of the Horizon 2020 project cycle.

[4] Although we worked with samples rather than full censuses of the underlying populations (due to computational cost constraints), sampling variability is limited by the large size of the datasets. Assuming simple random sampling and considering the most conservative case (p = 0.5), the maximum margin of sampling error at the 95% confidence level is approximately ±2 percentage points for each type of data (H2020 projects, patent applications and scientific publications).

it to the economic activities that use that technology for innovation. By contrast, our LLM-based classification clearly identifies both the technological domain and the field of application of each patent based on policy-relevant information contained in their application titles that is not captured by existing classification systems.

Table 2. Illustrative examples of the classification of patent applications

Patent Title	IPC to NACE concordance table (Eurostat, 2014)	LLM classification
Automatic detection and differentiation of pancreatic cystic lesions in endoscopic ultrasonography	Manufacture of computers and peripheral equipment [26.2]	Digital Technologies applied to Health and Wellbeing
Automatic detection and differentiation of biliary lesions in cholangioscopy images	Manufacture of computers and peripheral equipment [26.2]	Digital Technologies applied to Health and Wellbeing
Generic xr game-based system for industrial training	Manufacturing N.E.C. [32.9]	Digital Technologies applied to Education and Training
Method for the production of a textile material for radiation protection	Manufacture of Other Special Purpose Machinery [28.9]	Material Technology applied to Textiles, apparel, and footwear
A method and device for automatic integration of farm climate and biometric variables	Manufacture of Communication Equipment [26.3]	Digital Technologies applied to Agrifood

Moreover, by consistently applying our methodology to classify all documents (i.e., patents, R&D projects and scientific papers), we enable a comprehensive assessment of R&D&I capacities, facilitating direct comparisons across different types of R&D&I data. This approach allows for a clearer understanding of the areas where transformative activities are more likely to emerge.

3.4 The map of Portuguese capabilities

Here we use the case of Portugal to illustrate the advantages of mapping capabilities based on both technological domains and fields of application of R&D&I activities and outputs. We begin by showing how such a mapping would appear for Portugal if it were based on the WIPO IPC–technology categories used in the conventional patent-based approach. We then contrast this representation with the map obtained through our domain- and application-based approach, showing that the latter provides a more accurate and policy-relevant identification of potential areas for smart specialisation.

In the conventional approach, patents are allocated to technology fields using the WIPO IPC–technology categories and a relative technological advantage (RTA) index is computed for each field. Table 3 reports the RTA values for Portugal in those technology fields with higher RTAs (values above one indicate relative specialisation). Fields such as furniture, games, analysis of biological materials, biotechnology, food chemistry, and pharmaceuticals stand out as areas of relative specialisation.[5]

Table 3. Relative Technological Advantage using IPC technology fields (RTA>1.25)

Technology Field	Portugal (share)	Benchmark (share)	Relative Technological Advantage
Furniture, games	5,8%	1,3%	4,4
Analysis of biological materials	1,5%	0,6%	2,5
Biotechnology	5,5%	2,6%	2,1
Food chemistry	1,8%	0,9%	2,0
Pharmaceuticals	7,9%	4,0%	2,0
Other special machines	3,9%	2,1%	1,9
Other consumer goods	2,7%	1,8%	1,5
Control	2,7%	1,8%	1,5
Civil engineering	3,3%	2,2%	1,5
Basic materials chemistry	2,8%	1,9%	1,4
Organic fine chemistry	3,5%	2,5%	1,4
Handling	3,7%	2,7%	1,4
Transport	5,0%	3,9%	1,3
Medical technology	9,2%	7,2%	1,3
Textile and paper machines	1,4%	1,1%	1,3

Such single layer analysis conceals significant heterogeneity in capabilities across specific applications of technologies. By crossing the 8 technological domains with the 24 economic fields of application of our taxonomy, we identified 21 out of the 192 possible combinations, which, although representing only around 10% of the total potential areas, accounted for nearly 50% of Portuguese R&D projects (both nationally and EU funded) and scientific publications, as well as over 40% of the country's patent applications. Portugal's degree of specialisation in all these areas is notably higher than the average, according to one or more of the comparative indicators shown in Table 4.

[5] In this example, for illustrative purposes, we use the level of aggregation followed by Balland *et al.* (2019). Using a more disaggregated level of analysis leads to similar conclusions.

Table 4. High potential areas for Portugal's S3

Field of application	Technological domains	Relative R&D advantage (H2020 projects)	Relative technological advantage (patents)	Relative scientific advantage (papers)	Revealed comparative advantage (exports)
Agrifood	Biotechnology	1,1	1,7*	1,1	1,3*
	Digital technologies	1,5*⁺	5,4*	1,1	1,3*
	Chemistry	1,0	2,2*	1,5*	1,3*
Commerce	Digital technologies	0,9	1,3*	1,2	-
Construction and architecture	Digital technologies	1,3*⁺	0,8	1,2	1,6*
	Materials technologies	1,1	2,3*	1,7*	1,6*
	Production technologies	1,0	1,7*	1,2	1,6*
Transport equipment	Materials technologies	0,7	1,7*	1,6*	1,6*
State and public administration	Digital technologies	2,2*	0,5	1,1	-
Tools, industrial equipment and machinery	Digital technologies	1,6*	0,5	0,8	0,6
	Production technologies	1,4*	0,4	0,9	0,6
Water and waste management	Digital technologies	1,3*⁺	0,9	1,2	-
Fishing, aquaculture and fishery products	Biotechnology	1,6*⁺	4,5*	2,4*	1,8*
Energy	Digital technologies	1,3*	0,6	1,1	2,1*
Health	Biotechnology	0,7	1,8*	0,9	0,6
	Digital technologies	0,7	1,4*	0,9	0,6
	Materials technologies	1,0	2,4*	1,5*	0,6
IT services	Digital technologies	1,4*	0,4	0,7	1,0
Transport and logistics	Electronics	1,3*	0,7	1,1	1,8*
	Digital technologies	1,3*	0,6	1,0	1,8*
Textiles, clothing and footwear	Materials technologies	1,7*	1,7*	1,1	2,0*

* Denotes an activity index, RTA or RCA>1.25 (i.e. 25% or more concentration vis-à-vis the baseline).

⁺ These cases should be interpreted with caution due to the limited number of observations.

Note: The four indicators correspond to the weight of each area of specialisation in Portugal in the corresponding domain (H2020 R&D projects, patent applications, scientific papers, and exports, respectively) divided by its weight in all the countries included in the analysis. The data on exports is extracted from: https://atlas.cid.harvard.edu/ and refers to the average RCA for the period 2019-2021 (authors' calculations).

At a broad level, the results of the two approaches are largely compatible: both suggest that Portugal has relevant capabilities in life-science-related technologies, in chemicals and materials, and in selected machinery- and equipment-related activities. The comparison reveals, however, that the conventional classification is often too generic for S3 purposes.

Several of the high-RTA patent fields combine very different activities under the same label. For example, biotechnology, analysis of biological materials, food chemistry and pharmaceuticals all point to some strength in the life sciences, but they do not distinguish whether these capabilities concern agrifood, health care, environmental applications, or other domains. Likewise, medical technology and civil engineering encompass a wide variety of potential transformative activities, ranging from hospital equipment to smart construction solutions, that remain indistinguishable in the conventional mapping. Our intersectional methodology decomposes these broad categories into specific combinations of technological domains and fields of application (e.g. biotechnology applied to agrifood, health or environmental remediation; materials technologies applied to construction or textiles).

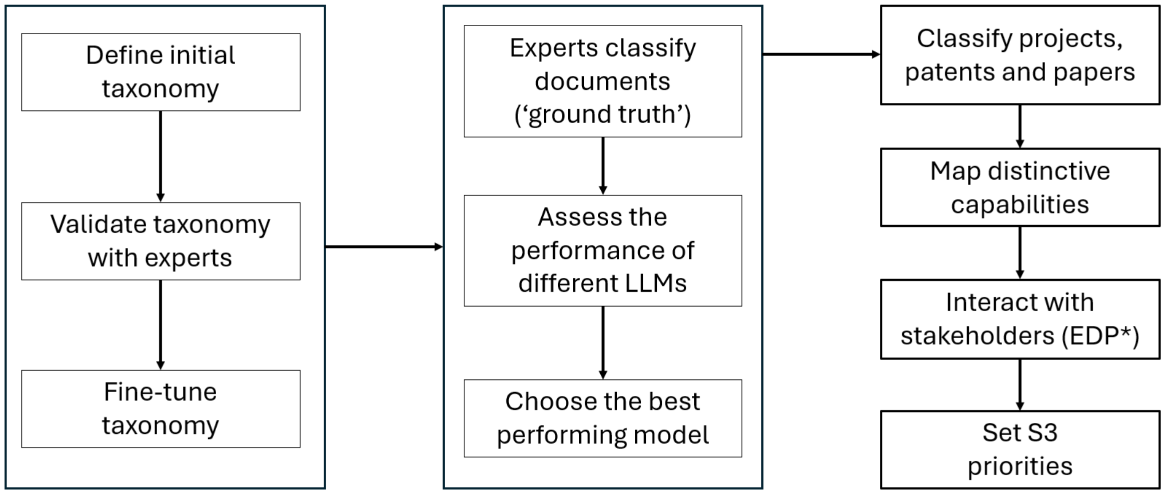
Beyond this lack of granularity, the domain- and application-based approach also brings to the fore several areas of specialisation that are largely invisible in the IPC-only perspective. Table 4 shows, in particular, a set of combinations in which digital technologies underpin innovation across a wide range of activities – from agrifood, commerce and construction and architecture to state and public administration, IT services, transport and logistics, water and waste management, energy and health. These combinations register above-average values in at least one of the three indicators used (R&D projects, patents and publications), yet there is no corresponding "digital technologies" field in the WIPO IPC categories that would allow this transversal capability to be captured directly.

These illustrative cases show that, although the patent-based exercise confirms the consistency of our methodology with established indicators at an aggregate level, conventional classifications remain too coarse-grained to guide the design of S3 priorities. By contrast, our approach translates capabilities into a more operational and context-sensitive map of transformative activities.

4. Discussion

This section discusses the implications of the proposed method for the analysis and governance of S3. To clarify how the different elements of our approach are articulated – from the construction and validation of the taxonomy to the policy-oriented use of capability mapping – Figure 1 summarises the main steps of the proposed framework.

Figure 1. Setting S3 priorities using our LLM-based approach



* EDP=Entrepreneurial Discovery Process

As illustrated in Figure 1, our mapping of capabilities feeds into the participatory use of this information in policy making processes. Our contribution is specifically focused on the systematic identification and characterisation of scientific, technological and productive capabilities, which constitute a key analytical input into the setting of priorities. The actual prioritisation itself remains, by nature, a political and collective process that lies beyond the scope of this paper but which, according to the logic of S3, should take into account multiple criteria, including existing capabilities, their potential contribution to national or regional development, and their relevance for addressing societal challenges.

Our proposal raises a set of analytical and normative questions regarding how capabilities are interpreted, mobilised and translated into strategic orientations. In what follows, we discuss: how the proposed mapping contributes to reframing the traditional diversification/specialisation dichotomy in S3 debates (subsection 4.1); how the same framework can be mobilised to address societal challenges in a more concrete and operational manner (subsection 4.2); and, finally, the main limitations of our approach, clarifying the scope and conditions under which the method can inform strategic policy choices (subsection 4.3).

4.1 Beyond the diversification/specialisation dichotomy

A longstanding tension in S3 scholarship concerns the trade-off between further exploiting existing strengths or diversifying into new domains. The standard objection in this respect is that focusing solely on current specialisations might reinforce structural lock-in, while others warn that attempting to diversify without related capabilities is risky and thus prone to failure

(Asheim, 2019; Hassink & Gong, 2019; Boschma, 2025). Our mapping offers a practical solution to this dichotomy by revealing activities that are sufficiently anchored in local capabilities to be feasible, yet can be distinct enough from the status quo to drive structural change.

The high-potential areas identified for Portugal (Table 4) encompass several potential types of structural transformation. On the one hand, the mapping identifies modernisation and transition opportunities in sectors where Portugal already holds strong comparative advantages in exports, such as fishing, agrifood, and textiles. In these instances, the strategy lies not in re-enforcing existing structures ("more of the same"), but rather in upgrading established industries through the integration of novel technological domains (e.g., materials technologies applied to textiles). On the other hand, the method reveals diversification opportunities in areas like tools, industrial equipment and machinery, and health. In such industries, Portugal exhibits strong R&D&I capacities that have not yet translated into significant export specialisation.

The proposed framework, therefore, does not enforce a binary choice between specialisation and diversification. Instead, it illuminates both pathways, while ensuring that "the focus of the policy does not fall on the most important industries in the region, but on their transformation" (Gianelle *et al.*, 2025). It allows policymakers to identify where existing scientific and technological capabilities can be leveraged to upgrade mature sectors, and conversely, where they can support the emergence of new productive activities.

4.2 Addressing societal challenges

While S3 initially focused on economic structural change, the literature increasingly suggests that prioritisation should align with broader societal goals (e.g. Gianelle *et al.*, 2019; McCann and Soete, 2020). In this sense, S3 intersects with mission-oriented approaches to innovation policy, incorporating concerns regarding the direction of technological upgrading. Recent contributions have highlighted that aligning S3 with mission-oriented policy can help reframe priority setting around broader societal goals, thus enhancing the legitimacy and coherence of regional innovation strategies (Cappellano *et al.*, 2024; Gianelle *et al.*, 2025; Molica *et al.*, 2025).

Our mapping framework is well-suited to support this shift. By extending the LLM-based classification logic to classify R&D projects, patents, and scientific publications according to their contribution to societal concerns, we can assess the relevance of R&D&I capabilities to specific missions. To illustrate this, we mapped the previously identified 21 high-potential areas for Portugal's S3 against four critical challenges highlighted in Portugal's official S3 for 2014-2020: food security, healthy ageing, CO_2 reduction, and resource efficiency. Table 5 presents the specific technology-application intersections that show the highest density of projects contributing to these goals.

Table 5. Areas whose R&D projects contribute most significantly to addressing societal challenges

Societal Challenges	High potential areas for Portugal's S3
Food Security	• Biotechnology and Digital technologies applied to Agrifood • Biotechnology applied to Fisheries, aquaculture and fishery products
Healthy Ageing	• Biotechnology, Materials technologies, and Digital technologies applied to Health • Digital technologies applied to IT Services • Materials technologies applied to Textiles, clothing and footwear
CO_2 Reduction	• Digital technologies applied to Energy • Materials technologies applied to Transport Equipment • Materials technologies applied to Construction • Digital technologies applied to Transports and mobility
Resource Efficiency	• Digital technologies applied to Energy • Materials technologies and Digital technologies applied to Construction • Digital technologies applied to IT Services • Digital technologies applied to Water and waste management • Materials technologies applied to Transport Equipment

Of the 21 high-potential areas for Portugal's S3 listed in Table 4, we find that 14 address, to some extent, at least one of the societal challenges outlined in Table 5. This can be regarded as an additional criterion for prioritising transformative activities within Portugal's S3.

4.3 Limitations

Our proposal has a number of possible limitations that should be borne in mind when interpreting the results.

First, our choice of 8 technological domains and 24 fields of application involves an element of arbitrariness, even if informed by expert-led iterations and guided by the need to balance granularity and interpretability. Alternative taxonomies may be deemed more appropriate for other empirical settings or policy purposes. Our taxonomy should therefore not be seen as universal, but as a context-sensitive framework that nonetheless supports the identification of robust and policy-relevant capability profiles.

Second, in our global analysis we draw on data on both direct and indirect public support instruments, which together tend to cover virtually all firms that perform R&D in Portugal. However, when it comes to Horizon 2020 projects, which are the subset we use for international comparison, funded R&D projects tend to reflect the behaviour of firms and organisations that are more active or successful in applying for public support at the EU level.

This may bias the representation of capabilities towards actors and activities that are more visible to policymakers.

Third, while we mitigate the limitations of patent-based indicators by combining them with funded R&D projects and scientific publications, this does not fully resolve the underlying coverage issues. Service-based, organisational and design-intensive innovations remain partly under-represented, particularly in sectors with structurally low patenting rates and a lower propensity to engage in formal R&D activities. This limitation is less critical in the specific context of Smart Specialisation Strategies, which are explicitly designed to inform targeted research and innovation policies. It should nonetheless be borne in mind when the analysis is mobilised to inform broader strategies of productive specialisation, where non-technological and service-based forms of innovation may play a relevant role.

Finally, despite the high precision and recall achieved in our validation exercise, LLM-based classifications remain subject to potential biases and errors that are difficult to fully trace back to the underlying training data. Our results should therefore be interpreted as approximate assessments of capabilities, rather than as deterministic labels.

5. Conclusion

This paper contributes to the literature on S3 by proposing and operationalising a methodology to map R&D&I capabilities at the intersection between technological domains and fields of application. By moving beyond approaches that treat technologies or sectors in isolation, we offer a way to identify capabilities in terms of transformative activities that connect knowledge bases to societal and market needs.

The type of capability mapping resulting from this approach is particularly relevant for the governance of S3. It can support the strategic planning phase by offering a structured and fine-grained picture of where technological strengths meet specific fields of application, and it can serve as a starting point for Entrepreneurial Discovery Processes by signalling concrete transformative activities and associated actor constellations. The mapping also helps to prioritise policy attention towards those societal challenges where the potential for transformative impact appears greatest.

By focusing on specific intersections between technological domains and fields of application, our framework identifies focal points that are sufficiently concrete to orient participatory processes, while still flexible enough to accommodate different policy priorities and stakeholder perspectives. Compared with very broad or loosely defined priorities, these focal points make it easier to structure dialogue, align expectations and design intervention logics tailored to actual configurations of capabilities. Moreover, the sources we use contain detailed information on the organisations involved, including their collaborative ties, which can be mobilised to analyse microsystems of innovation and the networks that underpin them. In the present paper we do not yet exploit this network information systematically, but we see it as a promising extension for future research on microsystems of innovation and the relational underpinnings of transformative activities.

In this paper we apply the method at the national level, but the underlying data can be readily disaggregated to subnational scales (e.g., NUTS regions). An extension of the analysis to regional applications and geo-referenced maps, which could not be accommodated here due to space constraints, will enable a more thorough engagement with other debates in economic geography on place-based drivers, regional path dependence and differentiated development trajectories.

As discussed in the preceding section, our approach has some limitations that warrant a cautious interpretation of the empirical results. Nonetheless, the analysis presented here shows that combining large-scale textual data with an intersectional taxonomy can generate policy-relevant insights into the configuration of R&D and innovation capabilities. Our intention is not to offer a complete blueprint for economic transformation, but rather a critical tool that can inform collective reflection among policymakers, stakeholders and researchers. In this sense, the method is best seen as a support for informed experimentation in the design of S3, contributing to a better understanding of the complex relationship between specialisation, diversification and the pursuit of societal goals.

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Declaration of interest

The authors report there are no competing interests to declare. This work was supported by the Portuguese National Innovation Agency.

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Appendix

Table A.1 Example of a prompt (for R&D projects)

```
# Instructions for Classifying Projects in Relation to a Taxonomy of Types of Business Activities (corresponding to the fields of application of specific technologies) and Technological Domains

## Context

Your task is to analyse descriptions of business R&D projects and classify them according to a taxonomy defined along two axes: technology domains and types of business activities. Each project involves the application of one or more technology domains to improve products and/or processes within one or more business activity types. Your role is to assign the appropriate categories based solely on the information provided in the project descriptions. Adhere strictly to the available details and avoid suggesting categories that are not explicitly supported by the text.

## Taxonomy

### Types of Business Activities

{taxonomy_apps}

### Technology Domain

{taxonomy_techs}

## Project descriptions

{descriptions}

## Response structure:

To ensure your response is structured for easy processing and analysis, use the following JSON format:

___START___

{{
"PROJX": {{
          "A": [...],  # list with strings of the applicable category code(s), if any
             "T": [...]}},
"PROJY": {{ "A": [...], "T":[...]}}
}}

___END___


## Guidelines

Some notes: The letter A in the response json stands for Types of Business Activities axis and T for Technology Domain axis.

## Answer
```

Table A.2 Classification by technological domain

Technological domain	Coverage
Biotech	Biological sciences and biotechnologies related to the use and development of processes, products, and techniques based on biological systems. May include chemistry only if applied to biological organisms.
Chemistry	Technologies related to chemical engineering, organic and inorganic chemistry. Includes the development and use of chemical products and processes and polymers. Does not include biological sciences nor biotechnologies [which are classified as *Biotech*].
Digital technologies	Includes: digital network systems; protocols for transmitting and receiving information; IoT (internet of things); algorithms; processing, storage and analysis of data by computers; machine learning and prediction; artificial intelligence; information security and cyber security; virtual and augmented reality; blockchain; and cloud computing. It also includes mathematical modelling.
Electronics	Development, application or integration of electrical and electronic engineering. Includes the development and use of microelectronics, computer hardware, photovoltaics, electronic sensors, communication equipment, and other electronic devices. It covers integrated circuits, semiconductors, and other electrical and electronic components.
Materials	Material engineering for the development and application of new, advanced or improved materials.
Nanotechnology	Manufacture and application of nanotechnology, nanostructures and nanomaterials in industrial processes, products and other materials.
Optics and photonics	Use and development of processes or devices that generate, emit, detect, manipulate or utilise visible or invisible light. Includes optical technologies like those used in cameras, optical sensors, light sensors, lasers and glasses. It also includes the use and development of technologies related to radiation, like UV or electromagnetic waves.
Production technologies	Development and use of mechanical engineering, automation, robotics, 3D printing, system control and numerical control machines, with the aim of improving the efficiency and quality of production.

Table A.3 Classification by field of application

Field of application	Coverage
Aeronautics, aerospace and defence	All activities related to the aeronautics, space, and defence industries, including the design, development, manufacturing, assembly, and maintenance of aircraft, spacecraft, defence systems, satellites, military equipment, and associated technologies.
Agrifood	All activities related to agricultural production, livestock breeding, and the production and processing of food and beverages. It does not include fishing, aquaculture, or the processing of aquatic species [which are classified in *Fishing, aquaculture, and fish industry*].
Arts, entertainment, and social media	Includes all activities related to cultural production, entertainment, arts, media and creative industries, including cinema, music, literature and advertising.
Chemicals, rubber, and plastics	All activities related to the production and transformation of chemicals, petrochemicals, rubbers, plastics (including plastic packaging) and cosmetics. Does not include pharmaceutical activities [which are included in *Health*].
Construction	All activities related to the planning, design, construction and management of buildings and urban infrastructure.
Education	All activities related to education like teaching, training and lifelong learning.
Electric, electronic and optical equipment	Production of electric, electronic and optical equipment for end users. Does not cover the production of machinery and equipment used in other productions, nor their use in the context of economic activities and professional environments [which are classified in *Tools, machinery and production equipment*].
Energy	Includes the generation, storage, and final distribution of electricity and various fuels such as gas, oil, diesel and biodiesel. Does not include applications aimed at enhancing the energy efficiency of products or industrial processes, nor the extraction of oil and natural gas.
Extraction of mineral resources	All activities involved in the exploration and extraction of mineral resources and non-renewable materials, including metallic and non-metallic minerals, coal, oil, and natural gas.
Financial services	Banking, insurance, investment management, as well as fintech.
Fishing, aquaculture, and fish industry	All activities related to fishing, aquaculture and the conservation and processing of fish, crustaceans, molluscs and other aquatic invertebrates.
Forest, timber, cork and furniture	All activities related to the sustainable management of forest resources, and to preventing and fighting forest fires, as well as the production of wood and cork products, pulp and paper, and furniture.
Government	Provision of public services, public governance, public administration, social security, tax administration, and public policies at national, regional and local levels.
Health	Medicine, physical and mental well-being services, and the development and production of drugs and medical devices.
IT services	Development and maintenance of computer software. Does not include applications of computer technology to other economic activities [which are classified in the adequate fields of application].
Metallic products and non-metallic minerals	Activities related to the production of metals, metal products, and non-metallic minerals, including cement, ceramics and glass. Does not include the production of machines tools and production equipment [included in *Tools, machinery and equipment*].
Services for enterprises	Business support services, such as management consulting, marketing consulting, legal consulting, accounting, and human resources management.

Field of application	Coverage
Textiles, apparel, and footwear	Production of non-plastic textiles, clothing and footwear, as well as their raw materials like threads, fabrics, fur and leather.
Tools, machinery and production equipment	Production and development of machinery and equipment used in industrial and manufacturing processes, as well as moulds and specialised tools for production.
Tourism and cultural heritage	All activities related to the production for end users of goods and services related to tourism and leisure, such as travel, accommodation, restaurants and the promotion and preservation of cultural and historical heritage. It does not include the production of food or beverages [included in *Agrifood*].
Trade	Sale and distribution of goods and services to end users. Does not include activities related to food and beverages [included in *Agrifood*], health [included in *Health*], pharmaceuticals [also included in *Health*] or tourism [included in *Tourism and cultural heritage*].
Transport equipment	All activities related to the production of transport equipment, including automobiles, ships, boats, vessels, trains, locomotives, wagons, motorbikes and bicycles. Does not include transportation services [which are included in *Transportation, logistics, and mobility*], nor aeronautical, space or military transport equipment [included in *Aeronautics, aerospace and defence*].
Transportation, logistics, and mobility	Planning, management and operation of transportation and logistics systems, including road, rail, maritime, air, and multimodal transportation. Does not include the production of transport equipment like automobiles, ships, locomotives, wagons and bicycles nor their components [included in *Transport equipment*].
Water and waste management	Activities related to the supply of drinking water, sewage and treatment of wastewater, recycling, reuse of solid waste and landfill management.