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RESEARCH

Building deep-tech entrepreneurial ecosystems: factors that promote the presence of deep-tech startups in European regions

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Abstract

Deep-tech startups aim to implement and commercialize novel technologies that have the potential to address societal challenges. Due to current geopolitical trends and the potential of such technologies to rejuvenate the industrial power of regions, European governments are attempting to foster the creation of this type of startups within their borders. However, they struggle to do so effectively due to a limited understanding of the factors that support the emergence of deep-tech startups. We combine the generic entrepreneurial ecosystem framework with specific deep-tech enabling elements to develop and test hypotheses about which factors influence the presence of deep-tech startups on a regional scale. We develop a thesaurus to identify deep-tech startups at the regional level and test our hypotheses using quantitative analyses in 272 European NUTS-2 regions located in 27 EU countries and the UK. We show that the presence of specific deep-tech enabling knowledge and talent is more important for facilitating the emergence of deep-tech startups than the quality of the generic entrepreneurial ecosystem and the presence of specific deep-tech enabling formal institutions. The results of our study thus provide timely guidance to support public administrations in facilitating the emergence of deep-tech startups in regions.

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1 Introduction

Novel breakthrough technologies can contribute to economic development and help address societal challenges (Boschma, 1999; Mewes, 2019; Verhoeven et al., 2016). In addition, they are considered of vital importance to enabling strategic autonomy (Draghi, 2024). However, most potential breakthrough technologies never reach the market (Swamidass, 2013). This is of particular concern in Europe where the Draghi report (Draghi, 2024) highlights the need for large-scale investments in breakthrough technologies to maintain European competitiveness.

The increasing geopolitical tensions and the urgency of several societal challenges have placed breakthrough technologies prominently on the agenda of European policymakers. They are introducing policies that aim to facilitate the development and introduction of these technologies, such as the EU's *Competitiveness Compass* (European Commission, 2025a) and the *Startup and Scale-up Strategy* (European Commission, 2025b).

These policies often focus on the creation of startups to commercialize breakthrough technologies. Startups are small and young entrepreneurial ventures in the process of exploring a technology to develop a fast-growing business (Bjornali & Ellingsen, 2014; Fontes & Coombs, 2001; Klotz et al., 2013). The high-risk/high-reward nature of startups aligns with the challenges that come with commercializing novel technologies (Munari & Toschi, 2011; Swamidass, 2013).

Recently, practitioners and scholars have started to distinguish startups working on breakthrough technologies as a specific set of startups. They classify these startups as *deep-tech startups* (Romasanta et al., 2022; Romme et al., 2023; Ruiz De Apodaca et al., 2022). The term deep-tech is used by policymakers and practitioners to refer to technologies based on frontier science and engineering with the potential to change current industry dynamics and help address grand societal challenges like climate change, illnesses, defense, or energy production and storage problems (De la Tour et al., 2021; Ruiz De Apodaca et al., 2022).

Deep-tech startups can therefore be defined as *small and young entrepreneurial ventures in the process of exploring a novel technology*, *based on frontier science and engineering*, *with the potential to change industry dynamics and address grand societal challenges*, *that have not been previously implemented and commercialized.*

Deep-tech startups develop products based on emerging technologies related to advanced materials, artificial intelligence, robotics, semiconductors, electronics, chemistry, quantum computing, and biology, for applications in aerospace, agriculture, construction, defense, energy, food, healthcare, manufacturing, mobility, and many other industrial sectors (De la Tour et al., 2021). Due to their focus on developing products based on frontier scientific and engineering advancements, deep-tech startups face unique challenges of technology transfer (Haessler et al., 2023). These challenges are the result of the emergent nature of underlying technologies (Rotolo et al., 2015), the general lack of commercial capabilities and networks of technology developers (Neves & Franco, 2018; Rasmussen & Borch, 2010), and the inherent challenges of introducing these technologies in complicated value chains or to regulated markets (Romasanta et al., 2022; Ruiz De Apodaca et al., 2022). As a result, most potential breakthrough technologies never transfer from universities and research centers to practice (Swamidass, 2013).

To overcome these challenges, deep-tech startups rely on the entrepreneurial ecosystem (EE) of the region in which they are located. The EE literature describes how startups rely on other actors for resources and how they are influenced by the surrounding institutions in a region (Stam & van de Ven, 2021). In line with this literature, both practitioners and academics suggest that an ecosystem approach is required to facilitate deep-tech startup emergence (De la Tour et al., 2021; European Innovation Council, 2021; Romme et al., 2023). However, while the EE literature has extensively explored how different regional factors influence the conditions on which the occurrence of entrepreneurship depends (Acs et al., 2009; Alvedalen & Boschma, 2017; Shane & Venkataraman, 2000; Stam, 2015), there are no studies that focus on the needs of deep-tech startups.

There is thus a need to study which regional factors influence the presence of deep-tech startups in EEs. Literature on EEs has only recently started addressing the fact that different typologies of startups face different challenges and thus might require different support from their EE (Brown & Mawson, 2019). In recent years several studies have emerged that link startups to EEs in specific sectors, such as digital (Bejjani et al., 2023), biotech (Auerswald & Dani, 2017), and fintech (Alaassar et al., 2022), or for specific types of entrepreneurs, such as social entrepreneurs (Thompson et al., 2018) and creative entrepreneurs (Loots et al., 2021). Most notably, Leendertse and Van Rijnsoever (2025), studying EEs for sustainable startups, suggest that specific types of startups need EEs that contain both generic and specific elements. By distinguishing generic and specific elements, we can understand which elements kickstart the creation of entrepreneurial flywheels that facilitate regional economic development (Defort et al., 2025; Spigel, 2017).

We apply this conceptualization to deep-tech startups, studying how both the generic EE and specific deep-tech enabling EE elements influence the presence of deep-tech startups in regions. As such, we answer the following research question:

What generic and specific elements of entrepreneurial ecosystems influence the presence of deep-tech startups in a region?

We use quantitative analyses on deep-tech startups established between 2019 and 2021 in 272 different European NUTS-2 regions located in 27 EU countries and the UK. We identify deep-tech startups by building and applying a thesaurus of keywords. Our results show that the presence of specific deep-tech enabling knowledge and talent drives the regional presence of deep-tech startups. General elements of the EE framework and specific formal institutions seem to be less influential in facilitating the emergence of deep-tech startups.

By studying the preconditions for the creation of specific types of startups, we contribute to the generic EE literature (Stam & van de Ven, 2021) and the emerging literature on specific EEs (Leendertse & van Rijnsoever, 2025). Our results also contribute to the emergent stream of literature on deep-tech startups (Romasanta et al., 2022; Romme et al., 2023; Ruiz De Apodaca et al., 2022). By better defining the theoretical boundaries of the deep-tech concept, we are able to provide a scalable, operationalizable definition and employ a methodology that allows the identification of deep-tech startups at the regional level.

Our results align with the most recent recommendations from European policymakers, emphasizing the importance of increasing investments in education and research on frontier technologies as key drivers of regional industrial renewal and potential growth (Draghi, 2024), providing timely and important evidence-based support for regional policymakers willing to foster the emergence of more deep-tech startups in their regions.

The paper is organized as follows. In Sect. 2 we introduce the theoretical background. In Sect. 3 we describe the data collection and introduce the operationalization of the variables and the methods used to analyze data. Section 4 shows the results of negative binomial regressions and the robustness tests. In Sect. 5 we provide the conclusions, theoretical and practical implications, the limitations of our work, and our suggestions for further research.

2 Theory

In this section, we first elaborate on the concept of deep-tech startups, the challenges that might limit their emergence, and the potential of EE in overcoming these challenges. Second, we argue that the generic EE framework should be complemented by specific deep-tech enabling elements. We end the section by formulating hypotheses.

2.1 Deep-tech startups

The term deep-tech startups refers to startups that meet two specific criteria. First, deep-tech startups focus on developing and commercializing technologies based on frontier scientific or engineering advancements that have not yet been successfully implemented or brought to market (Romasanta et al., 2022; Ruiz De Apodaca et al., 2022). Second, to be considered deep-tech, startups must have the potential to contribute to changing industry dynamics and solving major societal challenges (De la Tour et al., 2021; Ruiz De Apodaca et al., 2022).

Deep-tech startups thus develop products based on emerging technologies at the frontier of scientific and engineering knowledge, including advanced materials, artificial intelligence, robotics, semiconductors, electronics, chemistry, quantum computing, and biology, investing heavily in R&D activities to enable the development of such technologies (Romasanta et al., 2022; Ruiz De Apodaca et al., 2022).These technologies are applied across a wide range of industrial domains, such as aerospace, agriculture, construction, defense, energy, food, healthcare, manufacturing, mobility, and many others (De la Tour et al., 2021), and often originate from researchers working in universities and public research organizations (Romasanta et al., 2022; Ruiz De Apodaca et al., 2022).

Deep-tech startups are often active in industries that are considered high-tech industries. High-tech industries are commonly defined based on R&D intensity, capturing the extent to which sectors rely on innovation and advanced knowledge (OECD, 2017). Startups in these industries are traditionally referred to as high-tech startups. Within this broad category, we conceptualize deep-tech startups as a distinct subset of high-tech startups. Deep-tech startups differ from high-tech startups in the fact that they face a higher level of technological uncertainty derived from their focus on technologies that still need to be proven to have commercial potential (De la Tour et al., 2021; Romme et al., 2023; Ruiz De Apodaca et al., 2022). In sum, every deep-tech startup is a high-tech startup but not every high-tech startup is a deep-tech startup.

Deep-tech startups are characterized by markedly different funding dynamics and development cycles compared to firms operating in the same sectors but refining or recombining technologies that have already reached the market. Due to their focus on frontier scientific and engineering advancements, deep-tech startups face specific challenges related to technology transfer (Haessler et al., 2023). These challenges are related to two factors: the uncertainties that surround novel technologies, and the diffuse lack of commercialization capabilities in organizations that originate these technologies.

Due to the novelty of such technologies, the commercialization path of deep-tech startups is often accompanied by a high level of uncertainty. The "liability of newness" of such technologies indeed implies that large information asymmetries are usually present at the earliest stage of development (Rotolo et al., 2015). The process of opportunity identification, consequently, is central to the development of a deep-tech startup (Rotolo et al., 2015; Vohora et al., 2004). This process (on top of identifying interest from potential customers) requires overcoming the challenges of introducing these novel technologies in complicated value chains or regulated markets (Romasanta et al., 2022; Ruiz De Apodaca et al., 2022), or of creating entirely new markets from scratch. Support and legitimization from local institutions is therefore often required to facilitate new technologies uptake (De la Tour et al., 2021; Romme et al., 2023).

Addressing these uncertainties requires specific competencies that are often missing among researchers in public universities and research centers where these technologies originate. Decades of research indeed highlight that the personnel of these organizations are often characterized by a lack of entrepreneurial skills (Mosey & Wright, 2007; Rasmussen & Borch, 2010), limited social capital (Neves & Franco, 2018; Rasmussen & Borch, 2010), and insufficient incentives to engage in technology transfer activities (Jain et al., 2009; Lam, 2011; van Rijnsoever & Hessels, 2021).

All these problems generate friction in collaboration and in attracting the investments required to continue the development of these technologies (Vohora et al., 2004; Wright et al., 2006). This hinders the development of potential breakthrough technologies, consequently the majority of them never transfer from universities and research centers to practice (Swamidass, 2013). To overcome these challenges, an ecosystem approach tailored to facilitate the emergence of deep-tech startups is likely to be required (De la Tour et al., 2021; Romme et al., 2023; Ruiz De Apodaca et al., 2022).

2.2 The entrepreneurial ecosystem framework

Designing effective policies for startups requires knowing which factors influence their emergence (Brown & Mawson, 2019; Stam & van de Ven, 2021). The factors that influence startup emergence have been extensively discussed and studied in the EE literature (Stam & van de Ven, 2021; Leendertse et al., 2022). The EE framework includes resources critical to the development of new entrepreneurial activities, referred to as "resource endowments", as well as the institutions that facilitate or hinder the attraction and circulation of such resources, referred to as "institutional arrangements" (Stam & van de Ven, 2021).

Resource endowments include demand, leadership, intermediaries, knowledge, finance, and talent, while institutional arrangements include culture, formal institutions, and networks. Previous research has shown that these ten elements influence the presence and persistence of productive entrepreneurship in regions (Leendertse et al., 2022; van Dijk et al., 2025), and that different element configurations can drive the presence of startups (Schrijvers et al., 2023). Table 1 summarizes the ten elements of the EE framework.

Recently, scholars went beyond the generic focus of the entrepreneurial ecosystems framework to argue that different types of startups require additional and specific resource endowments and institutional arrangements (Alaassar et al., 2022; Bejjani et al., 2023; Leendertse & van Rijnsoever, 2025). The emergence of specific EEs thus entails that to under-

Table 1 Entrepreneurial ecosystem elements

Elements	Causal mechanisms
Institutional arrangements	
Formal institutions	Provide the fundamental preconditions for economic action to take place (Granovetter, 1992) and for resources to be used productively (Acemoglu et al., 2005)
Culture	Entrepreneurial culture represents the informal institutions regarding how entrepreneurship is perceived in society, which has a strong effect on the prevalence of entrepreneurship (Fritsch & Wyrwich, 2014).
Networks	Networks facilitate information flow, enabling a better distribution of knowledge, labour and capital (Malecki, 1997).
Resource endowments	
Leadership	Leadership is critical in building and maintaining a healthy ecosystem (Feldman, 2014) since it provides direction for the EE.
Physical infrastructure	A highly developed infrastructure is a key element of the context to enable economic interaction and entrepreneurship (Audretsch et al., 2015).
Access to financing	The ability to obtain finance is crucial for entrepreneurial projects with uncertain business models to be developed over a long-term horizon (Kerr & Nanda, 2009).
Talent	The presence of a diverse and skilled group of workers is required (Acs & Armington, 2004).
Knowledge	Knowledge, from both public and private organizations, is an important source of entrepreneurial opportunities (Audretsch & Lehmann, 2005).
Intermediaries	The supply of support services by a variety of intermediaries can lower barriers for new entrepreneurial projects, thus reduce the time to market of innovations (Howells, 2006).
Demand	The ability of the population to purchase goods and services is essential for entrepreneurship to emerge (Berkowitz & Dejong, 2005).

stand how EEs foster certain types of entrepreneurs a further specification of the framework is required (Wurth et al., 2022).

Leendertse and van Rijnsoever (2025) argue that an EE for a specific sector, technology domain, or type of entrepreneurship entails a combination of the generic EE framework with additional specifications in the resource endowments and institutional arrangements. They make this argument by building on the shared background of the EE and innovation system literatures (Bergek et al., 2008; Hekkert et al., 2007; van Rijnsoever, 2020; van Weele et al., 2017), and empirically validate it for the case of sustainable startups (Leendertse & van Rijnsoever, 2025). We follow the conceptualization of generic and specific EEs (Leendertse & van Rijnsoever, 2025) and argue that the emergence of deep-tech startups is influenced by both.

2.3 Deep-tech entrepreneurial ecosystems

In line with the specific EE conceptualization (Leendertse & van Rijnsoever, 2025), we categorize these additional specific elements as additional resource endowment and additional institutional arrangements specifically enabling deep-tech. Regarding resource endowments, we argue that the local availability of specific deep-tech enabling knowledge and specific deep-tech enabling talent might help overcome problems of technology transfer and facilitate deep-tech startup presence in regions. Regarding institutional arrangements, we argue that the government may be more or less oriented toward facilitating the emergence of deep-tech startups. The presence of specific deep-tech enabling formal institutions might therefore foster the presence of deep-tech startups.

The knowledge required to commercialize deep-tech is highly tacit (Hidalgo, 2015; Polanyi, 2009; Romasanta et al., 2022). Theories of industry emergence (Moeen et al., 2020) suggest that industrial development depends not only on technical or codified knowledge, but also (and often primarily) on non-codified forms of knowledge, such as demand understanding and experiential know-how. This type of knowledge is typically embedded in individuals and accumulated through practice (Polanyi, 2009), making it difficult to transfer or replicate across contexts. This is especially true for deep-tech entrepreneurship. The tacit nature of the knowledge required to successfully commercialize a novel technology implies that geography continues to play a crucial role in opportunity recognition and entrepreneurial activity. Seminal contributions by Jaffe (1989), Audretsch and Feldman (1996), and Audretsch and Stephan (1996) indeed provide strong empirical evidence of the spatial localization of knowledge spillovers, suggesting that innovative activity is disproportionately concentrated near its sources of knowledge creation. These insights have cumulated in what is now known as the Knowledge Spillover Theory of Entrepreneurship (KSTE) (Audretsch & Lehmann, 2005; Ghio et al., 2015). Based on this, we expect the drivers of deep-tech entrepreneurship to be largely confined within geographically bounded entrepreneurial ecosystems.

Figure 1 depicts the proposed deep-tech EE framework that combines the generic EE framework with specific deep-tech enabling elements. The next section describes the theoretical argumentation for the inclusion of these specific elements into the deep-tech EE framework and contains the hypotheses on how deep-tech EEs influences the presence of deep-tech startups in regions.

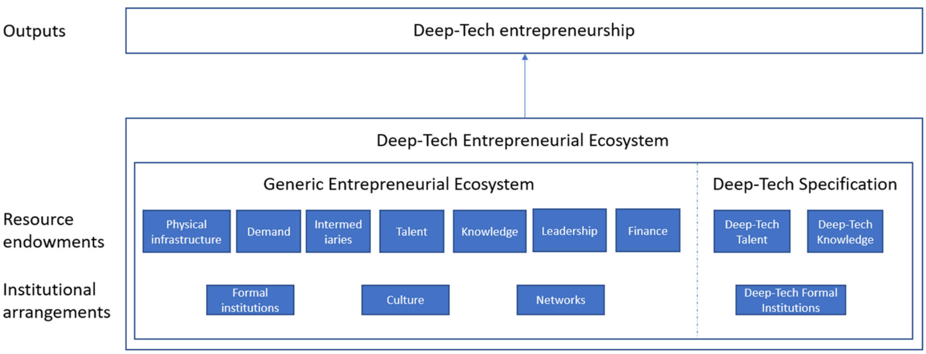

Fig. 1 - The deep-tech entrepreneurial ecosystem conceptual framework

2.3.1 Generic entrepreneurial ecosystem framework

Inside a well-developed EE, it is easier for startups to emerge, even when they are subject to additional challenges that might constrain them, since the presence of supportive EE might compensate for their challenges (van Rijnsoever, 2022). We expect that better-performing EEs lower barriers to the emergence of deep-tech startups, and therefore we hypothesize that:

H1 *The overall quality of the generic entrepreneurial ecosystem positively influences the presence of deep-tech startups.*

2.3.2 Specific deep-tech enabling knowledge

Economic geography literature suggests that the cumulation of knowledge in a specific field has a positive impact on the repeated occurrence of technological breakthroughs in that region (Boschma et al., 2023). Considering that deep-tech startups are based on the latest inventions (De la Tour et al., 2021; Romasanta et al., 2022; Ruiz De Apodaca et al., 2022), we hypothesize that the local cumulation of frontier scientific and engineering knowledge, such as top-quality scientific papers and patents, could positively influence the emergence of deep-tech startups. This specific element of the deep-tech EE framework should be interpreted as the stock of specific deep-tech enabling knowledge. The generic EE framework already considers a generic measure of knowledge, related to investments in knowledge generation, but captures neither the stock nor the quality of specific knowledge outputs upon which deep-tech startups can be built.

We therefore hypothesize that:

H2 *The presence of specific deep-tech enabling knowledge positively influences the presence of deep-tech startups in a region.*

2.3.3 Specific deep-tech enabling talent

Due to the challenges highlighted in previous chapters, transforming scientific and technological knowledge requires specific capabilities. Besides the presence of specific knowledge, there must be talent that can translate scientific and engineering knowledge into commercial applications. Regions thus might require the presence of specific deep-tech enabling talent capable of integrating the knowledge developed into innovative products and services. Examples are the ability to identify the potential value of new knowledge, the ability to forecast the development of competing technologies, product development skills, and other technological innovation management capabilities (Dogson, 2000; Hidalgo & Albors, 2008). In line with the KSTE (Audretsch & Lehmann, 2005; Ghio et al., 2015), we capture this by including a measure that accounts for the regional presence of human capital capable of translating such specific knowledge into entrepreneurial activity. Similar to the previous paragraph, the generic EE framework already considers the presence of generic talent in regions, but measures included in the generic element do not track the presence of specific deep-tech enabling competencies. We therefore hypothesize that:

H3 *The presence of specific deep-tech enabling talent positively influences the presence of deep-tech startups in a region.*

2.3.4 Specific deep-tech enabling formal institutions

Actors do not operate in a vacuum, but operate within a semi-coherent set of rules that guide their behavior under an "institutional regime" (Kemp, 1994). The presence of favorable institutional arrangements can be fostered via the implementation of policies and regulations (formal institutions). The presence of specific deep-tech enabling formal institutions, therefore, might play an important role in helping overcome constraints that hinder the emergence of deep-tech startups. For example, policies that incentivize and subsidize new technology development, or institutions that protect and enforce potential violations of IP rights upon which many deep-tech startups are built, might therefore facilitate the emergence of deep-tech startups. Considering this, we hypothesize that:

H4 *The presence of specific deep-tech enabling formal institutions positively influences the presence of deep-tech startups in a region.*

3 Method

3.1 Research design

We test our hypotheses using quantitative analyses of data on deep-tech startups established between 2019 and 2021, and the EE characteristics across 272 European NUTS-2 regions in 27 EU member states and the UK. Following Leendertse et al. (2022), we focus on the regional NUTS-2 level. The NUTS-2 boundaries are based on administrative divisions and population thresholds (European Commission, 2018). For our analyses, we exclude Spanish and French territories outside Europe and merged two London regions (UKI3 and UKI4) because it was not possible to distinguish between them for several variables. Finally, we exclude the Åland region (Finland) due to missing data.

3.2 Data collection

We collect data from different sources. We use Crunchbase to identify deep-tech startups and to count the overall number of startups in a region. Crunchbase is considered one of the most comprehensive startup databases for Europe (Dalle et al., 2017; Retterath, 2020), and is frequently used to study the outputs of EEs (Leendertse et al., 2022; Schrijvers et al., 2023). We downloaded all textual fields, the date of incorporation, and the location for each startup on the 30th of October 2023. Crunchbase is a suitable source for data on startups because it predominantly captures venture capital-oriented firms. About 17.4% of the startups in our Crunchbase data have attracted venture capital. Previous studes show that there is substantial overlap between data from a commercial startup registry (e.g., Crunchbase) and high-growth firms listed in a business register (El-Dardiry & Vogt, 2023; van Dijk et al., 2025). In addition, Leendertse et al. (2022) show that in Europe there is a high correlation

(0.841) between Crunchbase and Dealroom data. To only include startups and minimize potential endogeneity issues, we select firms founded between 2019 and 2021.

For the generic EE measures, we use data from Leendertse et al. (2022), which covers the period from 2013 to 2019. The deep-tech specific elements and population (one of the two control variables) are constructed using data from various sources, including Eurostat, OECD datasets and the World Bank.

3.3 Identification of deep-tech startups

We identify deep-tech startups at the regional level by analyzing the textual information available for each startup from Crunchbase. This information consists of a description of the activities of a company and of industry tags utilized by the platform to classify startups. The median number of words available per startup is 37. 80% of startups have between 20 and 110 words.

We use text analysis techniques to determine whether a startup could be considered a deep-tech startup. We use a thesaurus approach, which utilizes a set of terms to determine whether textual information matches particular topics. The thesaurus, a list of stemmed keywords, is used to identify whether the startup discusses the topic. This approach has been successfully applied to identify whether documents discuss the Sustainable Development Goals (Bogers et al., 2022; Romero Goyeneche et al., 2022) and to identify sustainable startups (Leendertse & van Rijnsoever, 2025).

We started by creating a thesaurus of deep-tech related keywords from the deep-tech taxonomy published by the European Institute of Innovation and Technology (EIT, 2023). We then iteratively refines the keywords included in the thesaurus. To operationalize our definition of deep-tech, comprising both a technological and an application element, we divided keywords into three categories. First, a list of keywords associated with technologies that alone can be considered sufficient to identify deep-tech startups (type 1). Second, a list of keywords associated with technologies that must be used in conjunction with applications of that technology to identify deep-tech startups (type 2). Third, a list of application-related keywords (type 3).

We consider a startup a deep-tech one if text analysis highlighted that it has at least one type 1 keyword (a technology-related sufficient keyword), or a combination of at least one type 2 (technology-related not sufficient) keyword and one type 3 (application field) keyword. For example, a startup working on “biomarkers” or “lithography” can be reliably identified as a deep-tech startup; thus, we classified them as type 1 keywords. Startups that instead have words like “battery” in their description can be either a reseller of batteries (not deep-tech) or a startup producing a novel type of battery (thus deep-tech). These keywords were classified as type 2 keywords. This distinction between deep-tech and not deep-tech is made possible by adding type 3 keywords, which include relevant applications (such as “energy production”, “energy storage”, or “energy conversion”) that combined with type 2 keywords (such as battery) helped in identifying deep-tech startups.

To develop our thesaurus, we used a broader set of startups including all firms founded between 2015 and 2021. We adopted an iterative approach that ended up encompassing five rounds. In each round, we selected 100 startups that were classified as deep-tech and 100 startups that were classified as non-deep-tech by the specific version of the thesaurus. We manually evaluated the textual descriptions of each startup and, in case of doubt, checked the startups website. We then removed, reclassified, or added keywords to better identify the deep-tech startups in this sample. In doing so, we carefully assessed how a change impacted other classifications. For certain keywords (such as biotech, type 1 keyword), removing or reclassifying them resulted in significantly more errors than leaving them unchanged. Therefore, we did not adjust some of these keywords.

After each round, we used confusion matrices to analyze how well the thesaurus performed. Confusion matrices are tables that allow to visualize and quantify the performance of a classification algorithm by comparing predicted values and real values. Four outcomes are possible: startups correctly coded as deep-tech, startups correctly coded as non-deep-tech, false positives (incorrectly coded as deep-tech), and false negatives (incorrectly coded as non-deep-tech). We continued this iterative process until there were no further keyword changes that improved the predictive capacity of the thesaurus. After the 5th classification round, and thus a total of 1000 manually evaluated startups, we found no further improvements for the thesaurus based on this sample.

We then evaluated the performance of the thesaurus by analyzing a new random sample of 2000 startups. These 2000 startups were not included in the training set. The accuracy (or overall precision), calculated as the number of startups correctly classified divided by the overall number of startups coded, is 96%. This is a satisfactory level of accuracy for our purpose, as we geographically aggregate this data to the NUTS-2 level.

The final data used for analyses comprises information regarding 1605 deep-tech startups (out of a total of 35,820 startups) established in 272 different European NUTS-2 regions between 2019 and 2021. Based on our approach, we thus identify 4.5% of startups as deep-tech startups.

As robustness checks, we built two additional thesauruses using the same process, but from different starting points. The first is based on keywords used to classify startups by Hello Tomorrow[1] (a French organization that aims to facilitate the development of deep-tech startups and related ecosystems). The second is built by collecting keywords from several public resources and complemented by personal expertise[2]. Both EIT and the Additional keyword-based thesauruses have been published open-access at the link provided in Appendix B.

To determine in which region the startups are located, we use the city, region, and country provided by Crunchbase as location data. We then use geocoding followed by region allocation. This methodology has successfully been applied in Leendertse et al. (2022) and Leendertse and van Rijnsoever (2025). To assign startups in regions, first we used the tmap package in R to geocode the given locations using OpenStreetMap (Open Street Map, 2024; Tennekes, 2018). This is an online map that allows users to pass a list of locations into the software and obtain their coordinates. For regions without a clear location match, we also use the postal code or the address (if available). Subsequently, we use Eurostat shapefiles to determine in which NUTS-2 region these coordinates are located. These shapefiles contain an exact overview of the NUTS-2 boundaries (Eurostat, 2022). We then use the sf package in R to assign the coordinates to the corresponding NUTS-2 region (Pebesma & Bivand, 2023). This process results in a clear location match for over 99,5% of the startups to NUTS-2 regions.

1 https://hello-tomorrow.org/.

2 One of the authors works in a university Technology Transfer Office since 2020.

Our dependent variable is obtained by counting deep-tech startups assigned to each different NUTS-2 region. To ensure that deep-tech startup counts at regional levels are not biased, we verify whether there are considerable differences between the overall count of deep-tech startups generated with different thesauruses across different regions. This step is performed by analyzing the regional correlation of EIT thesaurus classification results and a fictitious very stringent classification created by identifying a startup as deep-tech only if it is classified as deep-tech by at least two different thesauruses. This process led to a startup-level correlation of 0.98 between the EIT thesaurus and the fictitious stringent classification over the 2015–2021 period used to build the thesaurus. With the test performed, we are confident that allocation errors are similar across regions, thus the regional quantity of deep-tech startups is comparable across different thesauruses. Our methodology, therefore, allows for the reliable operationalization of the deep-tech concept at the regional level in large datasets, overcoming current literature limitations (Romasanta et al., 2022; Ruiz De Apodaca et al., 2022).

3.4 Independent variables

In this section, we describe the operationalization of our independent variables. Table 2 shows a full overview of the variables used for our models with a short description, their empirical indicators, and data sources.

3.4.1 Generic entrepreneurial ecosystem quality

Leendertse et al. (2022) developed a set of metrics to assess the quality of entrepreneurial ecosystems (EEs) across European regions, based on the ten elements outlined by Stam (2015). They utilized data from multiple sources to create a metric for each of these elements. In our study, we adopt the same approach as Leendertse et al. (2022) for operationalizing these elements. Empirical indicators and related data sources are available in Appendix A. Based on the indicators identified by Stam and van de Ven (2021), Leendertse et al. (2022) built an index to assess the quality of entrepreneurial ecosystems (EEs) by combining measurements of the ten components. After standardizing each indicator, they evaluated different methods to calculate an overall index. The additive approach (E1 + E2 + … + E10), where regions with average scores for each component will achieve a total index value of 10, is chosen as most suitable to measure the overall level of the entrepreneurial ecosystem. We use this variable to test H1.

3.4.2 Specific deep-tech enabling knowledge

To create a measure of specific deep-tech enabling knowledge that proxies the local availability of advanced scientific and engineering knowledge, we built a composite indicator consisting of three elements. The three elements are (1) international scientific co-publications (2) scientific publications among the top 10% most cited and (3) number of patent applications under the Patent Cooperation Treaty (PCT). The first two indicators are considered proxies for the quality of scientific research and of the research system. These are retrieved from the 2023 Regional/European Innovation scoreboard and cover the period between 2016 and 2019 (European Commission, 2023a, 2023b). The third indicator instead

Table 2 Operationalization of deep-tech Indicators and related data sources

Elements	Description	Indicators	Data source
Dependent variable			
Output	Deep-tech startups present in the region	Count of the number of deep-tech startups identified by EIT thesaurus in the region.	Crunchbase, data from 2019–2021.
Independent variables			
Generic entrepreneurial ecosystem index	The overall measure of the quality of the regional entrepreneurial ecosystem	Additive EE index Retrieved from Leendertse et al. (2022).	Leendertse et al. (2022), data from 2013–2019.
Specific deep-tech enabling knowledge	Measure of the quantity of high-quality technological output of the region	A composite indicator that considers: (1) International scientific co-publications; (2) Scientific publications among the top 10% most cited worldwide (3) log of the total number of PCT patent applications in the period per region. All values normalized with Min-Max. The composite index is the average of the three values.	(1) and (2) Regional Innovation Scoreboard, data from 2016–2018. (3) OECD, data from 2014–2019.
Specific deep-tech enabling talent	Measure of the presence of R&D talent	Number of people employed in R&D activities in full-time equivalents divided by the total annual average employed population.	Eurostat, data from 2014–2018. However, FR has only 2021 data available, while NL has only data for 2011-12. These values are imputed.
Specific formal institutions	The measure of the degree to which institutions formally support technological innovation	A composite index that considers: (1) share of government expenses in R&D as a percentage of budget and (2) IP protection index. Both variables were normalized with Min-Max standardization. The composite index is the average of the two normalized values.	(1) Eurostat, data from 2015–2018. (2) World Bank, data from 2017 and 2018.
Controls			
Population	The average population of the region	Log of the average number of people living in the region during the timeframe.	Eurostat, data from 2015–2018.
Startups in the region	Overall local presence of startups	Log of the total number of startups present in a region.	Crunchbase, data from 2015–2018.

represents the amount of new technologies in their early stages, since PCT patents can be filed a maximum of one year after the first patent has been filed. This data is retrieved from the OECD (OECD, 2024). For this element, we first assign patents to NUTS-2 regions (based on patent applicant information), and then count all PCT patents filed between 2015 and 2019 for each region. We then take the natural logarithm of the total number of PCT applications to avoid skewed results due to the normalization process. Each component is standardized between 0 and 1 through a Min-Max operation. The final indicator is the average of these three elements. The Cronbach-Alpha value for this variable is 0.79. We use this variable to test H2.

3.4.3 Specific deep-tech enabling talent

To create a measure capable of proxying the local availability of specific deep-tech enabling competencies, we account for the local presence of people employed in research and development activities. This measure includes not only people working in research but "all persons employed directly within R&D activities, as well as persons supplying direct services (such as managers, administrative staff, and clerical staff)" (Eurostat, 2023, 2024a). These people, due to the specificity of their training and jobs, can be considered the people who more realistically might possess the capabilities required to perform technology transfer activities. The data comes from Eurostat, which counts the share of people working in R&D (either in the private sector, government, higher education, or non-profit) expressed in full-time equivalents, divided by the total annual average of the employed population. This operationalization is clearly distinct from how talent is operationalized in the EE index, as that looks at human capital in a more generic way (see Appendix A). For this component, we retrieve data between 2014 and 2018 for most regions, and averaged available data (see Table 2 for details). We use this variable to test H3.

3.4.4 Specific deep-tech formal institutions

To measure the orientation of local institutions toward deep-tech, we built an element composed of two indicators. The first indicator is the overall expense that governments allocate to research and development activities as a share of the government's annual budget, which can be interpreted as a measure of the interest of the government in investing in innovation. This measure was retrieved from the Eurostat database (GBARD expenses), averaging the percentage values between 2015 and 2018 (Eurostat, 2024a, 2024b). The second indicator is a measure of the strengths of the local IP system. The measure is retrieved from the World Bank Global Competitiveness Index 4.0, and data refer to the period between 2017 and 2018 (World Bank, 2024). For both variables, data were available only at the country level; therefore, we assign to each NUTS-2 region the value of the related country in which they are located. Before averaging the values, the data were standardized between 0 and 1 through a Min-Max standardization. The Cronbach-Alpha value for this variable is 0.72. We use this variable to test H4.

3.4.5 Control variables

In our models, we also add the overall population and the lagged number of regular startups present in the region as control variables since both these variables might influence the number of deep-tech startups. The overall population is measured as the log of the average number of inhabitants of the region in the reference period 2015–2018, retrieved from the Eurostat database (Eurostat, 2024b). Similarly, the overall number of startups is measured as the log of the number of startups of the region in the reference period 2015–2018. We did not control for other regional characteristics since they are already extensively covered in the EE framework (See Appendix A for further reference).

3.5 Analysis

Table 3 shows descriptive statistics of the dataset and the correlation matrix.

To test our hypotheses, we estimate a series of negative binomial regressions in the R programming language (R Core Team, 2023). We use negative binomial regressions because our dependent variable is an over-dispersed count variable. To evaluate model improvement, we first fit a model with only the control variables. To test hypothesis 1, we then add the EE index. Following the argument that additional components of deep-tech EE function on top of the overall quality of the generic EE, we test further hypotheses by adding them individually in separate models. Finally, we test a model with all variables.

Before testing the models, we checked for possible multicollinearity problems due to high correlations among variables. The variance inflation factor (VIF) scores do not exceed the suggested threshold of 5 in any of the models.

We test the robustness of our model in different ways. First, since we are dealing with regions nested within countries, we use random intercept negative binomial regressions that allow us to account for country-specific effects that normal binomial regressions are not able to capture (Gelman, 2007). Results of these tests, nevertheless, must be interpreted with caution due to the presence of the deep-tech enabling formal institution variable that is measured exclusively at the country level. Second, we test the robustness of our thesaurus by comparing the results obtained with the EIT classification with the classifications of Hello Tomorrow and our Additional keywords thesaurus built from other public resources. Third, due to the relative stability of EEs over time (Coad & Srhoj, 2023), we perform robustness tests with a broader set of startups established between 2015 and 2021.

4 Results

4.1 Descriptive results

Figures 2 shows a map of Europe with the presence of deep-tech startups in NUTS-2 regions. The map shows that many regions have a relatively low number of deep-tech startups, with a strong concentration in a few regions. The top 10 regions account for 40% of all deep-tech startups identified. Figure 3 provides an overview of the count of deep-tech startups in the 10 regions with the highest number of deep-tech startups. The Inner London region (corresponding to UKI3 and UKI4 NUTS-2 regions together) has the highest number of deep-tech startups (210 startups between 2019 and 2021). Other notable regions with many deep-tech startups are Île-de-France (FR), Lombardy (IT), Cataluña (ES), North and South Holland (NL), the regions surrounding Oxford and Cambridge in the UK, Hovedstaden (region of Copenhagen) in Denmark, and Berlin region (DE). Rankings (generated by the count of deep-tech startups) are stable across different taxonomies.

When comparing the number of deep-tech startups and regular startups in regions, we find several regions that are similar in relative size for both. For example, the two entrepreneurial ecosystems with the largest number of regular startups, Inner London and Île-

Table 3 Descriptive statistics of the sample

	Statistic	Mean	Median	St. Dev.	1	2	3	4	5	6	7
1	Deep-tech startups	5.88	2	15.86	1						
2	Population	14.16	14.21	0.78	0.34	1					
3	Startups in the region	4.59	4.58	1.55	0.51	0.65	1				
4	Generic EE index	8.93	7.66	6.46	0.46	0.14	0.63	1			
5	Specific knowledge	4.46	4.64	1.59	0.38	0.25	0.67	0.85	1		
6	Specific talent	0.8	0.66	0.63	0.61	0.21	0.49	0.58	0.56	1	
7	Specific formal institutions	5.52	5.93	2.35	0.11	0.01	0.34	0.66	0.69	0.25	1

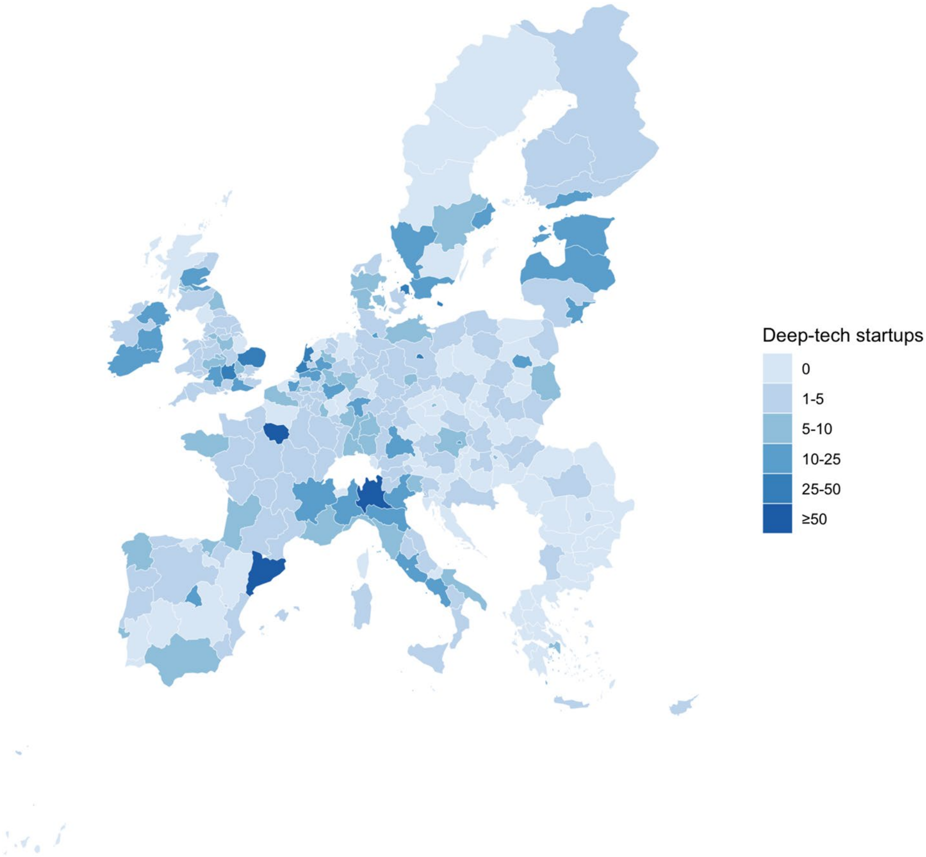

Fig. 2 Presence of deep-tech startups founded between 2019–2021 in European regions according to EIT classification

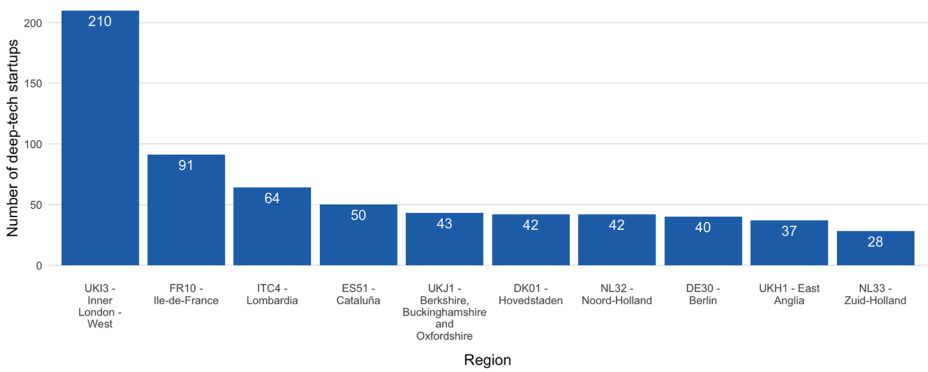

Fig. 3 Regions with the highest number of deep-tech startups founded between 2019–2021, according to EIT-based classification

de-France, are also the largest when it comes to deep-tech startups. However, there are also many regions with clearly more or less deep-tech startups compared to the number of regular startups in these regions. Two UK regions stand out. The East Anglia region (which includes Cambridge) is ranked 26th in the number of regular startups and 9th in the number of deep-tech startups. Similarly, Berkshire, Buckinghamshire and Oxfordshire (which includes Oxford) is 17th in regular startups and 5th in deep-tech startups. Both these regions are considered deep-tech hotspots by practitioners and come forward as such in our data. In a similar way, Italian Emilia-Romagna (Bologna) is ranked 28th overall and 11th in deep-tech and Swedish Sydsverige (Malmö and Lund) is ranked 52nd overall but in 19th when it comes to deep-tech startups. We also find the reverse for some regions. The UK region Manchester (14th overall and 67th in deep-tech), the Dutch region Utrecht (22nd overall and 79th in deep-tech), and the Romanian Region București-Ilfov (49th overall and 123rd in deep-tech) are notable examples of regions with less developed deep-tech entrepreneurial ecosystems. These examples illustrate that deep-tech entrepreneurship is correlated with regular entrepreneurship but that our thesaurus identifies relative deep-tech hotspots and deserts.

4.2 Regression analyses

Table 4 summarizes the results of the negative binomial regression models. The models show Incidence Rate Ratios (IRRs), which show the impact that an increase of one unit on the independent variables has on the dependent variable. As such, a value <1 indicates a negative effect, while a value >1 stands for a positive effect. The McFadden's pseudo R^2 of models 1 to 5 varies between 0.242 and 0.254, while the McFadden's pseudo R^2 of the complete model improves to 0.279. These values suggest a good fit for the negative binomial models. Using log-likelihood comparison tests, we found that models with additional specific deep-tech enabling variables consistently perform better than the simpler model with only control variables and the generic EE index, apart from the model with specific deep-tech enabling formal institutions.

Model 2 shows a significant positive relationship between the EE index and the presence of deep-tech startups in the region. This supports H1, that the overall quality of generic EE is important for the emergence of deep-tech startups. Model 3 supports H2: the presence of higher levels of specific deep-tech enabling knowledge has a positive impact on the emergence of deep-tech startups. Similarly, H3 is supported by model 4, suggesting that the presence of specific deep-tech enabling talent positively influences the emergence of deep-tech startups. The presence of specific deep-tech enabling formal institutions (H4) according to model 5, however, seems to not influence the emergence of deep-tech startups (and accordingly does not improve the explanatory power of the base model with only the overall EE measure). This variable, however, only contains measures available only at the country level, thus these results might be influenced by the reduced variability.

The final model that includes all variables (model 6) again confirms hypotheses 2 and 3 regarding the importance of specific deep-tech enabling knowledge and talent. However, regarding the importance of the influence of generic EE elements and of specific formal institutions, we found mixed evidence. In this model, increases in the generic EE and of specific formal institutions have a diminishing effect on the number of deep-tech startups.

Table 4 Negative binomial regression results, EIT-based thesaurus

Dependent variable: presence of deep-tech startups

	(1)		(2)		(3)		(4)		(5)		(6)	
Predictors	IRR	CI	IRR	CI	IRR	CI	IRR	CI	IRR	CI	IRR	CI
(Intercept)	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00
Population	1.46 ***	1.22–1.76	1.74 ***	1.42–2.14	1.63 ***	1.33–1.99	1.74 ***	1.42–2.12	1.74 ***	1.42–2.14	1.62 ***	1.34–1.96
Startups in the region	2.25 ***	2.05–2.48	1.90 ***	1.66–2.17	1.85 ***	1.62–2.11	1.82 ***	1.60–2.08	1.91 ***	1.66–2.20	1.71 ***	1.50–1.96
Generic EE index			1.03 ***	1.01–1.05	0.98	0.95–1.00	1.01	0.99–1.04	1.03 *	1.01–1.06	0.96 **	0.93–0.99
Specific knowledge					1.46 ***	1.28–1.67					1.53 ***	1.33–1.75
Specific talent							1.49 ***	1.22–1.80			1.45 ***	1.22–1.72
Specific formal institutions									1.01	0.95–1.07	0.97	0.91–1.03
Observations	272		272		272		272		272		272	
McFadden pseudo R^2	0.234		0.242		0.263		0.254		0.242		0.279	
AIC	1125.824		1116.532		1087.003		1101.185		1118.429		1068.262	

*$p<0.05$ **$p<0.01$ ***$p<0.001$

Our control variables, human population and the presence of fellow startups, positively influence the presence of deep-tech startups in regions in all models.

The results of the robustness test in which we use random intercept models are displayed in Table 5. The results are aligned with those in the main analyses. In addition, we find differences between countries. Measures of country-specific effects (such as the variance of the random intercept tau and the Interclass Correlation Coefficient, and the Conditional R^2) highlight that country-specific factors explain additional differences in the emergence of deep-tech startups across regions[3].

We also performed robustness tests by running the same models for the different classifications of deep-tech startups created with the two additional thesauruses. Table 6 summarizes the results of these additional robustness tests, highlighting similar results. The McFadden's pseudo R^2 of the complete models varies between 0.262 and 0.278 (complete tests are available in Appendix C). Comparable results were obtained when considering a larger set of data regarding startups established between 2015 and 2021.

Overall, we find full support for H2 and H3 regarding the importance of the presence of specific deep-tech enabling knowledge and talent to facilitate the emergence of deep-tech startups in regions. The hypothesis regarding the importance of the overall level of the generic entrepreneurial ecosystem (H1) is supported only in simpler models, but not in the full model. We do not find support for H4, regarding the importance of specific deep-tech enabling formal institutions for facilitating the emergence of deep-tech startups.

5 Discussion

5.1 Conclusion and theoretical implications

Our study further extends the literature on EE beyond its sector-agnostic focus (Stam & van de Ven, 2021) by investigating which EE elements influence the presence of deep-tech startups in a region.

Our study contributes to the debate about generic vs. specific entrepreneurial ecosystems (see van Rijnsoever and Leendertse, 2025) by demonstrating that technology specific resources, such as deep-tech enabling knowledge and human capital, are a valuable addition to explain the emergence of deep tech startups in a region. These insights also align with the KSTE (Audretsch & Lehmann, 2005; Ghio et al., 2015), highlighting how central the stock of human capital and knowledge are in enabling the emergence of different types of startups in a region.

These results therefore reinforce Leendertse and van Rijnsoever's (2025) conceptualization of specific EEs as a nexus between generic EE and specific innovation systems, demonstrating that understanding the influence of EEs on deep-tech startups requires the inclusion of elements that address the unique challenges faced by that type of ventures. However, while Leendertse and van Rijnsoever (2025) found that the overall quality of the generic EEs is the strongest factor in supporting sustainable startups presence, our results indicate

[3] Likelihood-based pseudo-R^2 measures used in the negative binomial regressions (such as McFadden's measure) are defined for fixed-effects models only, and are not comparable once random effects are introduced. For the random intercept models consequently the marginal and conditional R^2 displayed in Table 5 is the Nakagawa R^2.

Table 5 Random intercept negative binomial regression

Dependent variable: presence of deep-tech startups										
	(2)		(3)		(4)		(5)		(6)	
Predictors	IRR	CI	IRR	CI	IRR	CI	IRR	CI	IRR	CI
(Intercept)	0.00 ***	0.00–0.01	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00	0.00 ***	0.00–0.01	0.00 ***	0.00–0.00
Population	1.38 **	1.09–1.74	1.38 **	1.10–1.73	1.50 ***	1.19–1.88	1.38 **	1.10–1.75	1.49 ***	1.19–1.86
Startups in the region	2.16 ***	1.85–2.52	2.05 ***	1.76–2.38	1.96 ***	1.67–2.29	2.17 ***	1.86–2.53	1.85 ***	1.58–2.16
Generic EE index	1.04 **	1.01–1.06	0.99	0.96–1.02	1.02	0.99–1.04	1.03 *	1.01–1.06	0.97	0.94–1.00
Specific knowledge			1.38 ***	1.18–1.62					1.40 ***	1.19–1.66
Specific talent					1.39 ***	1.15–1.68			1.36 ***	1.14–1.63
Specific formal institutions							1.03	0.93–1.14	0.98	0.89–1.09
Random effects										
σ2	0.30		0.29		0.29		0.29		0.28	
τ00	0.20 country		0.19 country		0.19 country		0.20 country		0.14 country	
ICC	0.40		0.40		0.39		0.41		0.34	
N	28 country		28 country		28 country		28 country		28 country	
Observations	272		272		272		272		272	
Marginal R^2 / Conditional R^2	0.817 / 0.891		0.844 / 0.905		0.809 / 0.884		0.822 / 0.895		0.845 / 0.898	
AIC	1080.014		1065.157		1069.267		1081.628		1055.352	

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table 6 Negative binomial regression, comparison among classifications obtained with different thesauruses

Comparison among taxonomies						
	EIT		Hello Tomorrow		Additional	
Predictors	IRR	CI	IRR	CI	IRR	CI
(Intercept)	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00
Population	1.62 ***	1.34–1.96	1.56 ***	1.31–1.86	1.48 ***	1.25–1.74
Startups in the region	1.71 ***	1.50–1.96	1.75 ***	1.55–1.98	1.80 ***	1.60–2.02
Generic EE index	0.96 **	0.93–0.99	0.95 ***	0.93–0.98	0.97 *	0.94–0.99
Specific knowledge	1.53 ***	1.33–1.75	1.50 ***	1.32–1.70	1.45 ***	1.29–1.64
Specific talent	1.45 ***	1.22–1.72	1.46 ***	1.24–1.73	1.26 **	1.08–1.46
Specific formal institutions	0.97	0.91–1.03	0.95	0.90–1.01	0.92 **	0.87–0.98
Observations	272		272		272	
McFadden pseudo R^2	0.278		0.272		0.262	
AIC	1068.262		1161.382		1245.026	

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

that for deep-tech startups the specific EE elements are most important. By highlight that different types of startups might differ in how dependent they are on generic or specific EE elements, we argue that recognizing the differences among startups is therefore essential to explaining why certain types of startups emerge in some contexts but not in others, thus making it worthwhile to better integrate into the EE theory.

Understanding specific EE dynamics therefore might require the explicit inclusion of startup specific characteristics derived by adjacent theories. Future research should focus on better specifying these differences and integrating them into adapted and specific EE frameworks to better understand why certain forms of entrepreneurship emerge in some contexts but not in others.

Our study moreover makes two important contributions to the emerging literature on deep-tech (Romasanta et al., 2022; Romme et al., 2023; Ruiz De Apodaca et al., 2022). First, our extended conceptualization of deep-tech gives a theoretical grounding to the concept that was currently missing. Second, by outlining a method that enables a reliable identification of deep-tech startups at the regional level (based on the EIT taxonomy of deep-tech), we provide a tool to operationalize a concept that as far as of today was quite fuzzy.

5.2 Limitations and further research

This research comes with several limitations. First, the concept of what can be considered deep-tech evolves: what is deep-tech today may not be considered deep-tech in the future. We operationalize what is considered deep-tech during the time of our analyses; thesauruses must be updated and stress-tested over time to include novel technologies and exclude technologies that become established. Second, even though our thesaurus had a high accuracy (96%) in correctly predicting the type of startups and is thus well suited to analyze the regional presence of deep-tech startups, only a small percentage are deep-tech startups. Consequently, there is a class imbalance that entails challenges for the identification at the firm level. Future research may address these two problems and stress-test our findings by updating and refining the open-access (CC BY-SA 4.0 license) thesauruses created for this research.

Third, our research includes a cross-sectional design with a lag between our independent and dependent variables. Unfortunately, the data for our independent variable is not available in a panel format which limits our ability to perform longitudinal research. This is a limitation that should be addressed in future research. Despite the time lag included, dependent and independent variables still partially overlap due to the difficulties of creating EE indexes (composed by several terms and sub-terms). Even if EEs tend to be relatively static over time (Coad & Srhoj, 2023), future research should focus on these two aspects to better clarify potential issues of various forms of endogeneity that might limit the validity of our findings.

Fourth, there are potentially differences in the coverage of our dependent variable (Crunchbase) between countries. We partly account for this by controlling for country-specific effects and by including the absolute number of startups in a region as a control variable. However, given the increased use of Crunchbase data in EE research we do recognize that future research is needed to better understand potential regional differences.

Finally, we focus only on the presence of deep-tech startups, overlooking subsequent growth phases. Future research might further investigate whether the elements identified as important for the presence of deep-tech startups have the same importance for the scaling of such initiatives.

Future research can also look into how best to increase the amount of deep-tech enabling talent in a region. Our research shows that this is an important driver of deep-tech startups, but unfortunately there is not sufficient research on which types of education impact the development of specific deep-tech enabling talent and how this translates into regional capabilities. We therefore call for future research on the mechanisms through which education facilitates deep-tech capabilities development.

5.3 Practical implications

Our work offers several implications for government and university policy makers. Our study provides insights in where deep-tech startups in Europe are founded and which conditions enable the presence of deep-tech startups in regions. This is a crucial topic given changes today's geopolitical landscape which requires an increased focus on strategic autonomy in Europe. Deep-tech startups play a key role in enabling this strategic autonomy.

We provide insight in the distribution of deep-tech startups across Europe. We show that deep-tech startups tend to be clustered in a select number of regions and that there are stark differences regarding the share of deep-tech startups in regions. For example, the region around Cambridge in which 14.5% of startups are deep-tech, a share that fast exceeds the European average of 4.5%. Our research thus allows policymakers to identify regions that excel at the founding of deep-tech startups, and to learn why. In addition, the clustering of deep-tech startups serves as an indication that policies aiming to create deep-tech startups everywhere might not be relevant. We argue that deep-tech policies should focus on the regions with the highest potential.

Our results suggest that stimulating the creation of technological knowledge and developing (or attracting) talent with technology transfer capabilities are crucial for facilitating the emergence of deep-tech startups in regions, aligning with Draghi's recommendations to increase European competitiveness (Draghi, 2024b). We suggest that more attention should be paid to education that develops technology transfer competencies and to strengthening the capabilities to develop frontier technological knowledge. Universities play a crucial role in this endeavor. Universities can better align educational offerings to equip students with appropriate instruments to understand and manage the fast-changing technological landscape. In Europe, efforts in this regard have already been under implementation for a few years (i.e. the EIT Deep-Tech talent initiative[4], the DT Launchpad[5], or more in general the initiative under the Flagship 4 program[6]), but there is still a lack of effective impact (Draghi, 2024a, 2024b). Better monitoring tools are therefore required to verify the effective development of such important capabilities and knowledge required to strengthen future European competitiveness.

To conclude, our analysis highlights again that regional development strategies cannot rely on a one-size-fits-all approach. Instead, they must account for the heterogeneous

[4] https://www.eitdeeptechtalent.eu/.

[5] https://dtlaunchpad.eu/.

[6] https://research-and-innovation.ec.europa.eu/strategy/support-policy-making/shaping-eu-research-and-innovation-policy/new-european-innovation-agenda/new-european-innovation-agenda-roadmap/flagship-4-fostering-attracting-and-retaining-deep-tech-talent_en.

resource requirements associated with different types of startups. By doing so, our framework provides a more nuanced analytical lens for assessing regional strengths and bottlenecks, and for designing policies tailored to the specific entrepreneurial profiles of regions.

Appendix A: Elements of the generic entrepreneurial ecosystem framework

See Table 7

Table 7 Operationalization of the indicators of ten entrepreneurial ecosystem elements, adapted from Leendertse et al. (2022)

Element	Empirical indicator	Data source
Formal institution	A composite measure that considers the overall quality of government (consisting of scores for corruption, accountability, and impartiality) and the ease of doing business	Quality of Government Survey (QOG) and the World Bank Doing Business Report, 2015–2017
Entrepreneurial culture	A composite measure capturing the regional entrepreneurial culture, consisting of entrepreneurial motivation, cultural and social norms, importance of being innovative, and trust in others.	European Social Survey (ESS), Global Entrepreneurship Monitor (GEM), and OECD, Eurostat, and national statistics offices, 2008–2016
Network	Percentage of SMEs that engage in innovative collaborations as a percentage of all SMEs in the business population	Regional Innovation Scoreboard (RIS), 2016
Physical infrastructure	Four components in which the transportation infrastructure is measured as the accessibility by road, accessibility by railway and number of passenger flights and digital infrastructure is measured by the percentage of households with access to internet	Regional Competitiveness Index (RCI), 2014–2018
Finance	Two components: The average amount of venture capital per capita and the percentage of SMEs that is credit constrained	Invest Europe and European Investment Bank (EIB), 2014–2019
Leadership	The number of coordinators on H2020 innovation projects per capita	Community Research and Development Information Service (CORDIS), 2014–2019

Table 7 Operationalization of the indicators of ten entrepreneurial ecosystem elements, adapted from Leendertse et al. (2022)

Element	Empirical indicator	Data source
Talent	Four components: The percentage of the population with tertiary education, the percentage of the working population engaged in lifelong learning, the percentage of the population with an entrepreneurship education, the percentage of the population with e-skills	Eurostat and the Global Entrepreneurship Monitor (GEM), 2013–2014
New knowledge	Intramural R&D expenditure as a percentage of Gross Regional Product	Eurostat, 2015
Demand	Three components: disposable income per capita, potential market size expressed in GRP, potential market size in population. All relative to EU average.	Regional Competitiveness Index (RCI), 2014–2018
Intermediate services	Two components: the percentage of employment in knowledge-intensive market services and the number of incubators / accelerators per capita	Eurostat and Crunchbase. 2018–2018 data

Appendix B: Thesauruses and resources used to build the "Additional" thesaurus

The ***EIT*** and the ***Additional keyword*** thesauruses have been published open-access (CC BY-SA 4.0license) at this link: https://data.mendeley.com/datasets/9s8zyzk4tp/2.

The ***EIT*** thesaurus contains a total of 304 different keywords (74 type 1, 85 type 2, 145 type 3).

The ***Additional keyword*** thesaurus contains a total of 357 different keywords (114 type 1, 98 type 2,145 type 3). This is the list of references upon which the thesaurus has been built.

Resource	Link
EIT taxonomy	https://www.eitdeeptechtalent.eu/the-initiative/what-is-deep-tech/
TNO and NOW, 2023—Herijking sleuteltechnologieën 2023	https://www.tno.nl/nl/newsroom/2023/04/nieuwe-lijst-44-sleuteltechnologieen/
Dealroom, 2021—The year of Deep-Tech report	https://dealroom.co/blog/2021-the-year-of-deep-tech
Dealroom, 2023—European Deep-Tech report (January) (link to download the PDF file)	https://content.dealroom.co/uploaded/2023/01/Dealroom-European-Deep-Tech-2023report.pdf
Dealroom, 2023—European Deep-Tech report (November)	https://dealroom.co/reports/the-european-deep-tech-report-2023
MIT The Engine Reports	https://engine.xyz/reports

Resource	Link
Present Future: Business, Science, and the Deep Tech Revolution, 2021 – Perelmuter Guy, Fast Company Press	https://www.amazon.com/Present-Future-Business-Science-Revolution/dp/173542451X

The ***Hello Tomorrow*** thesaurus contains a total of 447 different keywords (97 type 1, 161 type 2,189 type 3). The keywords of this thesaurus are not publicly disclosable.

Appendix C: Additional robustness tests

Test with the thesaurus of keywords based on the Hello Tomorrow taxonomy. VIF of all variables is below 5.

Dependent variable: presence of deep-tech startups												
	(1)		(2)		(3)		(4)		(5)		(6)	
Predictors	IRR	CI	IRR	CI	IRR	CI	IRR	CI	IRR	CI	IRR	CI
(Intercept)	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00
Population	1.48 ***	1.24–1.75	1.65 ***	1.36–2.00	1.56 ***	1.30–1.88	1.64 ***	1.36–1.98	1.65 ***	1.36–2.00	1.56 ***	1.31–1.86
Startups in the region	2.18 ***	2.00–2.39	1.96 ***	1.73–2.23	1.90 ***	1.68–2.15	1.89 ***	1.67–2.14	1.95 ***	1.71–2.22	1.75 ***	1.55–1.98
Generic EE index			1.02 *	1.00–1.04	0.97 *	0.95–0.99	1.00	0.98–1.02	1.02 *	1.00–1.05	0.95 ***	0.93–0.98
Specific knowledge					1.42 ***	1.25–1.60					1.50 ***	1.32–1.70
Specific talent							1.54 ***	1.28–1.86			1.46 ***	1.24–1.73
Specific formal institutions									0.99	0.93–1.05	0.95	0.90–1.01
Observations	272		272		272		272		272		272	
McFadden pseudo R^2	0.230		0.233		0.253		0.247		0.233		0.272	
AIC	1219.497		1216.529		1187.449		1196.161		1218.382		1161.382	

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Test with the thesaurus of keywords based on Additional Keywords collected from different sources (See Appendix B for a complete list and references). VIF of all variables is below 5.

Dependent variable: presence of deep-tech startups												
	(1)		(2)		(3)		(4)		(5)		(6)	
Predictors	IRR	CI	IRR	CI	IRR	CI	IRR	CI	IRR	CI	IRR	CI
(Intercept)	0.00 ***	0.00–0.01	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00	0.00 ***	0.00–0.00
Population	1.41 ***	1.20–1.65	1.53 ***	1.28–1.83	1.48 ***	1.24–1.76	1.52 ***	1.28–1.82	1.54 ***	1.29–1.83	1.48 ***	1.25–1.74
Startups in the region	2.20 ***	2.03–2.39	2.03 ***	1.80–2.29	1.96 ***	1.74–2.20	1.97 ***	1.75–2.21	2.00 ***	1.77–2.25	1.80 ***	1.60–2.02
Generic EE index			1.02	1.00–1.03	0.97 *	0.95–0.99	1.00	0.98–1.02	1.02 *	1.00–1.05	0.97 *	0.94–0.99

Dependent variable: presence of deep-tech startups												
	(1)		(2)		(3)		(4)		(5)		(6)	
Specific knowledge					1.35 ***	1.21–1.52					1.45 ***	1.29–1.64
Specific talent							1.32 **	1.11–1.56			1.26 **	1.08–1.46
Specific formal institutions									0.97	0.92–1.02	0.92 **	0.87–0.98
Observations	272		272		272		272		272		272	
McFadden pseudo R^2	0.231		0.233		0.250		0.240		0.234		0.262	
AIC	1288.746		1287.417		1262.449		1278.397		1288.203		1245.026	

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

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Declarations

Competing interests The authors declare no competing interests.

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